DOCTORAL THESIS

EVOX-CPS: A Methodology for Data-Driven Optimization of Building Operation

Mischa Schmidt

Pervasive and Mobile Computing

LULEÅ UNIVERSITY OF TECHNOLOGY

EVOX-CPS: A Methodology for Data-Driven Optimization of Building Operation

Mischa Schmidt

Department of Computer Science and Electrical Engineering
Luleå University of Technology
Luleå, Sweden

Supervisors:

Prof. Christer Åhlund, Dr. Robert Brännström, Dr. Anett Schülke

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"I do not fear computers. I fear the lack of them." —Isaac Asimov

Abstract

Existing building stock's energy efficiency must improve due to its significant proportion of the global energy consumption mix. Predictive building control promises to increase the efficiency of buildings during their operational phase and thus lead to a reduction of the lion's share of buildings' lifetime energy consumption. Predictive control complements other means to increase performance, such as refurbishments as well as modernization of systems.

This thesis contributes **EVOX-CPS**, a **holistic methodology to develop data-driven predictive control for (existing) buildings and deploy the control in day-to-day use**. EVOX-CPS evolves buildings into Cyber-Physical Systems and addresses the development of data-driven predictive control using computational methods. The thesis' focus rests on accounting for the situation of existing buildings - which vary greatly regarding their physical characteristics, usage patterns, system installation, and instrumentation levels. The methodology addresses the aspect of building stock variety with its capability to flexibly adapt to different buildings' characteristics, e.g., by supporting the integration of varying levels of pre-existing building instrumentation. Furthermore, EVOX-CPS supports using different data mining, regression, or control techniques (i) to strengthen the support for a variety of buildings, and (ii) to cater to researchers' and practitioners' differing skills, experiences, or preferences concerning different data analysis techniques. Through its flexibility, the methodology addresses a vast potential installation base and lowers the barriers for adoption in day-to-day use, e.g., by being able to leverage prior investments in building instrumentation and supporting different data-analysis techniques. At the same time, EVOX-CPS provides researchers and practitioners with comprehensive guidance relevant to their daily work. Besides, EVOX-CPS supports addressing a building's known limitations in the daily operation, e.g., uncomfortable indoor conditions.

The experimentation in two real buildings validates the effectiveness of EVOX-CPS' data-driven control with high reliability due to prolonged experimentation periods combined with applying energy normalization and inferential statistics. The experiments during routine heating system operation establish high confidence in the recorded effect sizes: the improvements in operational efficiency are profound and statistically significant. More specifically, the experiments of controlling the grass heating system of the soccer stadium Commerzbank Arena, Frankfurt, Germany, in two winters saved up to 66% (2014/2015) and 85% (2015/2016) of energy consumption. Extrapolation to an average heating season leads to expected savings of 775 MWh (148 t of CO_2 emissions) and 1 GWh (197 t CO_2), respectively. The experiments also show that EVOX-CPS allowed

alleviating the known operational limitation of heating supply shortages which required nightly preheating in the stadium's standard operating procedures. In another set of experiments, we applied the methodology to control the heating system of the Sierra Elvira School in Granada, Spain. The experimentation occurred during the regular class hours of 43 school days in winter 2015/2016. A first experiment demonstrated the possibility to lower consumption by one-third while maintaining indoor comfort. Another experiment raised average indoor temperatures by 2K with 5% additional energy consumption. Again, that illustrates EVOX-CPS' capability to address a building's known operational issues.

Contents

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I am grateful for the flexibility granted to me and the support I received from both my employer NEC Laboratories Europe and Luleå University of Technology. Without it, I could not possibly have succeeded at participating in courses and lectures, pursued my research, and continued with the variety of my daily work responsibilities.

Finally, and most importantly, I would like to thank my friends, my family, and Anne-Kathrin for always being there, supporting and understanding. Without you, I would not be where I am now.

Heidelberg, March 2018
Mischa Schmidt

Part I

Chapter 1

Introduction

"Ninety-seven percent of climate scientists agree that climate-warming trends over the past century are very likely due to human activities, and most of the leading scientific organizations worldwide have issued public statements endorsing this position."

NASA Climate Change Website [1]

1.1 Motivation

Buildings take a central place in human life. They are globally ubiquitous, and they are significant consumers of energy. In 2010, the building sector accounted for 19% of all global greenhouse gas (GHG) emissions and 32% of global final energy use [2]. In the same year in the US, residential, commercial, and industrial buildings jointly accounted for 41% of the primary energy use of the US with close to 75% of this consumption being served by fossil fuels [3]. In Europe, the ODYSEE and MURE databases indicate that buildings accounted for 40% of the EU-28 final energy use in 2012, with residential buildings being responsible for two-thirds of the total building consumption [4]. For the US, residential buildings used slightly more than half of the total building energy consumption [5]. In 2013, 60% of New York City's GHG emissions stemmed from buildings in general - residential buildings as the most significant source accounted for 37% [6]. In densely populated areas of Taiwan, buildings account for more than half of the area's total CO_2 emissions [7].

In the US, the major end-uses are space heating (37%), water heating (12%), space cooling (10%) and lighting (9%). Together they exceed two-thirds of buildings' energy consumption [3]. For residential buildings, [8] illustrates the high variability of the energy end use breakdown due to regional differences, but thermal end uses dominate the energy demand consistently. In 2010, space heating as the most significant end-use accounted for one-third of the global building stock's final energy consumption [2].

Globally, buildings increased direct GHG emissions by 1% each year since 2010. While coal and oil use has remained approximately constant, natural gas consumption grew steadily by 1% annually. In addition, electricity demand in buildings outpaced the annual improvements in the electricity generation CO_2 intensity per kilowatt hour during the same period. Thus, buildings' indirect GHG emissions balance increased, too [9].

For typical buildings, irrespective of the type of construction, the building operational phase "dominates the life cycle energy use, life cycle CO2 emissions" [10]. For conventional buildings, it accounts for up to 90% of the life cycle energy consumption, for low energy buildings up to 50%. These figures confirm earlier findings in [11]. Thus, the potential impacts of solutions to improve the operational efficiency of buildings are enormous and globally significant: they could lower building energy cost, fossil fuel consumption, and the associated emissions.

Buildings' local environments differ due to climatic differences, economic aspects, differences in available technology and know-how, and differences in national regulation. Additionally, buildings' characteristics vary regarding usage patterns, age, materials used, and system installations. Hence, buildings vary exceedingly concerning the characteristics determining their energy demand. That presents a challenge to formulating generally applicable solution concepts as these must address that variety. To maximize their impact, they must apply to existing as well as new buildings, ideally with low barriers to adoption. Current practice shows that most measures to increase buildings' energy efficiency rely on equipment modernization and building refurbishment [12]. That concept is labor-intensive, costly, time-consuming, and may impact the building occupants. This thesis follows a different approach demonstrated feasible by multiple studies (see paper F [13]): to improve operation efficiency by applying computational methods, such as Artificial Intelligence (AI), to data from buildings.

1.2 Research Question / Objective

The approach of this thesis is to draw on information and communication technologies (ICT) and improve building operation efficiency by developing predictive building control using data-driven techniques. Leveraging computational methods to improve efficiency qualifies these studies - and this thesis - as belonging to the interdisciplinary field of *Sustainable Computing* (SC). Because data-driven methods control physical building processes, this work also belongs to the domain of *Cyber-Physical Systems* (CPS). Besides, the thesis is embedded in the field of *Pervasive Computing* as it draws extensively on sensors and actuators, computational methods, and applies to a ubiquitous target group: buildings.

A large body of research demonstrates the feasibility of applying data-driven methods to increase buildings' energy efficiency levels. Our survey paper F [13] identifies a lack of a comprehensive methodology guiding researchers and practitioners to develop and deploy CPS for controlling building operations. In particular, existing buildings are not addressed adequately by the literature - papers do not address aspects of integration with routine operation nor adopting pre-existing building instrumentation. Survey paper F [13] captures that gap in research question 1, which guides this thesis:

What is a suitable methodology to evolve existing buildings into a CPS for higher levels of operational efficiency?

Therefore, this thesis' research objective is to develop and validate a suitable methodology, ideally integrating pre-existing building instrumentation infrastructure and requiring only little extra equipment installation.

1.3 Research Method

This thesis focuses on existing buildings with at least a rudimentary level of instrumentation, i.e., some form of Building Management System and sensor installations. The following steps underpin this thesis.

- Literature review

  A review of the relevant studies, methodologies, and modeling techniques identifies the state of the art and gaps indicating the need for additional research. The review of literature for scientific progress continues throughout the Ph. D. project. With the conclusion of the thesis, paper F [13] captures the most recent survey version. In particular, paper F finds a lack of a comprehensive and flexible methodology for deploying data-driven predictive control to enhance the operational efficiency of existing buildings, which is captured in Section 1.2 guiding this thesis.

- Iterative methodology development, experimental validation, and refinement

  The initial hypothesis is that data-driven control can be developed for existing buildings leveraging their pre-existing automation infrastructure by treating each building as a software development project. From the project management discipline follows that discussions with stakeholders are essential to understand their expectations, the building operation, and the operational problems and targets. A data aggregation platform enables interfacing with the building infrastructure and additional data sources as needed. Exploratory data analysis supports the discussions with the stakeholders. Subject-matter literature review and discussions with the technical staff help to identify the possibilities and the limits of building operation.

  To validate the concept and confirm the hypothesis, we apply the approach in a first public building. The initial data-analysis and several rounds of technical discussions lead to an in-depth understanding of which system to focus on improving on. Defining operational boundary conditions and discussing first simple control algorithms with the operational staff surfaces misunderstandings and allows refinements.

  A first series of experiments with simple control heuristics confirms the hypothesis that data-driven control satisfies the control targets and improves operation. That allows to move on to advanced control concepts and changing the status-quo best practice heating operation. Iterations of data analysis and control algorithm evolution lead to additional performance increases. Online monitoring during the experiments allows quick fixing of programming errors and reacting to unexpected behavior. Publishing studies, concepts, and experiments' results at conferences allows to collect and integrate additional feedback from the scientific community.

These iterative experiments of gradually increasing sophistication successfully validate the initial methodology. The ongoing literature review identifies relevant concepts of general nature that can provide additional guidance to the practitioner. Consequently, the project-based approach is enhanced with aspects of these additional concepts adapted to the specifics of existing buildings' operations.

The enhanced methodology is applied to a second building, again in an iterative fashion. Again, stakeholder discussions, technical discussions with operational staff, and data analysis lead to a series of validation experiments to improve the building operation. Technical concerns during the first experiment are addressed and lead to adjustments in the control algorithms and the implementation of additional safeguards. The publication of a data modeling study allows to collect and integrate additional feedback from the scientific community. A thorough analysis of the second building's experiments and detailed stakeholder feedback confirm the methodology's applicability to improve the operational performance of existing buildings, leverage their infrastructure, and integrate the enhanced control within the routine operation.

Publishing the initial project-based methodology and the evolved methodology together with experimental results in two different scientific journals establishes high confidence in the applied and evolved methodological approach, as well as in the methods of analyzing and discussing the results.

- Discussion of methodology, experiment results, and the broader impacts on society

  The literature does not provide a building-specific methodology leveraging existing buildings' pre-existing infrastructure to compare against. Thus, the thesis focuses on the methodology's qualitative characteristics and aspects differentiating it from the concepts taken inspiration from.

  This thesis addresses a globally pressing problem: increasing the energy efficiency of buildings, ideally with low barriers to adoption and adaptive to the local situation. In light of the statistically significant and weather-normalized validation experiments' results, we infer and discuss the possible qualitative implications of a widespread adoption relying on global statistics, macroeconomics, and several recent studies from different fields based on the preceding discussions.

1.4 Thesis Outline

The subsequent Chapter 2 introduces concepts and methods that are relevant to our methodology in Chapter 3. Then, Chapter 3 presents the thesis' core contribution:

the methodology to improve existing buildings' operations using sensor data and other relevant information. The chapter summarizes the results of our validation experiments in the Commerzbank Arena in Frankfurt, Germany, and the Sierra Elvira School in Granada, Spain. Besides, it also presents our published papers A-G constituting this thesis. Chapter 4 discusses EVOX-CPS in relation to the state of the art and related work, and also puts it into the broader context of sustainability. Chapter 5 concludes the thesis by summarizing the main findings and providing an overview of future research directions.

Chapter 2

Background

"Less than 10% of the code has to do with the ostensible purpose of the system; the rest deals with input-output, data validation, data structure maintenance, and other housekeeping."

Mary Shaw

2.1 Introduction

This thesis summarizes our research on applying computational methods to building data and leveraging existing building automation information and communication technology (ICT) infrastructure as suggested in [14]. This chapter presents architectures, concepts, methods, and technologies relevant to that approach. They are candidate methods to be used in the different EVOX-CPS steps as presented in Chapter 3.1. Survey paper F [13] provides additional details on the described aspects.

2.2 Building Energy Application Key Performance Indicators

2.2.1 Section Purpose

Appropriate Key Performance Indicator (KPI) definitions enable to measure improvements of operational efficiency and to optimize building operations. The following list provides a summary of KPIs most commonly found in the literature. They are relevant for the EVOX-CPS for controlling the building and evaluating the control logic performance.

2.2.2 Key Performance Indicators

- *CO_2 emissions.* Considering buildings' emissions provided in Section 1.1, reducing these emissions is an intuitive efficiency target when operating building systems. Typically, this KPI is not measured directly but derived from the energy consumption by a conversion factor related to the system's energy source and consumption.

- *Comfort*: This term expresses how well a control application can create conditions in which human occupants feel comfortable. Several studies indicate that discomfort can have a profound socio-economic impact, adversely affecting, e.g., the productivity of office workers [15, 16] or the learning progress of students [17]. The literature covers different ways to assess comfort, and recent survey [18] provides more insights into the state of the art.

  - For *thermal* comfort, the current practice typically treats indoor air temperature targets or operative temperature ranges [19, 20] as proxies to meeting thermal comfort targets. Unfortunately, that practice neglects other parameters of importance, such as solar radiation or humidity. To address this, the most common thermal comfort index adopted by international standards is Fanger's *Predictive Mean Vote* (PMV) model [21]: ISO 7730 [22], ASHRAE 55 [23], and EN 15251 [24] rely on it. As calculating the PMV requires data that in real building operations is hard to come by, these standards make several assumptions and simplifications which can cause thermal comfort violations during building operation - in particular for buildings with low thermal mass [25].
  - Also *Indoor Air Quality* (IAQ) can be a source of (dis-)comfort. CO_2 and humidity levels, as well as the concentration of different pollutants, are the main parameters of concern. For example, by tuning the controllers of an underground station's ventilation system, particulate matter concentrations on the platform can be stabilized even during rush-hours [26].
  - *Light* levels, measured in lux, are relevant for applications of smart blinds and lighting control.

- Many studies use *Energy* - in kilowatt-hours [kWh], kilojoules [kJ] or tonnes of oil equivalent [Toe] over a defined period - to assess the efficiency and sustainability of building operation. Often, the energy consumption is normalized per visitor (public buildings), employee (office buildings), or floor area to enable comparisons among different buildings' operations or across different periods of consideration. For heating and cooling systems, additional normalization for weather effects (Section 2.6) is appropriate to enable proper analysis, benchmarking, and generalization across different years.

- *Exergy* measures the maximum available energy for doing work according to the Second Law of Thermodynamics. Unlike energy, exergy is not conserved. For example, low-temperature floor heating outperforms other high-temperature, boiler-based space heating systems regarding exergy [27].

- *Temperature*, measured in the controlled zone or system, can be used as an absolute reading or put in relation to an application-specific target temperature. Often, temperature is part of comfort KPI assessment.

- If a building system uses a mix of renewable and fossil fuel sources, the ratio of source use as captured in the *green factor* can give insights into the environmental friendliness of operation. It may well be ecologically sensible to increase energy consumption, if the increased consumption offsets CO_2 emissions caused by fossil fuels, e.g., in scenarios where rooftop photovoltaic panels provide the energy to air conditioning to cool the building down at times when cooling is not yet needed to avoid later electricity grid energy usage. For example, [28] weighs the *Non-Renewable Energy Consumption* against thermal comfort scores to control air conditioning.

- Typically, building systems have a defined range operational parameters or KPIs to achieve. The amount of time a system does not operate up to the defined target can be captured as *Underperformance Time (UPT)*. When this range is only in effect during distinct periods, such as office hours, then it is more appropriate to express the performance in terms of the *Underperformance Ratio (UPR)*, by putting the UPT in relation to the amount of time the target range was in effect.

- While heating is the single most significant end use of energy in buildings, indirect emissions originating from electricity generation represent the largest part of their GHG emissions [2]. For reducing electricity-related emissions, it is beneficial to shift and adjust building consumption patterns to renewable energy sources' generation patterns. Due to that, and for reasons of increasing the electricity grid's stability in the presence of renewables, grid operators actively pursue Demand Response (DR) [29]. DR requires communication capabilities between the electricity grid and the consumers [30]. The amount of DR requests met, i.e., the energy demand shifted is a meaningful control KPI. That KPI is related to the green factor, and similarly, DR may increase the total energy demand. However, that higher demand is "green" as it is associated with fewer GHG emissions and can serve time-flexible loads that otherwise would be served by fossil fuels.

2.2.3 Relevance to the Ph. D. Project Work

Publications A, B, C and D [31–34] contained in this thesis rely on the grass heating system's energy consumption for ease of exposition in discussions with the operation experts. For the initial data analysis, papers A and B [31,32] use the grass root temperature. To evaluate how well the validation experiments meet the thermal targets, papers C and D [33,34] use UPR. Finally, papers C and D [33,34] translate the energy savings into avoided CO_2 emissions based on the fuel characteristics as found in official statistics from Germany.

Publications E and G [35, 36] rely on indoor room temperature to assess pupils' thermal comfort and the heating system's energy consumption.

2.3 Smart Buildings as Cyber-Physical Systems

2.3.1 Section Purpose

This section establishes a link between Cyber-Physical Systems, buildings, and concepts relevant to data-driven predictive control for improving buildings' operations.

2.3.2 Cyber-Physical Building Systems

Newly constructed as well as already pre-existing buildings are often already equipped - to a varying degree - with building automation infrastructure to assist building operational staff. The automation and control strategies of existing buildings typically are somewhat simplistic, e.g., heating system supply temperatures are chosen based on the outside air temperature or systems operate based on fixed schedules. Studies of the field of SC[1] show that it is possible to improve building system operation by predictive control concepts. In the context of this thesis, buildings with at least rudimentary *smart*ness - sensing and automation capabilities - are considered *Cyber-Physical Systems* (CPS)[2]. [39] expects that CPS concepts will contribute to advances in the field of smart buildings. The general CPS definition of [38] includes simple rule-based mechanisms - the de-facto standard in existing buildings - as long as cyber components and physical components interact. However, this thesis focuses on CPS as using computational representations of the underlying physical processes to implement *predictive* control strategies - in particular by relying on data-driven techniques. Figure 2.1 [13] illustrates the concept adopted in this thesis:

1. Sensors and other information sources collect information on the building and its surroundings. A variety of related active research fields may contribute to this step: Wireless Sensor Networks (WSN) [40], the Internet of Things (IoT) [41], Machine-to-Machine communications (M2M) [42–45], Sensor and Data Fusion [46], Pervasive Sensing [47], and Building Automation [48].

2. For optimal control decisions, it is essential to understand the evolution of the controlled building's physical processes for a defined time horizon. This thesis focuses on using data-driven techniques to derive computational representations of the processes. This step comprises multiple aspects:

[1] We refer to [37] for a general introduction to SC.

[2] "Cyber-Physical Systems (CPS) are integrations of computation and physical processes. Embedded computers and networks monitor and control the physical processes, usually with feedback loops where physical processes affect computations and vice versa." [38]

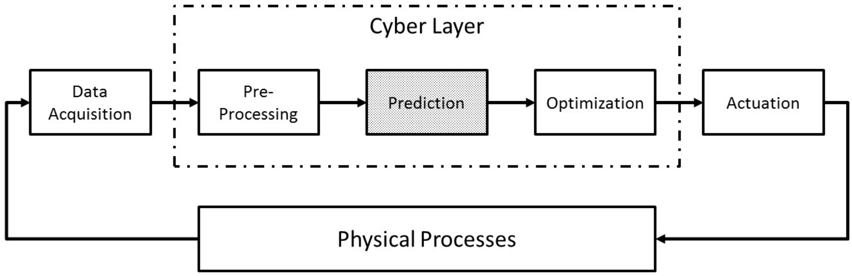

Figure 2.1: Block diagram of the predictive optimization CPS control loop (paper F [13]).

(a) *Pre-processing*, converting, cleaning, selecting, and standardizing data. The field of feature selection is a prominent research area surveyed in [49–51]. Many data-driven techniques operate on numeric features, which requires mapping categorical features to numeric values, e.g., day of week integer values represent the weekdays. Cleaning numerical data from outliers with data mining approaches as documented in [52–54] and standardizing each input feature, e.g., by shifting each feature datum by the feature's mean and dividing by its standard deviation, benefits many subsequent numerical techniques. Further, techniques such as Principal Component Analysis (PCA) [55], representation learning [56], and Auto-Encoders [57] can increase predictive accuracy.

(b) Model identification for deriving the cyber-representation for the *prediction* of the physical process' evolution. Recent publications apply two broad categories: *theoretical approaches* and *data-driven approaches* [13]. For the latter, recent advances in deep learning [57] demonstrate its ability of "discovering intricate structures in high-dimensional data" [58] - which allows the unsupervised discovery of highly non-linear, abstract, and meaningful feature representations from training data. As building data usually accumulates as time series data, we refer the interested reader to [59, 60] for overviews of different deep learning and more general machine learning approaches. Over time, the accuracy of a cyber-representation may deteriorate as a building's environment changes. Therefore, representations require updates to stay accurate. For the data-driven models focused on in this thesis, the field of *concept drift* [61, 62] is concerned with handling the changes.

(c) *Optimization* of the operation. If a given building's optimization problem formulation (the KPI to optimize, typically in terms of a defined cost function and the corresponding cyber-representations) is tractable, a variety of well-known optimization techniques can be applied, e.g., linear programs. Considering that several stochastic events influence building operations in daily life, optimization may take an amount of uncertainty into account when deciding on the building system operation. When exact optimization cannot be applied, it is plausible to rely on nature-inspired heuristics such as the following to improve the building operation. Alternatively, it is also possible to define control heuristics in conjunction with the building's operational staff.

- *Simulated Annealing* is a popular heuristic for optimization. Its primary operation consists of a local search to minimize a problem-specific cost function. Simulated Annealing attempts to avoid entrapment in local optima by sometimes proposing a move to a candidate solution that increases (worsens) the value of the cost function. A configurable acceptance probability determines the acceptance or rejection of this uphill move. Over time, the annealing process decreases the probability of accepting the uphill moves.
- *Particle Swarm Optimization* (PSO) is another popular heuristic, which relies on a population (*swarm*) of candidate solutions. PSO is based on a gravitational metaphor to iteratively update the candidate solutions (the *particles*) according to rules of attraction and inertia. Various variants and applications exist as illustrated in [63]. While many more nature-inspired optimization heuristics exist, [64] argues most of these only differ marginally from PSO.
- According to [65], the single most widely used nature-inspired heuristic in the building optimization field is the *Genetic Algorithm* [66]. This stochastic technique is inspired by the genetic recombination found in the process of natural selection. Iteratively, it searches a population of candidate solutions (represented by *chromosomes* consisting of *genes* - the choices for optimization variables) for the fittest members. A problem-specific cost function expresses this fitness, and during the evolutionary process only the fittest members' genes are mutated and exchanged stochastically to improve the solution.

3. After the step of optimization, control decisions are communicated to the building infrastructure to steer the physical processes as desired. In this step, again IoT and M2M aspects apply. Potentially, the decisions may be in the form of set-points that are communicated to lower layer control loops of the building automation infrastructure. This case resembles the approach of *supervisory control*, typically executed by experts supervising plant operations. The decisions, however, may also be directly communicated to actuators, which effectively constitutes a control loop.

4. Actuation impacts the physical process, affecting the sensor information after a process dependent time delay.

Note that steps are not always clearly delineated. For example, the field of *Reinforcement Learning* [67] learns to map sensed data to control actions optimally. Several Reinforcement Learning algorithms avoid predicting future evolutions, while others involve predictions of the future to plan actions.

Progress in ICT research benefits CPS use cases. Specifically for *smart building* and *smart city* use cases, we refer the interested reader to [68] tracking recent developments in the areas *middleware*, *computation model*, *fault tolerance*, *quality of data*, and *virtual run-time environment*.

2.3.3 Relevance to the Ph. D. Project Work

Papers C and D [33,34] rely on feature standardization and neural networks for predictive modeling due to empirical results. For controlling the grass heating system's operation, several different control heuristics were defined in cooperation with the operational staff.

Publications E and G [35, 36] rely on standardization of features, PCA, and Neural Networks for modeling zonal temperatures and heating system energy consumption. Paper G [36] experiments with the Genetic Algorithm as well as with Reinforcement Learning to optimize heating system control due to their respective popularity in relevant and recent literature.

2.4 Building Automation and Cyber-Physical Systems: The Predictive Building Control Architecture

2.4.1 Section Purpose

As this thesis targets existing buildings and aspires to leverage pre-existing building instrumentation for predictive control, this section elaborates on commonly encountered building automation systems. In light of the CPS concepts adopted in this thesis (Section 2.3), this section derives the high-level architecture underlying EVOX-CPS.

2.4.2 Integrating Building Automation and Cyber-Physical Systems

In building automation, hierarchical system structures are prevalent. Typical communication protocols at the different hierarchy levels are M-Bus, Modbus, BACnet, EIB/KNX, LON, and OPC. Usually, building automation systems are designed in a three-layered architecture [48]. In real deployments in medium to large-scale buildings, often a mixture of different standardized and proprietary communication protocols is encountered relying on different gateways and protocol conversions.

1. The *Field Level* is the lowest layer, consisting of sensors and actuation devices.

2. The middle layer (*Automation Level*) consists of controllers implementing control loops to meet configured set-points.

3. The *Management Level* hosts the Building Management System (BMS) offering a user interface and allows to configure set-points as well as rules and schedules to change these.

Traditional building automation systems are *reactive* Cyber-Physical Systems[3]. In contrast to that, this thesis' focus lies on *predictive* supervisory actions, e.g., by appropriate set-point manipulation to address anticipated situations based on captured data. For data acquisition and for sending control commands, we advocate integrating pre-existing building automation infrastructure as illustrated in Figure 2.2. That has multiple advantages:

- Ideally, the BMS acts as a single gateway to the automation infrastructure enabled by the protocols mentioned above. That alleviates the need for the Cyber Layer to support a variety of different automation protocols.
- Potential conflicts with pre-programmed BMS decision logic routines become visible. Also, already proven and trusted safety checks (e.g., set-point limits) and routine automation tasks (e.g., regular pump cycles for frost protection in pipes) can still be relied on.
- The existing infrastructure is reused. Hence, the approach leverages earlier investments in building instrumentation infrastructure, e.g., for data acquisition, and thus reduces the economic barriers to roll-out.
- By deploying the predictive control logic as an entity on top of the BMS (which may or may not be co-located in the physical BMS entity), all communication is screened by the BMS. That allows filtering sensitive data sent upstream to the predictive control as well as to reject or alter inappropriate control commands. Besides, the concept allows operational staff to deactivate predictive control in case of problems and revert to the status-quo BMS-based control. That increases the chances of acceptance and support by the operational staff when first introducing this concept.

However, the approach also has potential drawbacks:

- The BMS needs to offer an interface to the predictive control logic. Often, that requires unlocking or implementing additional functionality in the BMS and is associated with some cost.
- The predictive control logic depends on the BMS capabilities as boundary conditions. For example, if the BMS implementation updates readings and values every 5 minutes, the predictive control must not be designed to rely on higher time resolution BMS data.

[3] For simplicity of discussion, we classify schedules as reactive, despite that the operators may define these schedules with the intention to control the building anticipating specific patterns.

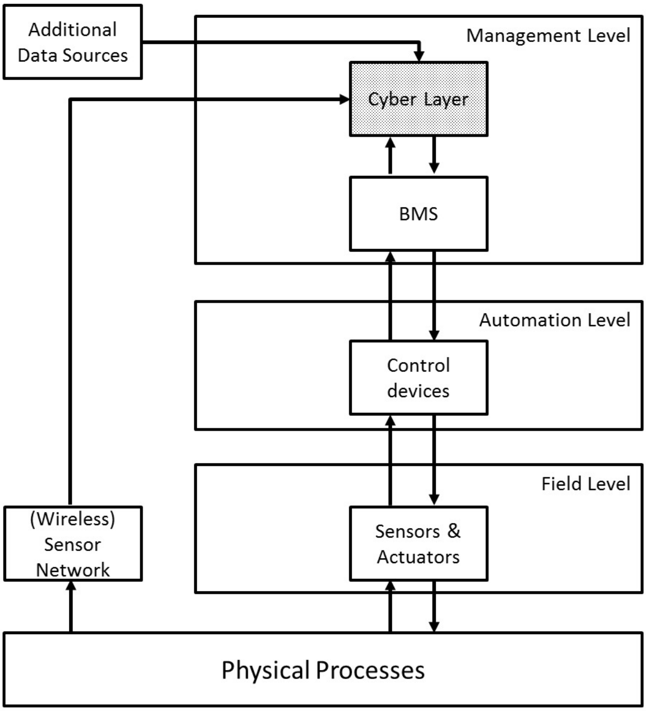

Figure 2.2: Integration of the predictive CPS concepts of Figure 2.1 (shaded) with the standard three-layer BMS structure described in [48]. The WSN indicates an example of additional sensing infrastructure deployed in the building and other technology options exist. Source: Paper F [13]

The integration of additional data sources may improve the effectiveness of predictive control strategies. Figures 2.1 and 2.2 suggest a Cyber-Physical System with closed-loop control [69]: control decisions will influence the future building data, which in turn will affect future control decisions (refer step 4 in Section 2.3).

2.4.3 Relevance to the Ph. D. Project Work

This section establishes with Figure 2.2 the high-level architecture that EVOX-CPS primarily targets.

Publications A, B, C and D [31–34] use BACnet to communicate with the building's BMS. The validation experiments [33, 34] additionally use an Internet weather forecast service.

Papers E and G [35,36] communicate with the building's BMS via BACnet[4] and also

[4]Formerly, the BMS hosted only the heating system data. After project start, additionally installed

use an Internet weather forecast service.

2.5 Building Information and Semantics

2.5.1 Section Purpose

This section provides an overview of information modeling commonly used in the context of buildings to provide background on the technologies that underpin a branch of the literature on optimizing building control. That literature applies the modeled information to, e.g., simulate the future evolution of a building's physical processes.

2.5.2 Technologies Building Information and Semantics

Ontologies conceptualize knowledge by establishing semantic relationships between classes and their properties. That enables applications to apply logical reasoning and inference. In the context of buildings, Building Information Models (BIM) capture relevant building information. Today, Computer Aided Design (CAD) software products for architects can directly populate BIM with information from the planning phase. However, BIM data is rarely used for the existing building stock due to the challenges of high effort, BIM maintenance, and the question of handling of uncertain data, objects, and relations [70]. In particular, the BIM creation for already existing buildings presents a major challenge for research [70]. [71] describes a possible application of BIM: a translation between BIM and Building Energy Modeling (BEM) to optimize control decisions in buildings - which paper F [13] classifies as a theoretical approach. While EVOX-CPS supports BIM-informed building simulations conceptually, this thesis focuses on existing buildings and relies mainly on predictive data-driven black box model in the validation.

2.5.3 Relevance to the Ph. D. Project Work

The technologies described in this section are applicable in several different EVOX-CPS steps as explained in Section 3.1. Also, Section 5.2 identifies how EVOX-CPS could benefit from BIM and semantic technologies in future. However, we focused exclusively on data-driven control in our experiments.

2.6 Methods for Analysis And Inference

2.6.1 Section Purpose

This section provides information about the methods the Ph. D. project applied to assess the significance of experiment outcomes and to generalize the results.

room temperature sensors and a local weather station were integrated and accessible via the BMS.

2.6.2 Weather Normalization

The *Heating Degree Day*[5] (HDD) normalization technique accounts for weather influences on heating system energy consumption [72]. It normalizes energy consumption Q by dividing it by a normalization factor HDD that captures the extent to which the measured outside air temperature T_{air} is below a use case specific *base temperature* $T_{HDD,base}$.

$$HDD = \int f(t)dt \tag{2.1}$$

where

$$f(t) = \begin{cases} T_{HDD,base} - T^t_{air} & T_{HDD,base} > T^t_{air} \\ 0 & T_{HDD,base} \leq T^t_{air} \end{cases} \tag{2.2}$$

T^t_{air} denotes the air temperature at time t. In practice, due to finite time resolution and possibly unreliable weather data, different approximations and quantizations to equations 2.1 and 2.2 are used. We follow the German standard [73] by relying on daily mean air temperature ($\overline{T_{air}}$) for approximating HDD:

$$HDD \approx \begin{cases} T_{HDD,base} - \overline{T_{air}} & T_{HDD,base} > \overline{T_{air}} \\ 0 & T_{HDD,base} \leq \overline{T_{air}} \end{cases} \tag{2.3}$$

Usually, $T_{HDD,base}$ is defined as the outside air temperature below which the studied building requires heating. For typical building operation scenarios, the German standard HDD base temperature is $15°C$ [73]. When calculating daily energy statistics, days with $HDD = 0$ are excluded as $Q_{grass,HDD7} \rightarrow \infty$.

Degree-day-based calculations are especially sensitive to the choice of $T_{HDD,base}$ as it has a big effect on the proportional difference between different periods' HDDs (e.g., winter seasons). Additionally, on days where $\overline{T_{air}}$ is close to the building's $T_{HDD,base}$, the building will often require little or no heating possibly leading to misleading or erroneous energy consumption statistics. That the HDD base temperature is building-specific is illustrated by [74]: based on a statistical analysis of more than 100 non-domestic buildings in Cardiff, UK, the average base temperature identified was 1.2K higher than the British standard HDD and varied according to buildings' characteristics.

2.6.3 Descriptive Statistics and Statistical Inference

Descriptive statistics [75] of an experiment's recorded energy consumption are a natural first choice for analyzing the impact of the control logic experimented with. These measures do not assume that the observations are samples of a larger population. However, to assess the impact of changing the heating control more reliably, we interpret the change of control as a change in the underlying population's characteristics. Hence, to derive generalizable results from measured data *statistical inference* allows characterizing the data sets of the individual control strategies [75].

[5] The concept of *Cooling Degree Days* (CDD) is defined analogously to normalize a cooling system's energy consumption.

2.6.4 Relevance to the Ph. D. Project Work

For achieving representative and robust results from the validation experiments, publications C, D, and G [33,34,36] apply Heating Degree Day based weather normalization. To accommodate the buildings' specifics mentioned by [74], we chose $T_{HDD,base}$ in coordination with the respective building operations team. Paper C [33] analyzes the experiments' data relying on descriptive statistics. More specifically, our publications use the notions of mean, standard deviation, median and interquartile range to describe observed data. To account also for stochastic uncertainty when quantifying the effects of applying the different data-driven control algorithms, papers D and G [34, 36] calculate a robust estimate of the pairwise differences between two heating control regimes. For doing so, we use statistical inference for *two populations*.

Chapter 3

Thesis Contribution

"A system of methods used in a particular area of study or activity."

Definition of "Methodology", Oxford Dictionaries [76]

3.1 Optimizing Building Operations with Data

This section elaborates the thesis' contribution addressing the gaps in research as formulated in Section 1.2. First, Section 3.1.1 provides a summary. Then, Section 3.1.2 introduces the methodologies that inspired our design of EVOX-CPS. Section 3.1.3 details EVOX-CPS by documenting its two phases and the individual steps to be taken when facing a particular building. Besides, it links the steps back to the input methodologies used. Section 3.1.4 summarizes the validation experiments' results.

3.1.1 Summary

This thesis' main outcome is a methodology to improve existing buildings' operations without requiring extensive modernization measures by using building data and contextually relevant information [36]. The methodology to **EVO**lve an e**X**isting building into a closed-loop **C**yber-**P**hysical **S**ystem with predictive control (EVOX-CPS) is holistic and comprehensive as it promotes accounting for involved stakeholders' perspectives, e.g., the needs in daily operation. EVOX-CPS is flexible, because it adapts to existing buildings due to its data-driven nature, while it also supports BIM and building energy simulations, if available. As EVOX-CPS advocates supervisory control concepts leveraging on existing building automation infrastructure, it has a low barrier to adoption due to reusing earlier investments and by being a support to human building operators. Additionally, it inherits the precautionary mechanisms (e.g., anti-freezing pump cycles, and temperature thresholds) already existing in the building's infrastructure. In addition to supporting supervisory control, EVOX-CPS is also flexible to accommodate lower level control, i.e., actuating field level devices.

Two established approaches inspired EVOX-CPS:

- the *Model-Based Design Methodology for Cyber-Physical Systems* (MBD-CPS) [77], and
- the *CRoss-Industry Standard Process for Data Mining* (CRISP-DM) [78].

As outlined in the following sections, we select aspects from both MBD-CPS and CRISP-DM, and combine, merge, and adapt them to the building context. Figure 3.1 illustrates the high-level concept of our methodology. Figure 3.2 visualizes how its steps relate to MBD-CPS and CRISP-DM - despite their adaptation to the building context. Our extensive experimentation validates that EVOX-CPS is suitable for day-to-day use in real building operations. Further, the validation establishes high confidence in the results.

3.1.2 Related Methodologies

With the goal to steer building operation towards higher levels of efficiency, this section describes a general methodology to turn legacy buildings into predictive CPS. As elaborated earlier and illustrated in Figure 2.2, for typical medium/large-scale buildings already equipped with automation infrastructure the proposed concept leverages any pre-existing building automation infrastructure and deploys additional sensing equipment only when needed. The information provided by the building automation infrastructure, by the deployed sensors, and possibly by other sources (e.g., internet services) allows deriving computational (or *cyber*) representations of the building and the associated physical processes. These representations are instrumental to predictively control building systems. The predictive CPS issues appropriate control commands to the building automation infrastructure to enact these, and hence, the commands are of supervisory nature.

As we consider buildings as CPS, the *Model-Based Design Methodology for CPS* (MBD-CPS) [77] lends itself to adaptation. Given a problem statement, it designs a CPS from scratch by applying the following ten steps, not necessarily executed in sequence and possibly repeated:

1. *State the Problem*: a common language definition of the problem to be solved.
2. *Model Physical Processes*: derivation of a model representation of the physical system to be controlled.
3. *Characterize the Problem*: identification of the fixed, adjustable and controllable parameters and how the physical process may interact with the computation and vice versa.
4. *Derive a Control Algorithm*: determination of conditions under which the physical process is controllable. Possible requirements on the computation (e.g., runtime, jitter, delays) can be derived from the previous steps.

5. *Select Models of Computation*: definition of an allowable set of instructions and rules on the control flow of computational components. If derived, an explicit representation of the computation models allows for formal analysis.

6. *Specify Hardware*: based on the problem's environment, its characteristics, and the computation models described, the hardware necessary to meet the requirements must be selected.

7. *Simulate*: by using suitable simulation tools of the various components designed and interacting, it can be assessed if the problem is solvable with the selected models, computation, and hardware. If not, a refinement of the earlier steps is needed.

8. *Construct*: building the CPS as designed, and depending on the situation possibly a re-iteration of earlier steps is needed.

9. *Synthesize Software*: code synthesizers may be used to derive software from the simulation environments. Otherwise, the software has to be implemented with standard tools and skills according to the defined computation models.

10. *Verify, and Validate, and Test*: testing the CPS and its individual components in simple test environments provides diagnosing of the CPS. Possibly refinements of the earlier steps are needed based on the test results.

With access to BMS data, it is possible to use data-driven techniques to address the model identification step of MBD-CPS step 2. Hence, this thesis approaches the model identification as a data mining project. Following that notion, the standard *CRoss-Industry Standard Process for Data Mining* (CRISP-DM) [78] consisting of six phases applies:

1. *Business understanding*: the data mining problem definition based on the project objectives and requirements from a business perspective.

2. *Data understanding*: the initial data collection to identify data quality issues and forming hypotheses. This step should also include the identification of where available data is lacking with respect to the business understanding.

3. *Data preparation*: performing all activities needed to construct the data set that is fed into the models.

4. *Modeling*: various modeling techniques are applied, and their parameters are tuned. An alternation between the data preparation phase and this phase may be needed, depending on the specific techniques.

5. *Evaluation*: objective assessment if the business objectives can be met by the model(s) created.

6. *Deployment*: actual use of the model(s) created in the business environment, if the evaluation was positive.

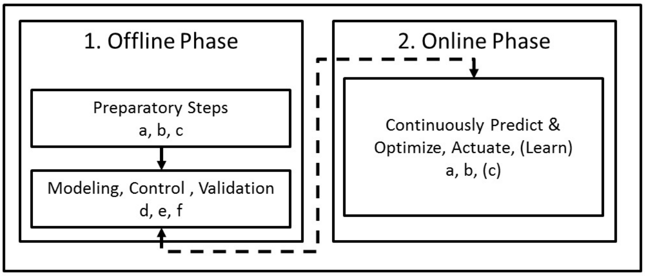

Figure 3.1: EVOX-CPS, high-level. The offline phase consists of a preparatory phase (steps 1a-1c) and a phase of data-driven modeling, control, and validation (steps 1d-1f). Once control is validated, the online phase continuously executes steps 2a, 2b, and optionally 2c. The dashed arrow indicates that step 1f may use phase 2 already and that step 2c may re-execute steps 1d and 1e. From paper G [36].

3.1.3 EVOX-CPS: A Data-Driven CPS Methodology for Predictive Building Control

In the context of buildings, several of the MBD-CPS steps are already pre-determined. For example, the largest part of the hardware is already given, if the building is pre-equipped with automation infrastructure. Furthermore, many building processes - thermal processes in particular - have low requirements on delay, and jitter. Typically, their inertia is in the range of tens of minutes. For these reasons, we develop our own step-wise approach to **EVO**lve an e**X**isting building into a closed-loop **C**yber-**P**hysical **S**ystem with predictive control (EVOX-CPS) that reuses the already installed building infrastructure. Our approach is inspired by MBD-CPS and CRISP-DM in that we merge several MBD-CPS steps, combine these with the appropriate CRISP-DM phases, and adapt them to the context of predictive supervisory building control. Besides, we introduce additional steps where there are no corresponding MBD-CPS steps or CRISP-DM phases. That results in the following step-wise approach to evolve an existing building into a closed-loop CPS with predictive control that reuses the already installed building infrastructure.

The individual steps map to CRISP-DM and MBD-CPS as indicated in brackets. Not necessarily all steps are executed in sequence, and some may be repeated. Figure 3.1 provides a high-level illustration of the methodology. Figure 3.2 provides more details on the relation of MBD-CPS and CRISP-DM to the framework's different steps.

1. Offline phase:

   (a) Business target, data, and system understanding (CRISP-DM 1, 2; MBD-CPS 1, 3)
   Before any in-depth analytical work, it is necessary to investigate the available data sources and to understand the business target. Also, the possible ways of interacting with the building infrastructure need to be understood. This

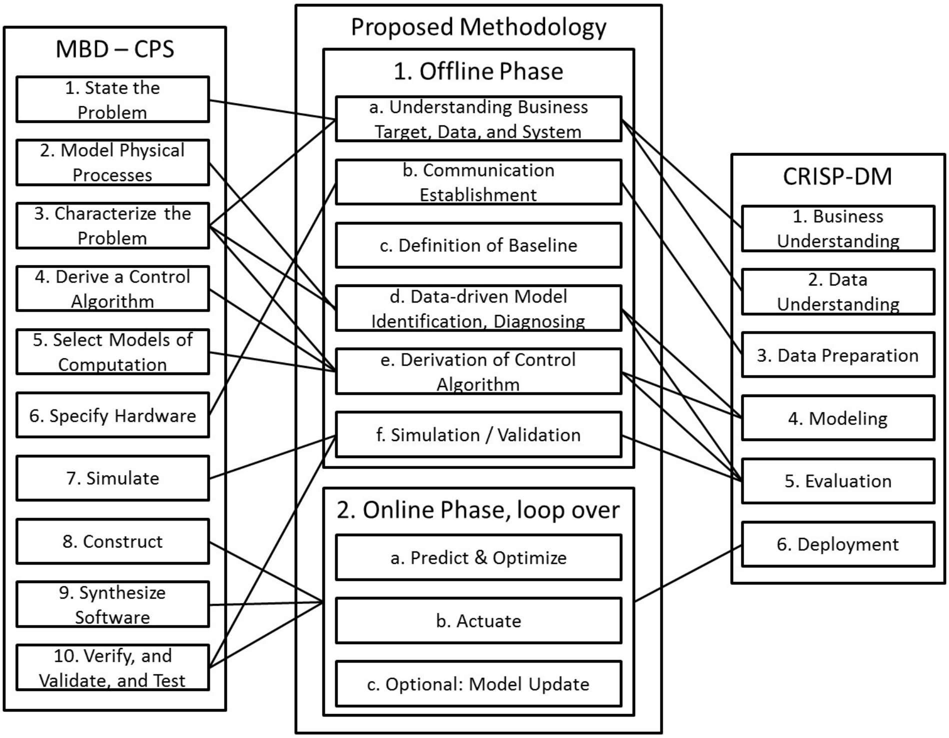

Figure 3.2: EVOX-CPS, detailed. Methodological steps to develop data-driven predictive building control in legacy buildings mapped to those of MBD-CPS and CRISP-DM.

assessment reveals if any additional sensor, meter, or actuator installations are necessary, or if additional data sources such as internet services need to be taken into account. The assessment also defines the space of possible solutions and methods to apply. Possibly, formalization of the interaction among stakeholders may help, similarly the form of design contracts between control and software engineers [79]. In the worst case, the building's situation is such that the goal of energy efficiency with the help of a predictive CPS control is technically or economically infeasible. This outcome requires abandoning the project.

(b) Establishment of communication, possibly with additional installations as needed (CRISP-DM 3, MBD-CPS 6)

If the preceding assessment concludes that the overall goal may be reached, establishing bi-directional communication with the building infrastructure, e.g., with the BMS by relying on communication platforms [80, 81], allows extraction of relevant operational data and instruction with actuation commands. Section 2.4 and Figure 2.1 suggest a suitable architecture for supervisory predictive control as advocated by this thesis.

(c) Definition of a reference baseline for performance assessment (CRISP-DM NA, MBD-CPS NA)

Defining a performance baseline enables quantifying the effectiveness of the predictive control. Both historical information or data collected by the communication platform during a monitoring phase can serve to set the baseline. The establishment of a reference baseline does neither the generic MBD-CPS methodology nor the general CRISP-DM process address. Note that the term *reference baseline* is different from the term *baseline energy use* as used in [82]. EVOX-CPS relies on the reference period's data defining the baseline to assess the effectiveness of the control measures. In contrast to that, [82] refers to baseline as the energy consumption that always occurs, irrespective of building occupancy or outdoor temperature - the *baseload*.

(d) Data-driven model identification including diagnosing (CRISP-DM 4, 5; MBD-CPS 2, 3)

Relevant control variables are identified from system specifications and in discussions with operational experts. In light of these variables, based on a suitable amount of data, predictive models of the building's thermal and energetic behavior are derived. This *Model Identification* step [83] may benefit from commonly used data preparation techniques such as data standardization. Sensitivity analysis techniques can assess the identified models' robustness to changing input data.

The information from building experts gives valuable insights for developing the models. The selection of an appropriate modeling technique depends on the individual building, its systems, and the intended use case. Further, it also depends on the information sources' characteristics and the technical skills available to the project. The building's system configuration may also require a combination of multiple models: for example, large Heating Ventilation and Air-Conditioning (HVAC) system installations may require a hierarchy of models (possibly of different types) to reflect their various components accurately. If available, digital information on the building and its facilities stored in a *Building Information Model* (BIM), e.g., compliant to the *Industry Foundation Classes* (IFC) standard [84], can be incorporated in the model identification. For example, [85] suggests two alternative approaches to deriving thermal building simulation models from BIM data as received from architectural CAD tools - which then allows pursuing the approach of [86]. Another possible use is the Building Energy Model Recommendation System proposed in [87] to guide the model type selection.

If a BIM is available, it is possible, to avoid purely data-driven approaches and use building energy simulations to predict the building's reactions to control decisions - and many publications apply that concept. However, often even calibrated building simulations fail to capture the building dynamics correctly as mentioned in [88]. Due to that, purely data-driven approaches can outperform simulation-based predictive control in the real deployments. Due to that insight, and because for many existing buildings BIM is not readily available and costly to create [70], EVOX-CPS focuses on data-driven approaches but leverages BIM data, if available.

(e) Derivation of control algorithm subject to targets and specified constraints (CRISP-DM 4, 5; MBD-CPS 3, 4, 5)

In this step, it is necessary to form an understanding of the different systems under study with their individual operation needs and constraints. Typically, meetings with technical staff and the study of corresponding documentation provide the required information. Further, an analysis of the baseline data used in Step 1c may also provide deep insights into the status-quo operation as shown in paper B [32]. Besides, the project goals influence the choice of constraints, e.g., concerning thermal comfort. The modeling language proposed in [89] could be one way to express application-specific as well as system-specific constraints. Depending on the building and the system to be optimized, the required complexity of the control may vary. For example, large HVAC system installations may require a hierarchy of decisions to reflect different distribution elements and branches accurately.

(f) Simulation / validation (CRISP-DM 5; MBD-CPS 7, 10)

Using building simulation tools, such as *Modelica* [90] or *EnergyPlus* [91] for validating the predictive models' accuracies and the control algorithm's performance allows gaining confidence in the approach before deploying it in the real building. That requires access to simulation models (e.g., derived from a BIM as in [71], if available) to check the developed model against. Alternatively, it is also possible to use experimental validation with close supervision by staff as in our publications. In the latter case, this step blurs the demarcation line to the subsequent online phase. During and after the validation, stakeholders' feedback should be collected and analyzed to ensure that the data-driven control satisfies their needs and targets.

2. Online (productive) phase - loop over: (CRISP-DM 6; MBD-CPS 8, 9, 10)

(a) Predict & Optimize

The model(s) developed in steps 1d and 1e enable anticipating different control decisions' effects within a problem-specific prediction horizon. These predictions are key to identifying the optimal decisions.

(b) Actuate

The predictive CPS control decisions are then communicated in the form of adjusted set-points to the BMS at appropriate times. The BMS enforces these via lower level control loops in the building's automation infrastructure. This approach of reusing the BMS as building actuation gateway prevents situations where predictive control commands conflict with the lower layer automation infrastructure. Special attention is necessary in cases where the BMS has its own pre-programmed logic of set-point manipulation, or when a human operator can modify set-points manually. In these cases, appropriate measures need to be taken to avoid confusion or conflict. Possible means are communication with staff about the presence of predictive CPS control, as well as the possibility to switch the BMS between enacting (i) its internal logic and (ii) supervisory control commands received from the CPS.

(c) Optional: continuous adaptation of the predictive models based on prediction errors

As the predictive CPS controls the building systems and collects more data, it is sensible to continue fine-tuning the predictive models to increase their predictive accuracies and also account, e.g., for any systemic changes such as deteriorating equipment. In particular, machine learning methods relying on gradient-based iterative learning such as neural networks are suitable to adapt to batches of new data continuously. Also, other methods for handling of concept drift [61, 62] may apply.

3.1.4 Validation

To validate EVOX-CPS, we experiment in two buildings with different levels of instrumentation, different usage patterns, and different operational purposes within their normal operation setup. The experiments documented in papers C, D and G [33, 34, 36] validate that EVOX-CPS is capable of developing data-driven predictive control by relying on the architecture suggested by Figure 2.2. In the experiments, we successfully integrated the buildings' instrumentation as well as additional data sources. The early stakeholder involvement allowed to identify operational issues in the routine operation and savings potentials. The prolonged experimentation periods demonstrate the feasibility to integrate predictive control in the day-to-day operation. The experiments could address the identified operational issues successfully as confirmed by the stakeholders. Additionally, papers D and G [34, 36] analyze the buildings' recorded energy consumptions. They show that the efficiency improvements are profound, statistically significant, and of practical importance.

- The experiments of controlling the grass heating system of the soccer stadium Commerzbank Arena, Frankfurt, Germany, saved in two winters up to 66% (2014/2015) and 85% (2015/2016) of energy. Extrapolation to an average heating season leads to expected savings of 775 MWh (148 t of CO_2 emissions) and 1 GWh (197 t CO_2), respectively. The experiments also alleviated the known operational limitation of heating supply shortages which required nightly preheating in the stadium's standard operating procedures. Feedback from the operational staff was positive.

- Furthermore, we validated the methodology by controlling the heating system of the Sierra Elvira School in Granada, Spain. The school building has very little insulation and suffers from low indoor comfort due to budget constraints. The experimentation occurred during the regular class hours on 43 school days in winter 2015/2016. We demonstrated the possibility to lower consumption by one-third while maintaining indoor comfort. Another experiment raised average indoor temperatures by 2K with 5% additional energy consumption, compared to the reference period. When proxying operative temperature by indoor air temperature, the increased air temperature moves the Sierra Elvira School into the range of comfort category C defined in [22] as presented in [25] (Table 1) - a significant improvement. Again, that illustrates the possibility to address a building's known operational issues (e.g., low thermal comfort) in an energy efficient way. All stakeholders' feedback was positive - after an initial phase of lower-than-anticipated indoor comfort.

From survey paper F [13] follows that existing literature does not offer comparable experiment durations or the integration into the routine operation. Normalizing for weather impacts and applying a thorough statistical analysis of collected data establishes confidence that the experiments' effect sizes truly stem from the interventions. Paper F shows that this thesis' validation by combining statistical analysis and weather normalization goes beyond what the relevant studies on energy efficient buildings typically provide. In addition, our analysis of the feedback from building managers and other involved stakeholders is not commonly found in the literature. The received feedback documents the suitability of the methodology and the experimental control in real world operation scenarios.

3.2 Roadmap and Summaries of the Publications

Section 3.2.1 summarizes the seven publications that constitute this thesis. The thesis contributes to pervasive computing research as an existing building's data informs computational methods to improve system control decisions concerning well defined KPIs predictively. The 12 additional publications embed this thesis in a broader context. Overall, the 19 peer-reviewed works [13, 31–36, 45, 80, 81, 92–100] consider aspects of smart homes, machine type communications, Cyber-Physical Systems, IoT data security, energy analytics, and data-driven optimization of existing buildings' operations. Figure 3.3 outlines the relations among the works.

3.2.1 Summaries of Included Publications

Paper A: Predictability of Energy Characteristics for Cooling, Ventilation and Heating Systems in Sports Facilities [31]

"In this paper we analyze operational energy data of the cooling, ventilation and heating systems of the professional soccer stadium *Commerzbank Arena* in Frankfurt, Germany. We analyze data collected over a six month period in 2014 statistically and show that depending on the stadium's operational context consumption patterns vary largely among

Figure 3.3: A map of our 19 publications, green color indicates the seven papers included in this thesis. Filled boxes indicate journal papers. Publications with myself as the first author have solid outlines. Arrows show the logical flow of the papers. The dashed horizontal line separates the starting point of this thesis from earlier, yet relevant works.

the different systems resulting in very different behaviors. The results provide insights into what drives the energy consumption for different systems of a large commercial sports facility: the static heating system is purely dependent on outside air temperature, ventilation exhibits a pronounced daily consumption pattern irrespective of the temperature and cooling is driven by a combination of event operation and air temperature. These insights will allow us to predict, plan and balance the energy demands of different subsystems more accurately, resulting in energetic improvements of the stadium operation in the form of load shedding while maintaining the systems' service levels."

My contributions to this paper, beyond editorial contributions to all sections:

- Selection and description of the selected methods
- Analysis of the energy data of the cooling system, the ventilation system, and the

heating systems.

- Majority of the discussion and conclusion sections

Published: IEEE Innovative Smart Grid Technologies Conference (ISGT), 2015.

Paper B: The Energy Efficiency Problematics in Sports Facilities: Identifying Savings in Daily Grass Heating Operation [32]

"Recently, reflections on modern sports stadiums' environmental impacts have gained substantial attention. Large-scale stadiums of e.g. professional soccer teams are characterized by having installations of grass heating systems serving the crucial commercial asset and at the same being the sub-system with the highest yearly thermal energy consumption. Public buildings of this size imply situation-specific operational modes combined with high levels of safety and comfort requirements. In this paper we provide a first study on the energy savings potential of a professional soccer stadium's grass heating system during day-to-day operation. In practice, limited heating capacities of the arena have to be adhered to, which causes the current operation to often result in underperformance of other, less critical facility units. Our analysis of dynamic operational and contextual data serves as foundation for long-term energy efficiency measures. We study relevant parameters related to the current control schemes and the stadium's context. Concretely, the grass root temperature as critical observable is studied with respect to weather conditions and the resulting thermal behavior. We provide an improved control strategy and quantify the anticipated savings of this strategy to be as high as 34% compared to the last heating season. For the future, the documented thermal characteristics will enable the formulation of more advanced control strategies to positively influence the grass heating operation. This will lead to further improvements in balancing the heating demand across all thermal facility sub-systems by integrating operational context with forecasts of the thermal behavior in the future."

My contributions to this paper, beyond editorial contributions to all sections:

- Analysis of heat meter data reporting behavior.

- Analysis of the soil's thermal evolution subject to grass heating system operation and the system's energy consumption

- Derivation of a first simple heating strategy to reduce soil temperature and estimation of effect size on energy consumption

- Majority of results, discussion, and conclusion sections

Published: ACM/IEEE Sixth International Conference on Cyber-Physical Systems (ICCPS), 2015.

Paper C: Energy Efficiency Gains in Daily Grass Heating Operation of Sports Facilities through Supervisory Holistic Control [33]

"In recent reflections on environmental impacts of buildings, medium to large scale sports stadiums have gained substantial attention. These stadiums of e.g. professional soccer teams are characterized by special system installations like grass heating systems serving the crucial commercial asset(s) and by event-driven usage patterns. Public buildings of this size imply situation-specific operational modes combined with high levels of safety and comfort requirements. In this paper we provide experimental verification of the energy savings potential of a professional soccer stadium's grass heating system during day-to-day operation. Our supervisory holistic control based on state of the art information and communication technology (ICT) is verified by seven experiments which we executed within the real operational setup of the Commerzbank Arena in Frankfurt, Germany. Our experiments operated different control strategies of increasing complexity. In winter 2014/2015 we achieved weather normalized energy savings of more than 56% compared to the last heating season. In an average heating season this would amount to savings of approximately 780 MWh and 150 t CO_2. At the same time we violated minimum temperature targets less than 6% of the time. These results stress the feasibility and benefits of applying holistic context-aware control strategies to large scale legacy consumption systems using supervisory ICT platforms. We demonstrate significant efficiency improvements and establish a new energy baseline that future control strategy evolutions will have to benchmark against."

My contributions to this paper, beyond editorial contributions to all sections:

- Lead of related work summary
- Lead of methodology definition, including selection of KPIs, and weather normalization techniques
- Control strategy definitions
  - Discussions with site staff for definition of temperature target band and daytime heating control heuristics
  - Supervision of neural network model training underlying predictive control
- Control algorithm implementation, experiment execution, analysis and discussion of baseline and experiments' data

Published: 2$^{\text{nd}}$ ACM International Conference on Embedded Systems for Energy-Efficient Built Environments (BuildSys), 2015. **This paper received the conference's best paper award**.

Paper D: Cyber-Physical System for Energy Efficient Stadium Operation: Methodology and Experimental Validation [34]

"The environmental impacts of medium to large scale buildings receive substantial attention in research, industry, and media. This paper studies the energy savings potential of a commercial soccer stadium during day-to-day operation. Buildings of this kind are characterized by special purpose system installations like grass heating systems and by event-driven usage patterns. This work presents a methodology to holistically analyze the stadium's characteristics and integrate its existing instrumentation into a Cyber-Physical System, enabling to deploy different control strategies flexibly. In total, seven different strategies for controlling the studied stadium's grass heating system are developed and tested in operation. Experiments in winter season 2014/2015 validated the strategies' impacts within the real operational setup of the *Commerzbank Arena*, Frankfurt, Germany. With 95% confidence, these experiments saved up to 66% of median daily weather-normalized energy consumption. Extrapolated to an average heating season, this corresponds to savings of 775 MWh and 148 t of CO_2 emissions. In winter 2015/2016 an additional predictive nighttime heating experiment targeted lower temperatures, which increased the savings to up to 85%, equivalent to 1 GWh (197 t CO_2) in an average winter. Beyond achieving significant energy savings, the different control strategies also met the target temperature levels to the satisfaction of the stadium's operational staff. While the case study constitutes a significant part, the discussions dedicated to the transferability of this work to other stadiums and other building types show that the concepts and the approach are of general nature. Furthermore, this work demonstrates the first successful application of Deep Belief Networks to regress and predict the thermal evolution of building systems."

My contributions to this paper, beyond editorial contributions to all sections:

- Elaboration of this work's relation to the CPS concept
- Problem Statement, Hypothesis definition, Relationship to related and earlier works in particular also to CPS and BMS concepts
- Lead of methodology definition, including selection of KPI definitions, statistical analysis, weather normalization, and regression techniques
- Summary of status quo control analysis and past control effects based on earlier works, and regression model performance analysis
- Summary of past experiments in addition to definition and implementation of additional heating experiment
- Statistical analysis of experiments' effect sizes on weather normalized energy consumption and inter-strategy analysis, discussion of limitations and transferability

Accepted: ACM Transactions on Cyber-Physical Systems (TCPS), 2018.

Paper E: Context Sensitive Indoor Temperature Forecast for Energy Efficient Operation of Smart Buildings [35]

"This paper analyzes the potential of knowledge discovery from sensed data, which enables real-time systems monitoring, management, prediction and optimization in smart buildings. State of the art data driven techniques generate predictive short-term indoor temperature models based on real building data collected during daily operation. The most accurate results are achieved by the Bayesian Regularized Neural Network technique. Our results show that we are able to achieve a low relative predictive error for each room temperature in the range of 1.35% - 2.31% with low standard deviation of the residuals."

My contributions to this paper, beyond editorial contributions to all sections:

- Identification of relevant sate of the art and methodologies to analyze sensor data
- Contribution to exploratory sensor data analysis
- Analysis and discussion of selected regression techniques' performances

Published: IEEE 2nd World Forum on Internet of Things (WF-IoT), 2015.

Paper F: Smart Buildings as Cyber-Physical Systems: Data-Driven Predictive Control Strategies for Energy Efficiency [13]

"Due to its significant contribution to global energy usage and the associated greenhouse gas emissions, existing building stock's energy efficiency must improve. Predictive building control promises to contribute to that by increasing the efficiency of building operations. Predictive control complements other means to increase performance such as refurbishments as well as modernizations of systems. This survey reviews recent works and contextualizes these with the current state of the art of interrelated topics in data handling, building automation, distributed control, and semantics. The comprehensive overview leads to seven research questions guiding future research directions."

My contributions to this paper, beyond editorial contributions to all sections:

- Scale of the problem of energy consumption of buildings, motivating research on data-driven approaches for existing buildings, and discussion of political context
- Identification and description of relevant concepts.
- Development of taxonomy to categorize literature and summarization of selected works.
- Discussion of the identified literature and identification of gaps to formulate research questions. Research question 1 is this thesis' focus, the other questions serve to guide possible future work.

Submitted, revised: Elsevier Renewable & Sustainable Energy Reviews, 2018.

Paper G: Optimizing Legacy Building Operation: The Evolution Into Data-Driven Predictive Cyber-Physical Systems [36]

“Fossil fuels serve a substantial fraction of global energy demand, and one major energy consumer is the global building stock. In this work, we propose a framework to guide practitioners intending to develop advanced predictive building control strategies. The framework provides the means to enhance legacy and modernized buildings regarding energy efficiency by integrating their available instrumentation into a data-driven predictive Cyber-Physical System. For this, the framework fuses two highly relevant approaches and embeds these into the building context: the generic *Model-Based Design Methodology for Cyber-Physical Systems* and the *CRoss-Industry Standard Process for Data Mining*. A Spanish school’s heating system serves to validate the approach. Two different data-driven approaches to prediction and optimization are used to demonstrate the methodological flexibility: (i) a combination of Bayesian Regularized Neural Networks with Genetic Algorithm based optimization, and (ii) a Reinforcement Learning based control logic using Fitted Q-Iteration are both successfully applied. Experiments lasting a total of 43 school days in winter 2015/2016 achieved positive effects on weather-normalized energy consumption and thermal comfort in day-to-day operation. A first experiment targeting comfort levels comparable to the reference period lowered consumption by one-third. Two additional experiments raised average indoor temperatures by 2K. The better of these two experiments only consumed 5% more energy than the reference period. The prolonged experimentation period demonstrates the Cyber-Physical System-based approach’s suitability for improving building stock energy efficiency by developing and deploying predictive control strategies within routine operation of typical legacy buildings.”

My contributions to this paper, beyond editorial contributions to all sections:

- Introduction, motivation, identification of state of the art, and relevant methods to be used for experiment analysis
- Methodology to develop data-driven predictive control for existing buildings
- Description and analysis of demonstration site and status-quo control
- Experiment execution
  - Collection of boundary conditions set by operational staff as requirements for implementation
  - Supervision of implementation of control algorithms to demonstrate the developed methodology’s versatility, effectiveness, and robustness
  - Definition of experimental plan
- Collection and analysis of experiments’ data, discussion of results and the study’s limitations

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Chapter 4

Discussion

"When you look at yourself from a universal standpoint, something inside always reminds or informs you that there are bigger and better things to worry about."

Albert Einstein

4.1 Discussion: Relation to the State of the Art

4.1.1 The Methodology: EVOX-CPS

Considering the number of studies in the field of sustainable computing for buildings that document vast improvements in a variety of different KPIs, the absence of a prominent, validated, and commonly agreed methodology surprised us. There are CPS methodologies that guide, e.g., the deployment of sensor and actuator networks in smart buildings [101,102], but these ignore the installation base of building automation systems in existing buildings. To the best of our knowledge, EVOX-CPS is the first methodology to guide researchers and practitioners to develop and deploy data-driven predictive control in existing buildings and leverage their already installed instrumentation.

EVOX-CPS has several favorable characteristics which may help to overcome the building automation industry's skepticism towards methods of computational intelligence identified in [103].

- It integrates stakeholders' views. That helps to get early stakeholder buy-in by addressing concerns, which lowers barriers to adoption. It also helps to identify operational problems and needs.
- An early check about the feasibility of project targets ensures that stakeholders' expectations are realistic.
- EVOX-CPS is designed with existing buildings in mind, can leverage pre-existing instrumentation, and can integrate additional data sources, such as internet ser-

vices. EVOX-CPS can integrate additional sensor network installations and thus benefit from, e.g., WSN methodologies and technologies.

- It can target individual building systems or the entire facility and can be rolled out incrementally on a system-by-system or zone-by-zone basis.

- EVOX-CPS focuses on data-driven AI techniques, but it can accommodate control heuristics, as well as simulation-based approaches. According to the literature survey in paper F [13], data-driven predictive control studies are on par with building simulation-based approaches.

- The model identification step serves the adaptation to different buildings, usage patterns, and climate zones. The optional model updating allows catering to changes in usage patterns, refurbishments, modernizations, or system degradation over time.

- The advocated approach of supervisory control ensures that
  - already implemented protection mechanisms and safeguards can be reused,
  - existing building automation systems do not conflict with EVOX-CPS control commands, and
  - staff perceives the predictive control's interactions with the BMS as familiar because it mimics the way humans interact with the building.

EVOX-CPS takes inspiration from best practices in project management, e.g., the early checking of requirements and discussions with stakeholders, as well as the general CPS design methodology MBD-CPS and the general data mining process CRISP-DM. The previous chapter explains the relationship of EVOX-CPS with the referenced methodologies. EVOX-CPS makes use of the general nature of their steps and adapts them to the specifics of existing buildings. The following discussion reasons about why EVOX-CPS is a valuable contribution to the field in light of MBD-CPS and CRISP-DM.

- Considering the number of existing buildings with some level of automation but lacking predictive control, a methodology referring to the sector-specific technologies, architectures, and concepts facilitates real-world deployments by helping experts from the building sector. For example, EVOX-CPS step 1b provides more guidance than the general MBD-CPS step 6 and CRISP-DM step 3. It recommends the architecture introduced in Section 2.4 to enable supervisory predictive control and also indicates candidate solutions for establishing the communication with the BMS as used in the validation experiments. Providing guidance to practitioners increases the chances of adoption in real deployments. Since the buildings' global energy consumption is significant, the potential impact of increasing the number of deployments is tremendous - in particular in light of the validation experiments' effect sizes summarized in Section 3.1.4.

- MBD-CPS requires modeling of the physical process to be controlled, which then informs the subsequent steps. For existing buildings, that approach is problematic, as accurate simulation models are often not available and cannot be created due to non-existing BIM data. EVOX-CPS avoids these complications by relying on black-box (or gray-box) models to develop the predictive control.

- The establishment of a reference baseline (EVOX-CPS step 1c) is paramount for assessing the impacts of predictive control. Neither MBD-CPS nor CRISP-DM address that key aspect.

- According to Section 2.3 buildings change over time. Neither MBD-CPS nor CRISP-DM explicitly addresses that, whereas EVOX-CPS step 2c introduces the aspect of updating models during its online phase.

- During the literature survey documented in paper F [13], we could not identify any studies applying CRISP-DM or MBD-CPS to improve the operational efficiency of existing buildings for which no BIM exists.

4.1.2 The Validation Approach

As the continuous literature survey throughout the Ph. D. project (paper F [13]) does not identify a building-specific CPS methodology, the validation of EVOX-CPS is paramount. Therefore, this section discusses the approach underlying the experiments summarized in Section 3.1.4.

Paper F [13] reveals that usually, the studies of the field do not reference any established methodology for validation or measurement. This thesis considers the International Performance Measurement and Verification Protocol (IPMVP) [104] as the most relevant standardized approach. IPMVP guides practitioners on how to assess Energy Conservation Measures (ECM) with confidence. For ECM type interventions, IPMVP provides four high-level options, depending on the project.

(A) *Retrofit Isolation: Key Parameter Measurement.* "Savings are determined by field measurement of the key performance parameter(s), which define the energy use of the ECM's affected system(s) or the success of the project. Measurement frequency ranges from short-term to continuous, depending on the expected variations in the measured parameter, and the length of the reporting period. Parameters not selected for field measurements are estimated. Estimates can be based on historical data, manufacturer's specifications, or engineering judgement. Documentation of the source or justification of the estimated parameter is required. The plausible savings error arising from estimation rather than measurement is evaluated." [104]

(B) *Retrofit Isolation: All Parameter Measurement.* "Savings are determined by field measurement of the energy use of the ECM affected system. Measurement frequency ranges from short-term to continuous, depending on the expected variations in the savings and the length of the reporting period." [104]

(C) *Whole Facility.* “Savings are determined by measuring energy use at the whole facility or sub-facility level. Continuous measurements of the entire facility’s energy use are taken throughout the reporting period.” [104]

(D) *Calibrated Simulation.* “Savings are determined through simulation of the energy use of the whole facility, or of a sub-facility. Simulation routines are demonstrated to adequately model actual energy performance in the facility. This option usually requires considerable skill in calibrated simulation.” [104]

While not explicitly referencing IPMVP, most works in the literature tend to follow the “spirit” of option D and prefer simulation over experimentation to validate the interventions [13]. However, calibrated building simulations often fail to capture the building dynamics as good as data-driven approaches [88]. The Ph. D. project’s validation experiments conducted in two real buildings by deploying data aggregation platforms in the buildings and querying the appropriate energy submeter data throughout the baseline periods and the experiments. The publications quantify the savings compatible with IPMVP options B (papers C and D [33,34]) and C (paper G [36]). The normalization of the experiments’ baselines and the recorded energy data for weather as well as applying statistical techniques to get results of high confidence follows the guidance of [104].

Paper F [13] shows that typically, publications that do validate their interventions by experimentation run experimentation periods lasting no longer than a few days. Also, some studies run their interventions only on a subset of zones - areas within a building - to demonstrate the general feasibility of the proposed interventions and compare against other zones not intervened with, such as the recent [28]. That practice bears the risk that the zones might have a different orientation, or differ in usage patterns, occupant behavior, or equipment. However, other studies applying experimental validation follow an approach that is in principle compatible with the IPMVP (without referencing it). They train a facility-specific regression model on data from the reporting period to compare the experimentation data against. These regression models can be very sophisticated and use, e.g., AI techniques [105]. For two reasons, our studies [33, 34, 36] rely on a simpler model based on the Degree Day concept instead. First, Degree Days are a concept widely applied in the common practice of building assessment and the general statistics are readily accessible at [106]. Second, extrapolating the achieved effect sizes to average weather conditions is straightforward.

Paper F [13] indicates that most publications stop their analysis after identifying their individual intervention’s effect size compared to the routine operation. Our studies [34,36] go one step beyond by using statistical inference to establish confidence intervals of the typically achieved effect sizes. That allows establishing realistic estimates of possible results by accounting for uncertainties.

On top of that, EVOX-CPS promotes addressing operational issues and thoroughly analyzing stakeholder feedback. That feedback allows analyzing if operational shortcomings have been addressed or newly caused to fine-tune next steps. Ultimately, the stakeholder feedback is crucial to enable market acceptance of data-driven predictive control in existing buildings.

4.1.3 The Validation Experiments' Results

Paper F [13] surveys publications on data-driven control of buildings with a focus on the method of validation (simulation or experiments) as well as the effect sizes achieved. Paper F does not consider publications that focus purely on modeling building parameters such as deducing indoor temperatures from outside and facade temperatures [107]. The central insights from the review of related work and our validation experiments' relation to these are:

- The majority of studies focuses on optimizing the operational energy cost or energy consumption. Most take into account some form of thermal comfort - either as a constraint to the optimization or by formulating a multi-objective optimization problem. Less attention is given to alternative KPIs such as exergy, system performance (UPR), green factor, or CO_2 savings.

  The experiments in paper G [36] rely on the KPIs **energy** and **temperature** for the EVOX-CPS online phase. The experiments in papers C and D [33, 34] rely on the soil **temperature** for the EVOX-CPS online phase based on heuristics defined in collaboration with the stadium'ss staff. For analyzing the experiments' impacts, papers C and D [33, 34] rely on the weather normalized energy consumption, the associated CO_2 emissions, and the operational performance by UPR. Paper G [36] relies on the weather normalized energy consumption and the indoor temperature. It does not analyze CO_2 emissions as the school relies on local biomass.

  Paper F [13] indicates that for studies keeping temperature targets unchanged energy savings in the double-digit % range are typically reported. Paper G [36] confirms that range and establishes high confidence in the results by applying statistical inference and weather normalization. For the soccer stadium, a literature analysis led to a lowered target temperature range than used in the routine operation. Consequently, a large part of the recorded savings is due to lowering the target grass root temperature and not from data-driven predictive control per se. That may be criticized, as these savings originate from "lowered comfort", not from control logic enhancements as advocated by EVOX-CPS. However, we argue that the insight of lowering grass root temperatures originates from discussions with the stadium's operational staff and greenskeepers and literature study on growing conditions of grass as suggested by EVOX-CPS. Therefore, we attribute the identification of savings potential by lowering grass root temperatures while ensuring growing conditions to EVOX-CPS. Furthermore, by relying on statistical inference, paper D [34] separates the associated savings of using advanced control heuristics and predictive control compared to a control logic mimicking best practice heating system usage with lowered target temperatures. That delineates savings of lowering the grass root temperature targets from savings of improved control logic such as moving from nighttime-only heating to allowing daytime heating[1].

[1] With 95% confidence, daytime heating control saved 17.6-65.0% in the median daily consumption when compared to the strategy mimicking the best practice but targeting for lowered grass root temperatures [34].

- The current literature rarely studies systemic interdependencies or conflicting control commands. However, these can cause operational shortcomings and must be addressed for real-world deployments.

  For example, in the Commerzbank Arena experimentation site, the different heating sub-systems compete for limited boiler heating capacity [34]. The experiments demonstrate the capability to address operational problems by holistically considering the heating supply and demand situation.

- A minority of studies addresses the aspect of BMS integration. Most of the studies relying on experimentation deploy a complete sensing infrastructure and directly interface with the building equipment to be controlled.

  The experiments in the Commerzbank Arena and the Sierra Elvira School both leverage the existing building instrumentation by relying on a middleware developed for abstracting from the respective building specific protocols [80, 81].

- Most studies do not explain how the features taken into account are derived or why they are used.

  In contrast to that, our publications document the underlying exploratory data analysis motivating the selection and construction of features. For example, [32,35] elaborate on time-delayed impacts of weather on the modeled target temperatures (grass root temperature, classroom temperatures) based on the cross-correlation statistic informing feature selection.

- Nature-inspired optimization heuristics such as the Genetic Algorithm or Particle Swarm Optimization are frequently encountered.

  The Commerzbank Arena experiments in [33, 34] rely on control heuristics developed in close collaboration with the stadium's operational staff because the grass heating system's energy meter is difficult to model with high accuracy. Two of the Sierra Elvira School experiments [36] optimize the heating system's circuits' predicted energy demand and the predicted zonal temperature evolutions using the Genetic Algorithm - the most prominent nature-inspired heuristic in the building sector. At the beginning of each day, both school experiments iterate predicting temperature and energy models with optimizing control decisions resulting in heating set-point schedules for that day. In contrast to that, a third experiment avoids relying on multiple different predictive models (weather forecast models, six temperature evolution models per zone, an energy demand model per heating circuit), by applying Reinforcement Learning to a single KPI that trades-off thermal comfort and energy consumption for a shorter planning horizon.

In Europe, building energy efficiency measures achieved energy savings of 985 GW/year through a variety of measures [12]. The lion's share of the savings originates from refurbishments and component upgrades. While [12] mentions control systems and smart devices as measures for increasing energy efficiency, we argue that it refers to the aspect of components being controllable by a BMS by schedules or fixed rules. Our rationale is that to the best of our knowledge, the concept of data-driven predictive control relying on AI as surveyed in paper F [13] is rarely demonstrated in the day-to-day operation in buildings for prolonged periods, and thus the studies are to be considered as proofs-of-concept. Sustainable computing for buildings as supported by this thesis by proposing EVOX-CPS is a concept not yet applied in the daily routine of existing buildings. Section 4.3.3 will argue that data-driven predictive control is an efficiency measure complementary to the other measures such as improving insulation.

4.2 Considerations on Sustainability

4.2.1 Buildings and Sustainable Development

Existing buildings' combined energy consumption reaches an enormous scale, of which fossil fuels serve a sizable fraction (Section 1.1). A significant body of research demonstrates the feasibility of applying data-driven methods to increase buildings' energy efficiency levels. Hence, there is an opportunity for lowering energy consumption significantly. EVOX-CPS fills a gap identified in the research literature: a comprehensive methodology to develop predictive control for existing buildings and deploy it in routine operation. Our published works focus on that gap by discussing technical, experimental, and methodological aspects. However, the publications focus on building efficiency from an operational perspective and do not reflect on aspects of sustainability. This section complements our studies by reflecting on sustainability aspects. That broadens this thesis' context and provides additional reasons for applying the methodology in practice and motivating future research.

Sustainable development is to "meet the needs of the present without compromising the ability of future generations to meet their own needs" [108]. That entails *economic*, *environmental*, and *social* dimensions, as shown in [109]. This section starts with a discussion of the quantitative results of the EVOX-CPS validation experiments. While these experiments provide robust results of achievable efficiency increases in representative public buildings, the contribution to sustainable development must be debated with a broader perspective and within a wider context. Therefore, assuming a widespread adoption of data-driven predictive control in existing, newly built, and future buildings in developed and developing countries, we assess sustainability by focusing on qualitative indicators (one option in the sustainability assessment framework in [110]) and applying deductive reasoning to identify qualitative effects. The assumption of adopting EVOX-CPS in developing countries is realistic, as its required access to ICT is being met increasingly - and on a global scale[2].

After identifying the direct and indirect sustainability effects, this section reasons about the effects' contributions to two prominent sustainability concepts. First, we show

[2] Globally, 54% of households have Internet access, and 48% have a computer. Further, the emerging economies with a low Purchasing Power Parity (PPP) have shown the highest annual growth rates for electric and electronic goods [111].

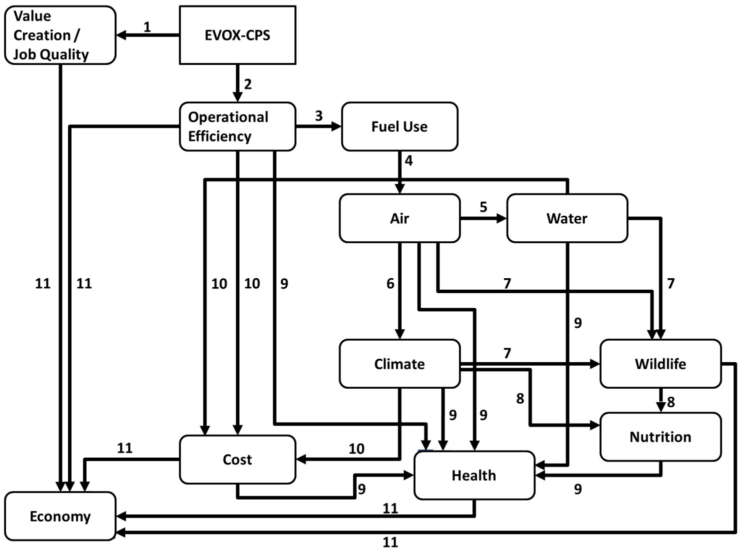

Figure 4.1: Qualitative sustainability effects of EVOX-CPS. Numbers relate to the textual description of each effect.

how the effects map to the United Nations' (UN) 17 *Sustainable Development Goals* (SDG) [112] that intend to guide humanity's global development until 2030. Second, we discuss the identified effects in the context of the *planetary boundaries* (PB) concept [113]. That concept provides an analysis of the risk that human activities will destabilize the Earth's ecosystem services [114]. Each PB's definition bases on the current scientific understanding of biophysical processes. Finally, we discuss how changes to energy mix affect the arguments provided in Section 4.2.2 about the qualitative effects.

4.2.2 EVOX-CPS' Effects

Assuming a widespread adoption of data-driven control of buildings as enabled by EVOX-CPS, this section derives a variety of direct and indirect qualitative effects addressing sustainability aspects by applying deductive reasoning. Figure 4.1 illustrates these effects and their interrelations. In a specific project, the local policies and regulations, the individual building, the obtainable increase in operational efficiency, and the energy mix affect the effects' strengths.

1. Implementing the methodology requires a diverse set of skills - knowledge in building automation, software development, data analysis, technical installation - to deliver and run products and services to buildings. That supports local value creation because of the building stock's geographic dispersion. Note that cloud

computing concepts may move some of the value creation to a remote location. Even in that case, several corresponding services, such as ICT support, are necessary, locally at the building. For the following discussion, we consider the topic of cloud-based service offerings for buildings orthogonal to the fact that data-driven predictive control enables additional value creation and services for buildings.

2. Various studies demonstrate significant increases in efficiency of operation in a wide range of buildings and setups supporting a diverse set of operation targets. Similarly, our experiments demonstrate significant increases in operational efficiencies in representative public buildings. Under the assumption of constant operation targets, that means that operation targets are achieved more efficiently. This efficiency increase typically offsets the additional overhead (such as energy consumption) of the ICT equipment required for providing the data-driven building control.

3. Currently, fossil fuels serve a major proportion of buildings' energy consumption [3]. Thus, operational efficiency increases (effect 2) translate to a significant reduction of fossil fuel combustion. Furthermore, predictive control has the potential of matching building energy demand over time to renewable generation patterns and thereby reduce emissions. In 2010, the residential and commercial buildings globally emitted more than 9 Gigatons of CO_2 equivalents, of which two-thirds are indirect emissions from electricity use [2][3]. At present, the International Energy Agency studies how much energy demand flexibility different buildings can offer and how to control the flexibility without compromising occupant comfort [115].

4. Reducing fuel combustion reduces emissions of pollutants (ultrafine particles [116], polycyclic aromatic hydrocarbons (PAHs)[4] [117], toxic metals[5] [118] and GHG to the air. [117] finds that the evidence"suggests that elevated levels of PAH are ubiquitous in the populated areas and not necessarily lower in the rural than in the urban environment. This is supported by other recent studies in Europe. High levels of PAH in air in central Europe have been related to advection of air from and across Ukraine, Romania, Poland, and Belarus." Note that even for locally grown biomass - sometimes advocated for climate change mitigation reasons, although it still incurs, e.g., transportation-related CO_2 in its GHG balance - the associated emissions are still harmful, e.g., due to small particle emissions [119]. Air pollution impacts *Urban Social Sustainability* as it, e.g., pollutes facades. If a neighborhood's

[3]Due to the high share of indirect emissions, [2] focuses on minimizing final energy use in buildings instead of GHG emissions. However, this may be misleading: preheating buildings with electricity when renewable energy is available increases the heating energy consumption while replacing combustion.

[4]PAHs "are an unavoidable byproduct of any kind of combustion, in particular incomplete combustion processes. [...] Among atmospheric trace chemical substances, PAHs are considered to pose the highest human health risk (WHO 2003)." [117]

[5]"Metals have been documented to be transported thousands of kilometers through the atmosphere, impacting even the remotest regions of the Earth. These metals are released in the atmosphere as a waste product from industrial processes, with metal production and **fossil fuel combustion** being the principal sources of emissions. Other sources include cement production, fertilizer use and refuse and **wood incineration**." [118] (own highlighting to stress building operation related emissions)

appearance degrades, the citizens' sense of attachment erodes, leading to less social interactions and lower levels of community participation [120].

5. As airborne pollutants also enter the water cycle by precipitation [121, 122], a reduction in emissions (effect 4) leads to less water pollution. "[...]Metal pollutants have also been documented to be concentrated by water runoff, accumulating in depositional environments such as lakes and estuaries (e.g. Conrad and Chisholm-Brause 2004; Spencer et al. 2003). From these environments deposited metals may be taken up by biological organisms, such as fish and filter feeders (Henry et al. 2004; Kirby et al. 2001; Mubiana et al. 2005) from where they are known to bioaccumulate through the ecosystem (WHO 2007)." [118] Furthermore, the reduction of CO_2 emissions lessens the ocean acidification effect [123].

6. As higher CO_2 concentration stimulates many plants' growth rates [124], it establishes a stabilizing feedback loop [114]. Unfortunately, the long-term upward trend of the atmospheric CO_2 concentration as expressed in the Keeling curve [125] implies that the plant growth effect does not suffice to stop the increase. As a consequence, the greenhouse effect becomes stronger and globally, temperature levels increase - which the international climate framework agreement attempts to contain [126]. An example of the effects of rising temperatures is the rise of sea levels due to melting glaciers and polar ice. The rising sea levels, which [127] recently found to accelerate, impact climate profoundly.

   For these reasons, the reduction of buildings' GHG emissions (such as CO_2) to the atmosphere (effect 4) addresses climate change.

7. Positively affecting air pollution (effect 4), water pollution (effect 5) and climate change (effect 6) has positive effects on air-, land-, and water-borne wildlife. More specifically, animal- and plant-health, as well as the biodiversity benefit.

8. Effect 7 improves human nutrition. Besides, extreme weather events, which are predicted to happen more often due to climate change, can severely impact food security. For example, floods reduced food supply by 5 % in Bangladesh in 2007 and by 8 % in Pakistan in 2010 [128]. "Undernutrition has been identified as the largest health impact of climate change in the 21^{st} century" [119] (and references therein).

9. Effects 4-8 impact public health positively [129]. Air pollution - which is usually worst in urban centers (i.e., places with many buildings and many people living their lives) - particularly harms children [116, 118]. Apart from other measures, it calls a reduction in fossil fuel combustion to reduce ultrafine pollution particles. When compared to the 1986 - 2008 average, the number of people older than 65 years exposed to heatwaves[6] between 2000 and 2016 increased by about 125 million, with a peak increase of 175 million additional people exposed to heatwaves in 2015.

[6]Heatwaves are a climate change symptom having a variety of severe impacts on human health [119].

Notably, heatwave events appeared in densely populated areas. In addition, [119] indicates how climate change endangers millions of humans through increased risks of diseases, under-nutrition, and social factors (e.g., poverty, mass migration, violent conflicts). Aside from these large-scale effects, improved building operation may also improve indoor air quality which also positively impacts health, e.g., by preventing mold. Also, the higher energy efficiency of building system operation lowers the operating costs (effect 10) which helps to tackle the *energy poverty* phenomenon and prevents its adverse impacts on physical and mental health [130].

10. Climate change implies societal costs for damages due to extreme weather and costs for protective measures such as flood warning systems [131–133]. Also, cleaner water (effect 5) requires less costly purification, and a higher supply of clean water lowers prices. Further, effects 2 and 8 suggests savings:

    (i) Lower fuel costs in the individual building,

    (ii) lower aggregate demand for fossil fuels leading to lowered prices according to macroeconomics,

    (iii) lower maintenance cost, e.g., due to fewer residues in burners, and

    (iv) increased food security leads to stable (and possibly lowered) prices, according to macroeconomics.

    Policy measures such as subsidies have a particularly strong influence on (i), (ii), and (iv).

11. Supporting local value creation for a diverse set of skills (effect 1), reducing the building operation costs (effect 10), and better public health positively impact economies. A healthy, diverse wildlife is also an economic resource. Additionally, mitigating climate change's adverse effects on human labor capacity [119, 129] benefits economies. Further, improved building system operation can improve human comfort - studies indicate that discomfort can have profound economic impacts by adversely affecting the productivity of office workers [15] or the learning progress of students [17].

    Aside from these positive effects, lower fuel costs negatively impact energy utilities' profits that might react with layoffs or pay-cuts. However, we argue that the local value and job creation by SMEs or energy service companies enabled by business models around data-driven methods for energy efficiency can mitigate or even exceed these negative consequences.

Figure 4.1 implies that the different effects create synergies, which confirms the reasoning of [134]. Along the same line of reasoning, but concerned with energy supply transformation towards sustainability, [135], chapter 17.7 argues that the measures targeting the different sustainable development objectives create synergies. Cost calculations isolated for a single objective such as *limiting climate change* or *limiting air pollution* *and health damages from energy use* distort the cost-benefit analysis. In particular, reducing fossil fuel emissions contributes to climate change mitigation, reduces air pollution, and has positive impacts on public health. Thus, the policies to achieve all three objectives can be less stringent and have lower associated cost than isolated cost-benefit analysis would predict. “An integrated policy design will thus be necessary in order to identify cost-effective “win-win” solutions that can deliver on multiple objectives simultaneously” [135]. Also [119] points to the benefits of climate change mitigation actions for global public health.

The indirect effects following from efficiency increases are of course not exclusive to EVOX-CPS as also measures such as building insulation and refurbishment increase efficiency. However, EVOX-CPS can complement these measures and strengthen the effects.

4.2.3 Sustainable Development Goals

This section outlines how the identified effects relate to many of the United Nations' 17 Sustainable Development Goals (SDG) [112] defined in 2015.

Goal 1: No poverty. Effect 11 indicates positive impacts on the economy, from which the entire society should benefit. Also, when applied to medium and large-scale buildings such as social housing apartment buildings, effect 10 helps to combat the energy poverty phenomenon [136], as “energy efficiency is embedded in almost all the listed [energy poverty] indicators” [130]. These effects may not help to address extreme poverty directly, which requires political and social action. However, the food cost related aspect of effect 10 may help the poor as well as the extremely poor.

Goal 2: Zero Hunger. Effect 8 increases food security. However, atmospheric CO_2 complicates the discussion. On the one hand, rising CO_2 levels (see effect 6) increase the yield of harvestable crops. Hence, higher efficiency may reduce a potential positive effect for human nutrition. On the other hand, rising CO_2 changes the composition of crops' tissues, increasing carbohydrates, reducing nitrogen and protein concentrations [124] (and references therein). That may have negative consequences for human nutrition, and therefore higher building efficiency (effect 2) may positively impact nutrition. “Under elevated CO_2 most plant species show higher rates of photosynthesis, increased growth, decreased water use and lowered tissue concentrations of nitrogen and protein. Rising CO_2 over the next century is likely to affect both agricultural production and food quality.” [124]

Goal 3: Good health and wellbeing. Effect 9 captures several positive impacts to human health, such as lower air and water pollution, better nutrition, and the mitigation of energy poverty.

Goal 6: Clean water and sanitation. Effect 5 positively impacts water-related ecosystems due to a reduction of pollutants as well as ocean acidification. Furthermore, mitigating climate change (effect 6) reduces the stress on ecosystems in general, which benefits their restoration.

Goal 7: Affordable and clean energy. Effect 2 includes improved building energy service operation. Effect 10 indicates reduced costs of building energy services. Figure 4.1 illustrates that effect 3 causes most of the indirect effects. In light of the high number of buildings globally and with their significant proportion in global energy consumption, the effect sizes reported in the related work indicate an immense potential to increase the global rate of energy efficiency improvements. In particular, the possibility to shape building energy demand to match renewable energy production (effect 3) will help to reduce the impact the indirect emissions from buildings' electricity use. For example, pre-heating water with solar energy in a building with a nighttime-only usage pattern during the day may increase the overall energy demand (as heat is lost over time), but reduces the overall emissions.

Goal 8: Decent work and economic growth. Effects 1 and 11 address this goal. Further, buildings' higher operating efficiency levels free economic resources for productive use (effect 10). Increasing building operation efficiency levels (effect 2) helps to decouple economic growth from environmental degradation. Also, developing data-driven predictive control for buildings requires a diverse set of skills, some of which are unaffected by certain types of physical disabilities. That helps equality and inclusion.

Goal 10: Reduce inequality. Among others, economic aspects play an important role to promote equality, inclusion, and participation. Effect 10 reduces operational costs. Due to diminishing returns of higher incomes on life quality and happiness [137], the relative impact of reduced cost on low-income households is stronger than on higher income households, which reduces inequality. Additionally, effect 11 leads to economic growth by which all should benefit, e.g., due to local value creation. Moreover, the positive effect on health (9) benefits the poor unable to afford medical services. On top of that, as extreme weather events as a climate change consequence "disproportionally affect poor people and communities, causing an increase in poverty incidence and inequalities" [138], effect 6 reduces inequalities as also argued for SDG 8.

Goal 11: Sustainable cities and communities. Reducing buildings' environmental impacts (effect 4 and its consequences) reduces cities' environmental impacts. Currently, regulations do not prescribe control enhancements as enabled by EVOX-CPS as building energy efficiency approaches (although the presence of automation systems is seen positively in [2]). We advocate EVOX-CPS as an additional efficiency measure complementing more traditional approaches. Leveraging existing buildings' ICT [14] and applying data-driven methods allows a wide range of different service implementations, building ages, climatic regions, and usage patterns which lowers the barriers to widespread adoption. Furthermore, effect 4 positively impacts Urban Social Sustainability. By mitigating climate change and its related extreme weather events, effect 6 contributes to this SDG [138].

Goal 12: Responsible consumption and production. Effect 3 reduces building fuel consumption. However, concerning the necessary ICT components to apply EVOX-CPS, we note that the recycling of electrical and electronic equipment is a global challenge - in 2016, only 20% of e-waste was recycled [111]. While that recycling rate is meager, for predictive control in buildings e-waste recycling rates may be higher than the global aggregate rate. First, global waste statics still have many flaws [111], and second, it appears feasible to mandate recycling of buildings' ICT components. We argue that if recycling levels of (building) ICT components comparable to those of refurbishment materials are reachable, the advocated methodology requires less, but different (e.g., rare earth elements), raw materials input than building refurbishments. Once the predictive models have been developed, the computational requirements are relatively low. For example, [139] combines video-based occupancy detection with a building energy simulation on a low cost embedded PC platform to predictively control a mosque's HVAC. Tests on several days indicate energy savings of one-third.

Goal 13: Climate action. As a shared resource, the atmosphere is susceptible to pollution by fuel combustion emissions. [140] predicts it may be economically sensible to pollute the air as the associated costs are paid by the community, whereas the benefits, e.g., a warm building, are exclusive to the building occupants - the *Tragedy of the Commons*. However, [141] argues that not all commons face the same tragedy due to cultural factors, institutional arrangements, and user self-organization and -regulation. Regarding global scale resources such as the atmosphere, [141] admits that tragedies are harder to prevent. Therefore, it proposes a form of state regulation in conjunction with user self-management on a large scale - a view that [2] shares: "Climate change is a global commons problem that implies the need for international cooperation in tandem with local, national, and regional policies on many distinct matters." The UN SDGs and the Paris climate framework agreement [112, 126] follow the advocated approach of international co-management as they are global coordination agreements leaving details to local governments' know-how to develop individual approaches towards generally accepted targets. EVOX-CPS is in line with this approach by adapting to the each building's individual situation. Besides, effect 6 captures the positive impacts of increasing the energy efficiency of buildings by computational methods on climate change.

Developed countries emit more GHG emissions than most developing countries and therefore contribute stronger to climate change, but its consequences are more severe for the developing countries [138]. That gives rise to an ethical obligation for developed countries to take the lead in implementing GHG reduction measures and disseminate the required know-how for increasing energy efficiency to assist developing countries as captured in [126][7]. The Ph. D. project tackles this aspect by addressing a prominent contributor to global fossil fuel consumption - the building sector. We argue that the deployment of data-driven predictive building control is a cost-efficient measure that addresses existing as well as newly built buildings. The work is compatible with other means of building modernization. As SDG 13 calls for international cooperation, support, and sharing of knowledge, this Ph. D. project - pursued under the umbrella of two collaborative EU research projects - contributes the publications contained within this thesis. The dissemination of concepts, studies, and best practices for buildings provides

[7]For example, [126] states: "[...]Also recognizing that sustainable lifestyles and sustainable patterns of consumption and production, with developed country Parties taking the lead, play an important role in addressing climate change [...] 4. Developed country Parties should continue taking the lead by undertaking economy-wide absolute emission reduction targets. Developing country Parties should continue enhancing their mitigation efforts, and are encouraged to move over time towards economy-wide emission reduction or limitation targets in the light of different national circumstances."

knowledge, methodologies, and tools to reduce buildings' GHG emissions globally.

Goal 14: Life below water. Effect 7 captures that mitigating water pollution, ocean acidification, and climate change helps marine and coastal ecosystems.

Goal 15: Life on land. Effect 7 helps all land-based ecosystems. Mitigating climate change (effect 6) reduces land-system changes due to desertification or extreme weather events (droughts, floods) and protects natural habitats.

Goal 16: Peace and justice. Strong institutions. At present, building stock predominantly relies on fossil fuel consumption. Effect 10 reduces the aggregate demand. That leads to an increase in national fuel security, which reduces international tensions due to fossil fuel scarcity. Further, by reducing freshwater pollution (effect 5), also national clean water security increases and tensions associated to clean water supply reduce [122]. Effect 11 stimulates local economic development which reduces tensions relating to poverty and inequality. Besides, mitigating climate change (effect 6) and its consequences (extreme weather events, desertification) reduces migratory movements and their implications - the current predictions of people displaced by 2050 due to climate change range from 25 million to 1 billion [119].

Different Views on Contributions to Sustainable Development Goals

Green building activities come to different conclusions regarding the contributions of energy efficient buildings to the SDG. [142] lists SDGs 7, 12, and 13 as contributed to, while [143] lists SDGs 3, 7-13, 15, and 17, most of which Section 4.2.3 identifies as well.

In contrast, Section 4.2.3 does not argue that EVOX-CPS meets SDG 9 ("Build resilient infrastructure, promote sustainable industrialization and foster innovation"), as there are no particularly strong effects specific to industry or infrastructure. Also, meeting SDG 17 ("Strengthen the means of implementation and revitalize the global partnership for sustainable development") requires institutionalized support, which is not covered by the advocated methodology itself, but which the [143] coordinates, fosters, and provides. However, the provided inter-disciplinary reasoning about the qualitative effects of widespread adoption of EVOX-CPS in buildings identifies additional contributions to SDGs 1, 2, 6, 14, and 16.

4.2.4 Ecosystem Services and Planetary Boundaries

The concept of sustainability encompasses economies, human societies and Earth's life support system as a whole [114,144]. The identified effects contribute to different aspects simultaneously, see Figure 4.1. Adopting a systems perspective to describe the interplay of different systems (ecosystems and social systems), [114] argues that negative feedback loops among interconnected systems tend to stabilize these towards equilibrium and provide resilience to disturbances, whereas positive feedback loops are detrimental to stability and resilience. Resilient systems can absorb disturbances and tend to return to that stable state unless thresholds are crossed. However, if threshold violations occur, these may cause the systems to settle on a new, different equilibrium. In the context of ecosystem services, a different stable state may or may not be detrimental to the quality of human life [114]. [145] analyzes recent literature to assess thresholds based on the PB concept [113]. That allows associating a risk level with each threshold, quantifying the risk that human activity will trigger Earth's life support systems to shift to new equilibria - with unforeseeable impacts. There are nine boundaries that also interact with each other: *Climate change*, *Biosphere integrity*, *Stratospheric ozone depletion*, *Ocean acidification*, *Biogeochemical flows*, *Land-system change*, *Freshwater use*, *Atmospheric aerosol loading*, *Novel entities*. For the PBs *Novel entities* and *Atmospheric aerosol loading*, it is not yet possible to define threshold values based on the current scientific knowledge. Alarmingly, *Climate change*, *Biogeochemical flows*, *Land-system change*, and *Biosphere integrity* show already medium to high risks of triggering systemic changes in future. *Ocean acidification* is close to entering the medium risk zone. The Ph. D. project's work addresses six PBs.

- Effect 4 contributes positively to *Atmospheric aerosol loading*.
- Effect 5 reduces *Ocean acidification*.
- Effect 5 increases the quality of available freshwater. Mitigating climate change prevents droughts (SDG 15). We argue that both aspects benefit the *Freshwater use* boundary as more clean freshwater is available.
- Effect 6 addresses *Climate change*, see also SDG 13.
- As argued for SDG 15, mitigating climate change reduces *Land-system change* (e.g., desertification).
- Effect 7 captures positive effects on biodiversity (see also SDGs 14 and 15) - one aspect of *Biosphere integrity*.

There are different opinions on how ecosystems behave concerning threshold violations, depending on the perception of environmental risks [134, 146]. Irrespective of the risk perception, the identified qualitative effects provide the means to help to avoid *unintentionally* triggering ecosystem state shifts by lowering buildings' effects on the PBs.

4.2.5 Implications of the Energy Mix

The provided deductive reasoning about EVOX-CPS' qualitative effects relies on a global statistics-based approach. This subsection outlines how changes to the energy mix affect the arguments regarding the qualitative effects. We identify two main aspects:

- The building sector is a prominent consumer of fossil fuel consumption and a significant GHG emitter. Replacing fossil fuels by biomass reduces the GHG impacts and weakens effect 6 and its consequences, but still pollutes the atmosphere with ultrafine particles, PAHs, and toxic metals, see effect 4.

- Electricity generation defines a big part of buildings' emissions [2]. Emission-free electricity generation will drastically weaken effect 3 and its consequences. Assuming the even more extreme - technological breakthroughs make it possible to avoid all building-related combustion emissions - effects 1 and 2 will still be valid, as well as parts of effects 9-11. Even with this extreme assumption, the building sector's sustainability will benefit.

4.3 Limitations

4.3.1 Methodology

Data-privacy and data-security aspects generally pertain to data-driven approaches. EVOX-CPS does not address these topics explicitly. We argue that the methodology allows specifying data-security needs in the first step, the discussions with the stakeholders to understand their requirements. The data requirements of the different kinds of sustainable computing applications for buildings are likely to be heterogeneous. For example, some applications use system specific data points only, whereas others take occupancy data into account[8]. Local regulations and legal frameworks add requirements and constraints due to which we exclude this sensitive topic from the thesis. Decision-makers need to assess stakeholder interests and the legal situation when facing a specific project and use appropriate approaches such as [98] to secure data sharing with third-party application providers.

Dependability and reliability are essential to any CPS, including buildings. It is for further study how EVOX-CPS can accommodate dependability concepts increasing CPS autonomy and self-awareness [148, 149]. Also, a combination with the Failure Analysis and Reliability Estimation framework for benchmarking reliability of cyber-physical systems [150] to assess the building CPS' reliability during routine operation should be investigated.

4.3.2 Validation Experiments

In publications C and D [33, 34] the experiments could not rely on optimization techniques, as the energy consumption could not be modeled accurately enough [34]. Instead, several different control heuristics defined in cooperation with the operational staff. A more accurate energy meter modeling would allow applying optimizing techniques in the data-driven control. That promises additional improvements in the operational efficiency. Furthermore, the experiments relied on the grass root temperature and direct communication with the operational staff to assess the grass' health - in line with the premise to minimize the need for additional equipment installation. Possibly, more direct means of

[8]Modeling the occupant behavior and finding the right balance between BMS automation and possible interaction of occupants with the BMS is a field of research that can increase the effectiveness of the building control [147].

sensing the soccer pitch's grass health would allow more aggressive control schemes for additional savings while ensuring soccer pitch quality.

Publication G [36] could not rely on more advanced thermal comfort concepts than the indoor temperature because of the aim to keep the sensing equipment installations to a minimum. With additional sensing equipment to infer, e.g., clothing factor, humidity, radiant temperatures, IAQ, or light levels, a more sophisticated comfort assessment could improve the operational situation further.

4.3.3 The Limits of Data-Driven Predictive Control and Complementarity with Modernization Measures

The validation experiments' effect sizes are significant, even for the poorly insulated school building. However, insulation and systemic modernizations may in certain situations be necessary to bring about the full-potential of data-driven predictive control. The analysis of a building's operational data performed during EVOX-CPS can help to identify potential modernization measures.

While this thesis does not discuss that at length, Figure 4.2 illustrates data collected during the reference period at four different points (Figure 4.3) in the Commerzbank Arena's grass heating system. Figure 4.4 infers the different segments' median temperature differences. When active, the grass heating system's fluid loses more than 2K on the way from the heat exchanger to the start of the distribution piping heating the soccer pitch. In that area - the heating system's area of concern - the fluid loses about 2K to the soil. On the way back from the pitch to the heat exchanger, the fluid cools by almost an additional 1K of heat. While a more thorough investigation is pending, the data analysis indicates that the grass heating system loses more than half of the energy consumed in the piping to and from the soccer pitch. That energy is not getting to the target area. This analysis resulting from early EVOX-CPS steps suggests an investigation, if, and to what extent, additional insulation is possible and economically viable. At the time of writing this thesis, the feasibility of a project for improving the piping insulation is being investigated.

After improving the pipes' insulation, the data-driven predictive control heuristics developed for the grass heating system will work with lower supply temperatures. That will result in additional increases of the grass heating system's operational efficiency because of three synergistic effects, which demonstrate the complementarity of refurbishment measures and EVOX-CPS.

1. The insulation reduces pipe losses, hence less energy is lost on the way to the pitch, which allows using lower supply temperatures or shorter heating cycles.

2. Figures 4.2 and 4.4 indicate that lower fluid temperatures in the heating circuit result in lower energy losses: 2K on the segment to the pitch, 1K back from the pitch, with both pipe segments having equal insulation. That is because of the lower difference between heating system fluid temperature and the ambient temperature.

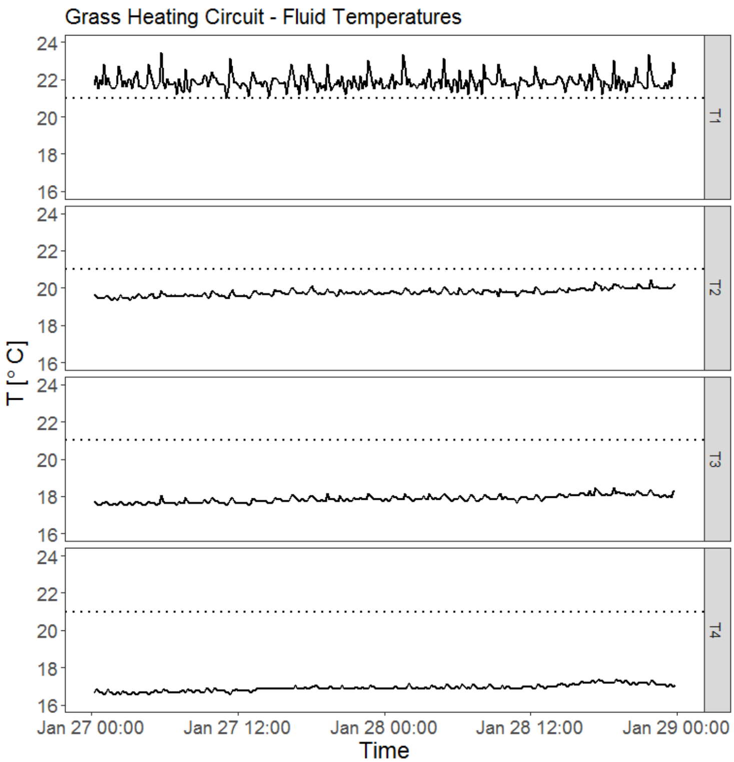

Figure 4.2: Commerzbank Arena's grass heating system: pipe segment temperatures on two days of continuous operation in January 2014. T1=Supply temperature within grass heating circuit at heat exchanger; T2=Supply temperature entering pipe loops in soccer pitch; T3=Return temperature exiting soccer pitch pipes; T4=Return temperature arriving at heat exchanger. The dotted line indicates the grass heating supply temperature set-point $T_{G,set}$. Figure 4.3 illustrates the points of measurement in the grass heating system.

3. All experiments have shown EVOX-CPS' capability to increase the efficiency of heating system operation compared to the status-quo control logic, see paper D [34]. Further investigation is necessary to confirm whether the effect sizes documented in paper D are also achievable with better piping insulation, or if the relative magnitudes reduce.

EVOX-CPS' optional model update step 2c already supports adjusting the data-driven control to changes in the building characteristics, for example, due to better insulation. Moreover, EVOX-CPS allows alternating between its online and offline phases to accommodate this kind of changes.

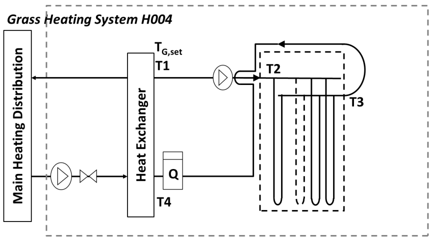

Figure 4.3: Commerzbank Arena's grass heating schematic indicating the measurements T1-T4 and the set-point $T_{G,set}$ in Figures 4.2 and 4.4. This illustration is based on paper B [32].

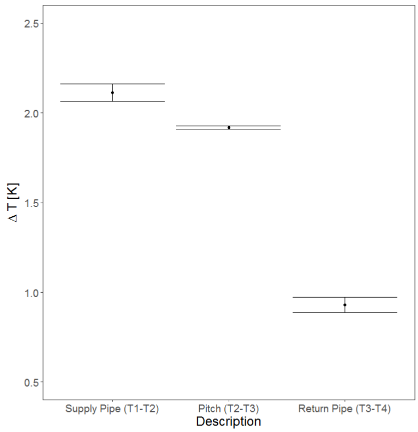

Figure 4.4: Bootstrap intervals of 95% confidence of the median pipe segments' temperature differences, based on 287 samples.

4.3.4 Sustainability Reasoning

Section 4.2 mostly argues deductively to analyze the sustainability effects of widespread adoption of data-driven predictive control in buildings enabled by EVOX-CPS. The reasoning relies on global statistics, macroeconomics, and several recent studies from different fields. It generalizes aspects of the built environment, assuming and anticipating a sufficient number of deployments in the real world. Hence, the arguments are of general nature and focus on large-scale qualitative effects instead of the quantitative effects of applying predictive control to a specific building - as the reasoning about SDG 16 exemplifies. However, when facing a specific project, each building and target application requires assessing the individual situation carefully to quantify effects and to decide optimally. Assuming constrained project budgets, a concrete project may have to weigh building modernization measures against applying EVOX-CPS. To assess sustainability in the context of a specific project, decision makers can use, e.g., [110]. They need to take into account the individual building's characteristics and the involved stakeholders' views. Moreover, they have to account for local factors of regulation, and the economic, ecologic, and social contexts to correctly understand the implications of what is ultimately a building-specific decision.

The arguments about energy poverty (see effect 10 and SDG 1) suffer from the lack of EU-wide energy poverty data [130]. Thus, it is unclear how strongly or weakly that phenomenon's contribution impacts the identified qualitative effects on a global scale. Nonetheless, mitigating energy poverty is generally beneficial to every society, for example by increasing operational efficiency.

Chapter 5

Conclusion and Future Work

"What gets measured, gets managed."

Peter Drucker

5.1 Conclusions

Of the seven research questions that the continuous review of the relevant literature identified in paper F [13], this thesis focuses on research question 1: "What is a suitable methodology to evolve existing buildings into a CPS for higher levels of operational efficiency?"

The thesis' main contribution is to propose EVOX-CPS. The novel methodology is embedded in the fields of sustainable computing, pervasive computing, and cyber-physical systems: it draws extensively on sensors and computational methods to increase existing buildings' operational efficiency by interacting with building control systems. This thesis establishes the following insights into the implications of applying EVOX-CPS.

- Developing data-driven predictive control for existing buildings and integrating it into routine operation using EVOX-CPS is feasible and has significant positive effects on the efficiency of operation. Moreover, predictive control can mitigate operational issues as shown in our experiments and confirmed by the stakeholders.

- Integrating existing building instrumentation as suggested in [14] allows leveraging prior investments. Furthermore, by advocating supervisory control, EVOX-CPS can reuse already engineered protection mechanisms, such as anti-freeze pump cycles.

- Stakeholders benefit and react positively when their concerns are taken into account appropriately at an early stage. Continuous communication with the stakeholders during routine operation is key to ensuring that control solutions are perceived as assistance, not as a nuisance or possibly even as a threat.

- EVOX-CPS is flexible to adapt to different buildings and individual systems. It can accommodate different operation targets as well as different techniques for modeling and control. Further, using data-driven methods in buildings to increase operational efficiency is complementary to traditional building modernization measures, such as building shell refurbishment.

- The data-driven optimization of building operations enables significant increases in efficiency as demonstrated in our experiments and reported in the related work. Increasing the operational efficiency of buildings has several positive effects: lowering emissions of greenhouse gases and pollutants helps the climate and the environment in general. Hence, EVOX-CPS turns buildings into Green Cyber-Physical Systems [151]. In addition, humans benefit in a variety of ways: nutrition quality increases, building operating cost can be reduced, public health improves, and multiple interrelated effects stimulate the economy. As national supply security (fuel, food, water) increases, international tensions decrease, and the reasons for migration reduce. [117–119, 129] provide more details on how combustion causes global effects detrimental to human lives.

In summary, on the level of an individual building, the validation experiments, as well as the related work, suggest a vast potential to improve the operational efficiency by applying computational techniques. To understand the bigger picture, Chapter 4 assumes widespread adoption of predictive control in buildings. The chapter relies on inter-disciplinary reasons to deduce large-scale impacts and qualitative effects on society. It shows that the identified effects create synergies supporting multiple aspects of sustainable development, implying the potential to impact the lives of billions of people positively. For that, EVOX-CPS is our proposal to help the global adoption of these techniques in existing and new buildings.

5.2 Future Work

To streamline the process of EVOX-CPS, automation of several steps will lower the demands of experts' labor and expedite the deployment of predictive control into existing buildings. For example, approaches to select features based on BIM information are beneficial [13]. Similarly, to select, configure, and train the predictive model in an automated fashion dramatically increases EVOX-CPS potential [152].

Many buildings exhibit similar characteristics regarding usage patterns, insulation, system installations. Once predictive control strategies have been developed, it would be a significant improvement to be able to quickly transfer and adapt control strategies to another building [13].

In the Commerzbank Arena experiments, the developed control logic could mitigate a real operational problem - insufficient heating supply capacity on very cold days at times of peak demand - by reacting to symptoms of scarcity. It should be investigated how to extend EVOX-CPS to automatically identify the systems involved in and the situations leading to potential resource or control conflicts, see [13]. The identification could be based on BIM information or based on mining operational data.

Controlling a building's different energy systems typically requires submetering as encountered in the Commerzbank Arena. Retrofitting a building with these installations is labor intensive and therefore expensive, especially if hydronic systems are involved. Therefore, the barriers to developing and deploying data-driven predictive control in buildings without a pre-existing submetering installation would drastically reduce, if energy disaggregation methods could suffice for predictive control purposes. For electricity, the topic is referred to as *Non-Intrusive Load Monitoring* (NILM), but most publications require sub-second data [153, 154]. That sampling rate is orders of magnitude higher than what typical BMS systems provide. By leveraging BMS data our work [100] achieves reasonable accuracy for disaggregating lower frequency electricity data (sampled in the range of minutes) but has yet to be proven to work in real building operations for the purpose of control. Besides, the approach needs validation for hydronic systems.

Another future work is to investigate which aspects of the "integrated "tool chain" for comprehensive Model-Based Design (MBD) of Cyber-Physical Systems (CPSs)" developed by INTO-CPS [155] EVOX-CPS might leverage. As the tool chain focuses on MBD-CPS, the aforementioned lack of BIM data for existing buildings poses a challenge that needs to be tackled in particular.

In addition, addressing the limitations in Section 4.3 will enhance EVOX-CPS.

- Explicitly addressing data-privacy and data-security aspects in the methodology's steps and phases, for example by applying technical protection means such as [98] or by adopting aspects from the data privacy concept of [101]. Also, it is for future work to investigate how conformance to the upcoming EU General Data Protection Regulation (GPDR) [156] can be embedded into EVOX-CPS.

- Dependability and reliability are essential to any CPS, including buildings. It is for further study how EVOX-CPS can accommodate dependability concepts increasing CPS autonomy and self-awareness [148, 149]. Also, combining EVOX-CPS with the framework to assess the building CPS' reliability during routine operation [150] should be investigated.

- The data-driven predictive control experiments' effect sizes are significant. That concept for improving buildings' efficiency levels is complementary to modernization and refurbishment measures. It is for future work to quantify the potential of applying both types of measures in buildings and what each contributes. That will allow decision-makers to prioritize and steer their resources to the steps and measures achieving the biggest impacts.

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Part II

Paper A

Predictability of Energy Characteristics for Cooling, Ventilation and Heating Systems in Sports Facilities

Authors:
Mischa Schmidt, Anett Schülke, Alberto Venturi, Roman Kurpatov

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Predictability of Energy Characteristics for Cooling, Ventilation and Heating Systems in Sports Facilities

Mischa Schmidt, Anett Schülke, Alberto Venturi, Roman Kurpatov

Abstract

In this paper we analyze operational energy data of the cooling, ventilation and heating systems of the professional soccer stadium *Commerzbank Arena* in Frankfurt, Germany. We analyze data collected over a six month period in 2014 statistically and show that depending on the stadium's operational context consumption patterns vary largely among the different systems resulting in very different behaviors. The results provide insights into what drives the energy consumption for different systems of a large commercial sports facility: the static heating system is purely dependent on outside air temperature, ventilation exhibits a pronounced daily consumption pattern irrespective of the temperature and cooling is driven by a combination of event operation and air temperature. These insights will allow us to predict, plan and balance the energy demands of different subsystems more accurately, resulting in energetic improvements of the stadium operation in the form of load shedding while maintaining the systems' service levels.

1 Introduction

Modern sports stadiums are challenged to meet today's expectations with respect to energy efficient operation. The usage patterns and operational modes of sports facilities are driven by planning patterns specific to the events in the respective stadium. This leads to a behavior different from those of other types of large-scale buildings. A soccer stadium accommodating 50.000 to 60.000 spectators has a yearly heating demand of about 6.800 MWh, a yearly cooling demand of approximately 500 MWh and a yearly electricity demand of roughly 4.500 MWh [1]. Our research especially targets energy efficiency solutions exploiting the synergies of operational information with building specific context. For understanding the operating schemes and dominating factors in daily operation, detailed monitoring of energy consumption of selected building subsystems and an online data aggregation platform have been deployed in the real operational setup of the Bundesliga soccer stadium *Commerzbank Arena* in Frankfurt, Germany (outlined in more detail in [2]). We will present an analysis of the energy demand patterns of the cooling, ventilation and heating systems and their dependencies on the operational context. The aim is to understand the predictability of energy consumption in order to schedule and balance the load of these systems without sacrificing on the systems' service levels. The paper is structured as follows: after a description of Related Work and the Methodology, the sections Cooling, Ventilation, Cooling and Ventilation and Heating will provide an overview of the energy consumption characteristics we observe in the current operation. We then conclude the paper with discussions on our findings and provide an outlook of our future work.

2 Related Work

For assessing and improving the energetic efficiency of sports stadiums, typically installed equipment and overall system efficiencies are studied. Modernization and refurbishment of equipment is a common approach and amortization times of the large variety of possible measures need to be considered, as studied e.g. in [3]. Typically, these measures do not reflect enhancements of efficiency by exploiting holistic approaches towards enhanced control strategies. When focusing on optimizing energy control scheduling in the building context, research provides mainly mathematical methods and schemes [4] or machine learning approaches [5], often supported by predictive models [6]. In the advent of studying human behavior and building usage impact, operational context dependent consumption characteristics also gain more attention. Typically, these studies are exercised on commercial buildings like office buildings. Special building types which exercise a stochastic event structure, often characterized by high energy profiles of these events are less focused on. Our studies focus on commercial sports facilities with strong stochastic energy usage profiles due to scheduled regular events as well as irregular events. This work provides a statistical analysis of the collected data for improving the understanding of the operational context's impact on the behavior of different subsystems and it will enable us to devise load shedding strategies for the daily sports arena operation.

3 Methodology

In order to enhance the energetic operation efficiency of the different subsystems by orchestrated operation, we aim to define the energy efforts for cooling, ventilation and heating by investigating their individual consumption, consumption due to correlated operation and context related energy usage depending on different operational modes. We analyze the data of multiple sensors and meters in time intervals of 10 minutes collected via a data aggregation platform [2]. The interrelationships of different variables are mainly investigated through linear regression analysis as to be found in e.g. [7]. To assess the extent to which the variance of the data can be explained by a regression we use the adjusted R^2 metric – the *coefficient of determination*. To decide if the observed data relation is beyond plain coincidence, we provide the statistical significance testing (p-values) for the associated F-Test. Probabilities below a pre-defined threshold of 1% provide confidence in the respective regression model. All models documented in this paper undercut this threshold by several orders of magnitude. When comparing effects of any efficiency measure in the building context, it is necessary to normalize for differences in weather conditions of the studied periods. The standard way is to normalize for so called *heating degree days* (HDD, when normalizing energy consumption of heating systems) or *cooling degree days* (CDD, when normalizing energy consumption of cooling systems). HDD (or CDD) express the number of days of a period on which the outside air temperature undercut (or exceeded) a pre-defined base temperature and thus allows to account for differing weather conditions across periods. The base temperature represents a balance point below (or above) which the heating (or cooling) system starts working and is considered to be building specific. A variety of calculation options e.g. using the mean or the maximum daily air temperature exists. In this work, we apply the mean daily temperature, as this approach is accepted widely as a standard method [8].

4 Cooling

Cooling is one of the major operations during summer time. We start by documenting the behavior of two representative components of the arena's cooling system: a chiller and a cooling table; we study their interrelation, their relation to the outside air temperature (T_{air}) and day-to-day operation patterns in the period of April – July 2014. Our first investigation shows a strong linear relation between the daily energy consumptions of the chiller (Q_C) and the cooling table (Q_{CT}) in Figure 1. In the subsequent analysis, we therefore focus on either one of the systems and transfer the findings to the other. The cooling table's daily electricity consumption exhibits two superimposed modes of operation (Figure 2):

1. the cooling table is switched off and does not consume energy, irrespective of the average T_{air}

2. the cooling table consumes electricity in relation to T_{air}

When the cooling system is switched on, the temperature dependent trend of the daily energy consumption is very well predictable by a linear regression (blue curve, Figure 3). Also, energy is only consumed for days with a mean T_{air} of about $15°C$ and above, thus we consider the stadium's base temperature for CDD normalization as $T_{base,CDD} \approx 15°C$

Looking at the usage pattern of the building, a dependence of the chiller energy consumption on business hours for specific weekdays is given as shown in Figure 4. Apart from outliers, the boxplots show that Tuesdays, Thursdays, Fridays and Saturdays cooling is required. On Fridays, switch-on of the chiller is at noon/ afternoon, on the other days typically during the period 9:00 – 11:00. Fridays and Saturdays, cooling is required until the evening whereas Tuesdays and Thursdays energy consumption drops already between 17:00 and 18:00.

5 Ventilation

Ventilation is another important system and might relate to the cooling operation; however we first look at the ventilation independently. According to the stadium operator, the kitchen ventilation system is the ventilation system that runs most. So, we present

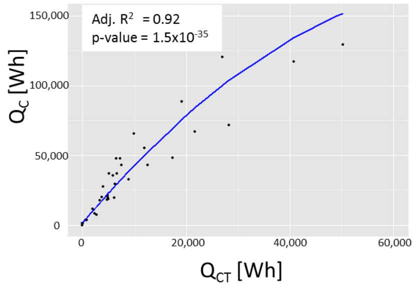

Figure 1: Daily energy consumption of chiller (Q_C) and cooling table (Q_{CT}) exhibiting a strong linear relation. Adjusted $R^2 = 0.92$.

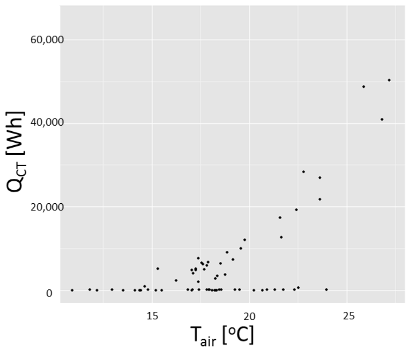

Figure 2: Cooling table's daily energy consumption (Q_{CT}) in relation to daily mean T_{air} showing two superimposed modes of operation.

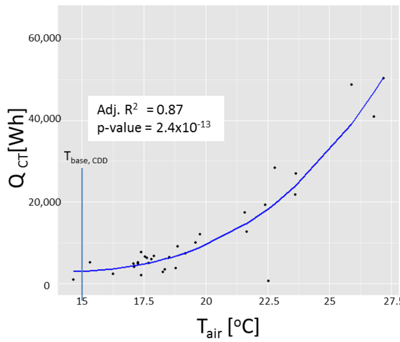

Figure 3: Cooling table's daily energy use in relation to daily mean T_{air}. Focus on temperature dependent trend; $T_{base,CDD} \approx 15°C$. Adjusted $R^2 = 0.87$.

the behavior of the kitchen ventilation system and its relation to T_{air} as well as daily operation patterns in the period of April – July 2014.

Our first investigation shows a strong linear relation between the daily energy consumptions of the ventilation supply ($Q_{V,s}$) and exhaust ($Q_{V,ex}$), as seen in Figure 5. Again, this allows us to analyze either of the systems and transfer the findings to the other.

The ventilation systems do not exhibit a trend related to the daily mean T_{air} (Figure 6), which implies that other factors of arena operation define the patterns of energy consumption such as office hours and events.

We find a very strong dependence of the energy consumption on the business hours,

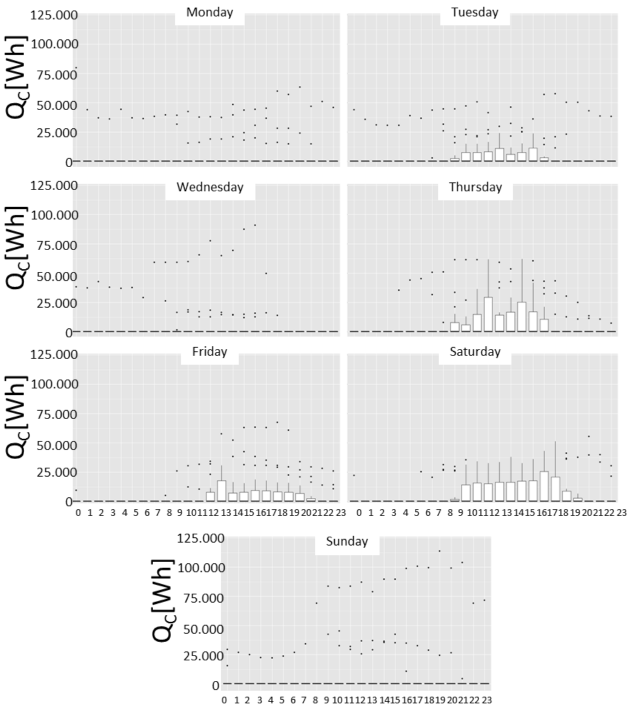

Figure 4: Hourly chiller energy consumption (Q_C) per weekday.

varying across the weekdays (Figure 7). For all weekdays, the main hours of energy consumption are between 6:00 and 18:00, i.e. the office hours. Moreover, for Monday – Friday the median as well as the 25th and 75th percentiles of the hourly energy consumption observations during office hours are higher than those of Saturday and Sunday. Thursday – Saturday switch-off times are later than on the rest of the days, caused by evening events on these days.

6 Cooling and Ventilation

Now, we investigate the possible relation between ventilation and cooling system operation following the intuition that cooled air requires distribution by ventilation. While we cannot find a clear-cut, statistically significant function expressing the relationship between daily cooling system energy consumption and the ventilation system, we are able to identify a qualitative correspondence between the two systems, presented in Table 1. It shows that for 100 days of energy consumption data in the period of April – July

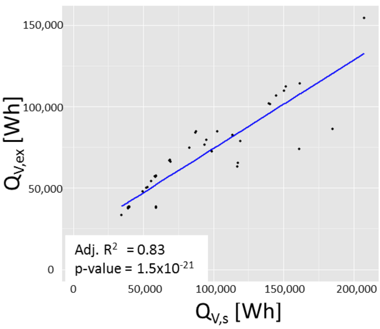

Figure 5: Daily energy consumption of ventilation supply ($Q_{V,s}$) and exhaust ($Q_{V,ex}$). Adjusted $R^2 = 0.83$.

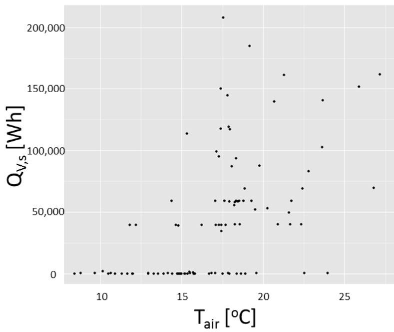

Figure 6: Ventilation supply's daily energy consumption ($Q_{V,s}$) in relation to daily mean T_{air}.

Daily Energy Consumption	$Q_{V,s} > 1000Wh$		$Q_{V,s} \leq 1000Wh$	
$Q_C > 1000Wh$	53 d	18.9° C	8 d	18.3° C
$Q_C \leq 1000Wh$	2 d	12.8° C	37 d	14.3° C

Table 1: Relationship of Q_C, $Q_{V,s}$ and Mean T_{air}.

2014, we find 53 days on which both systems consumed more than 1000 Wh (case 1, light shading) and 37 days on which both systems consumed very little energy (case 2, darker shading). We note here the difference of daily mean temperature for these two cases of 4.6K, as both systems are actually driven by their operational context and not by temperature only.

7 Heating

During the colder season, heating gains higher importance. Focusing on the static and the grass heating systems, we similarly document the energy behavior on normal operation and the relation to T_{air} for the heating period February – March 2014.

The static heating system's average hourly consumption of thermal energy during different calendar weeks shows a clear dependency on T_{air} (Figures 8 and 9) – as T_{air} grows, the consumed energy declines. In calendar weeks CW6-CW9, the start of the business day is characterized by a peak in energy consumption. The strong dependency on T_{air} is also evident in Figure 10, where a linear regression is able to predict the static heating system's daily thermal energy consumption from the daily mean T_{air} very well. But, unlike the cooling case, we are not able to find a temperature independent base heating load in Figure 10 and can therefore not establish $T_{base,HDD}$.

In contrast to the T_{air} dependent energy consumption of the static heating, the stadium's grass heating system – the major consumer of thermal energy – exhibits a diffe-

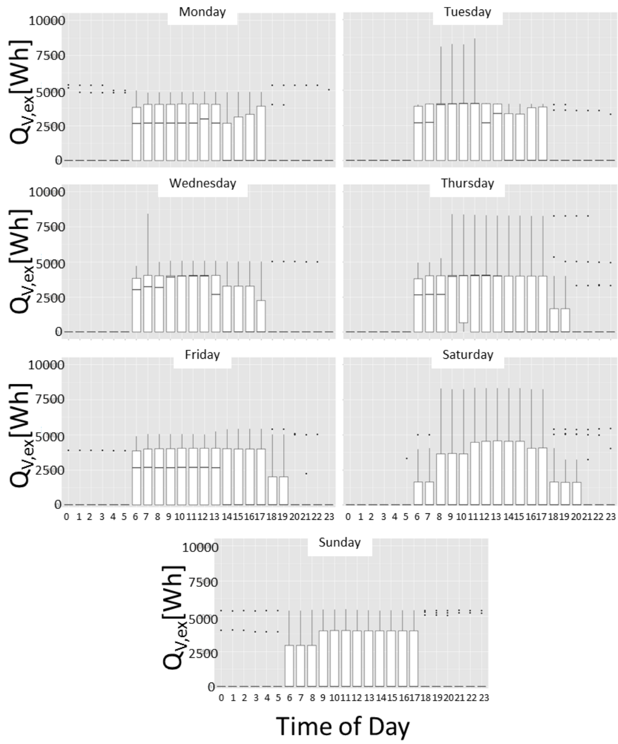

Figure 7: Hourly energy consumption of ventilation exhaust ($Q_{V,ex}$) per weekday.

rent behavior (Figures 11 and 12). The daily consumption pattern of the grass heating typically has troughs when the static heating system ramps up at business day start. According to the stadium operator, operational staff manually imposes this load shedding scheme by shutting the system off during office hours to reduce the aggregate peak energy demand.

8 Results and Discussion

The presented statistical analysis of the heating, ventilation and cooling systems' operational and energy consumption data collected in the Commerzbank Arena, Frankfurt, Germany during a six month period 2014 allows us to draw valuable conclusions regarding predictability of energy use. Key findings are:

- Cooling systems' energy consumption exhibits weekday related consumption pat-

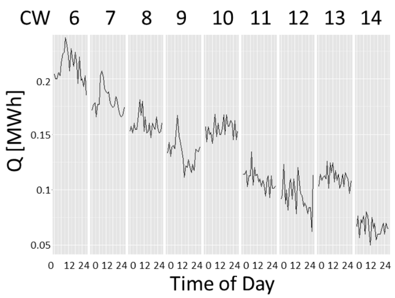

Figure 8: Average hourly energy consumption of the static heating system.

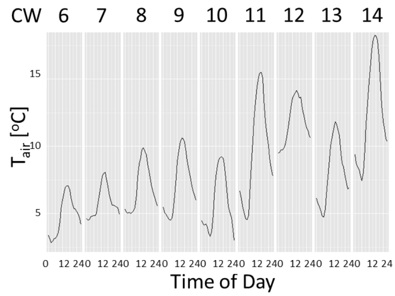

Figure 9: Average hourly air temperature T_{air}.

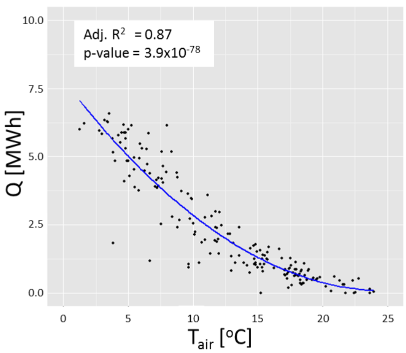

Figure 10: Daily energy consumption of static heating system in relation to daily mean T_{air}. Adjusted $R^2 = 0.87$.

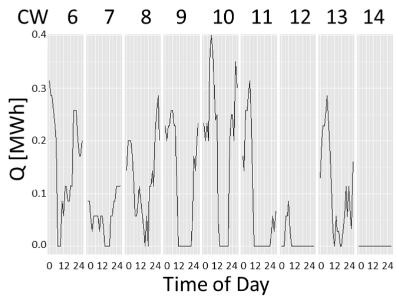

Figure 11: Average hourly energy consumption of the grass heating system. The heating period ended in CW 13, causing a zero energy use in week 14.

tern. The consumption is determined by a combination of T_{air} and whether the arena operational context is requiring cooling at all. If cooling is required, mean daily T_{air} obtained by e.g. a weather forecast predicts the cooling systems' daily energy consumption very well.

- The kitchen ventilation shows an evident repetitive daily energy consumption pattern during the office hours. The energy consumption is dominated by business hours rather than T_{air}. The consumption patterns vary among the weekdays but exhibit similar structure. It is for further study, if other ventilation systems behave similar to the kitchen.

- The static heating system exhibits a repetitive daily energy consumption pattern;

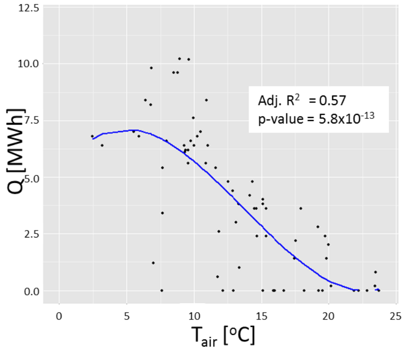

Figure 12: Daily energy use of grass heating system in relation to mean T_{air}. Adjusted $R^2 = 0.57$.

in the early weeks with noticeable peaks on office hour start to counter night cool-down. At the same time, its energy consumption is strongly related to T_{air}.

- The human interference with the grass heating system operation for manual load shedding purposes relies on the soccer pitch's thermal inertia and it results in a T_{air} and business hour dependent energy demand. The operational staff's approach to load shedding stresses that a systematic, data driven approach to load shedding is of relevance for day-to-day operation.

- Based on the observed data, we identified the stadium's balance points for CDD normalization as $T_{base,CDD} \approx 15°C$. We could not reliably determine $T_{base,HDD}$, which we will continue to study in the next heating season.

- Static heating, kitchen ventilation and cooling systems exhibit qualitatively different behavior: while static heating is purely T_{air} dependent, ventilation exhibits a pronounced daily consumption pattern apparently irrespective of temperature, and cooling systems are driven by a combination of event operation and T_{air}. While the relation to T_{air} is different for cooling and ventilation, 90% of the considered days show both systems are running or both are inactive with a notable difference in mean T_{air} of 4.6K between these.

With these conclusions, we are in the position to predict the energy demand of different subsystems based on context information (weekdays, business hours, match schedule) and weather forecasts for T_{air}. In future experiments we will perform energy planning and balance the demand of different subsystems in order to reduce the aggregate peak energy demand of the stadium operation.

9 Acknowledgment

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Paper B

The Energy Efficiency Problematics in Sports Facilities: Identifying Savings in Daily Grass Heating Operation

Authors:
Mischa Schmidt, Anett Schülke, Alberto Venturi, Roman Kurpatov

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The Energy Efficiency Problematics in Sports Facilities: Identifying Savings in Daily Grass Heating Operation

Mischa Schmidt, Anett Schülke, Alberto Venturi, Roman Kurpatov

Abstract

Recently, reflections on modern sports stadiums' environmental impacts have gained substantial attention. Large-scale stadiums of e.g. professional soccer teams are characterized by having installations of grass heating systems serving *the* crucial commercial asset and at the same being the sub-system with the highest yearly thermal energy consumption. Public buildings of this size imply situation-specific operational modes combined with high levels of safety and comfort requirements. In this paper we provide a first study on the energy savings potential of a professional soccer stadium's grass heating system during day-to-day operation. In practice, limited heating capacities of the arena have to be adhered to, which causes the current operation to often result in under-performance of other, less critical facility units. Our analysis of dynamic operational and contextual data serves as foundation for long-term energy efficiency measures. We study relevant parameters related to the current control schemes and the stadium's context. Concretely, the grass root temperature as critical observable is studied with respect to weather conditions and the resulting thermal behavior. We provide an improved control strategy and quantify the anticipated savings of this strategy to be as high as 34% compared to the last heating season. For the future, the documented thermal characteristics will enable the formulation of more advanced control strategies to positively influence the grass heating operation. This will lead to further improvements in balancing the heating demand across all thermal facility sub-systems by integrating operational context with forecasts of the thermal behavior in the future.

1 Introduction

Modern sports stadiums have gained public interest for large scale events since the beginning of the last century. Architects, construction companies and facility operators are challenged to meet today's expectations for energy efficient operation. The operational modes of sports facilities differ from those of conventional large-scale buildings as they are driven by planning patterns specific to the events in the respective stadium. The technical requirements of modern soccer stadiums with respect to safety and energy are very high in order to provision all systems like floodlighting, heating, ventilation, air conditioning, lighting, catering, lawn heating and supplying the event specific media. The various building systems are a prime example of cyber-physical systems, with varying degrees of complexity, intelligence and level of integration.

Investigations have shown that for a stadium of a size of 50,000 to 60,000 visitors, the heating demand of offices, catering, warm water, grass heating and training area sums up to about 6,800 MWh/a, whereby half of the demand is attributed to the grass heating system [1]. Additionally, the cooling demand amounts to about 500 MWh/a and the electricity demand to roughly 4,500 MWh/a [1]. Besides the modernization with cost- and energy-efficient equipment, one of the core measures for energy efficiency and realizing CO_2 savings is seen in holistic arena-wide monitoring of the types of energy profiles and material flows of the different systems.

The complexity of modern stadiums requires a professional facility management which enables a holistic analysis of all information coming from building units, usage and context in a continuous process in order to discuss facility specific measures for sustainable stadium operation. Starting with the FIFA World Cup^{TM} in 2006, the Fédération Internationale de Football Association (FIFA) initiated a stronger drive towards environmental conservation and sustainable management of sports stadiums [2]. For upcoming world cup events, environmental assessments of the applications are in progress. As the demand for sustainable building and facility operations is further increasing, systematic research for large scale facilities are in progress.

Our research targets energy efficiency solutions exploiting the synergies obtained from operational information with building specific context; in this work under the special conditions of sports arenas. We deployed a data aggregation platform for holistic data collection in the real operational setup of the Bundesliga soccer stadium *Commerzbank Arena* in Frankfurt am Main, Germany. The evaluation is performed under the given commercial conditions of limited heating capacities coupled with high priority for the lawn heating system serving the main commercial asset of the stadium.

In this paper, we will present the evaluation of the energy savings potential for the arena's grass heating system. Analyzing the heating system's behavior during the last heating period, we study in particular the grass field's thermal characteristics together with contextual information. This allows us to extrapolate the thermal behavior of the lawn for short time horizons. The collected insights enable to perform a rough calculation of potential energy savings over the last winter season if an alternate control strategy had been applied. These rough calculations serve as an indicator whether this approach should be experimentally verified in the next heating season or if other arena systems should be focused on instead.

The paper is structured as follows: after a description of the problem statement in Section 2, the following Section 3 will provide an overview of the grass heating system installed in the Commerzbank Arena and an illustration of the impacts of the currently applied control schemes. The analysis on context dependent thermal dynamics of the grass heating is presented in Section 4 followed by the discussion of possible strategies to improve the stadium's energy efficiency in Section 5. We conclude the paper in Section 6 with a summary of our studies and an outlook on future work.

2 Problem Statement

Large sports facilities like the Commerzbank Arena in Frankfurt are characterized by high lawn quality requirements complemented with high safety and comfort standards to support large-scale events, including soccer games and cultural events of different types. Beyond being a mandatory system in professional soccer stadiums according to soccer regulations, grass heating systems also help during winter to keep the playing field in high-quality conditions - *the* prime commercial target for the facility operation - and by helping to avoid replacing the field during the season more often they avoid costs associated to that process. Centered around this focus, the system operation shall ensure that the grass heating demand is served with priority. According to the Commerzbank Arena operator, the aggregate heat demand can exceed the capacity of the main heating supply (a gas - hydronic system) at peak times[1]. In case of heating shortages, the operational scheme needs to sacrifice the service quality and thermal comfort conditions in other areas like offices, conference center and meeting rooms.

Initial assessment of the deployed systems showed possibilities for energy savings and demand balancing by enhancing the current system operation with information about grass field conditions, heat flow relations, weather conditions and operation context. We focus on the grass heating system as the biggest consumer of thermal energy to fully understand the impacts of control parameters of the grass heating control system. With this knowledge we intend to develop a concept for automatic control of lawn heating schedules by impacting the operational parameters in a context-aware dynamic operational scheme. The core point of the modified scheme is the shift from the typical control schemes (deployed in majority of such systems) based on the external temperature (as lower-temperature boundary only rule) to a control strategy based on grass root conditions directly. This targets an increased efficiency of the thermal energy consumption related to grass conditions and a freeing of thermal capacity in favor of other systems.

While the grass heating can be modeled theoretically based on physical parameters, in the real world the thermal parameters very much depend on the real installations and local conditions. Thermal effects like heat losses and/or gains, influences of wind flow through open stadium gates, or solar irradiation by stadium roof operation are likely to impact the thermal performance of the grass field. The problem of the soil temperature profile estimation starting from meteorological data has been investigated in literature from different points of view and many models have been presented. Detailed knowledge of several physical ground parameters is necessary to be able to calculate the thermal diffusivity with enough precision. Meteorological context certainly plays a crucial role, like aspects of the ground as porous medium with different levels of water penetration or evaporation changing the humidity levels of air. The difficulties in measuring all the necessary parameters led to the development of simplified models based on physical processes. The classical [3] and the subsequent development by [4,5] have been demonstrated

[1]During the heating season (late October - early April) the grass heating system consumes up to 50% of the peak output of the main gas boilers. It accounts for approximately 40% of the annual gas consumption.

by [6] to be not precise enough to estimate the soil temperature near the surface[2]. They further propose an improved model in which the surface heat flux exchanges are supposed to be effective “over a small but finite distance below the land surface”. In a real-world setup, the relevant information to configure these models is often not collected with the needed spatial resolution to ensure that the aforementioned fine-granulated model of the real stadium situation can be properly applied.

We therefore follow a pragmatic approach to determine the thermal performance of the Commerzbank Arena’s soccer pitch based on the analysis of aggregated data captured from the stadium’s Building Management System (BMS) which are typically available in such system. We focus on simple statistical analysis of the captured data to illustrate the potential of identifying the variables of concern and closely monitoring these to realize efficiency gains with control schemes of low complexity. This builds the basis to formulate evolutions of the current grass heating operational scheme to address the outlined energetic problems of the current operation.

3 The Grass Heating System

3.1 System Design

In Fig. 1, we depict a high-level view of the heating distribution system of the Commerzbank Arena. The stadium’s grass heating is a glycol-based subsystem which is connected to the main heating network through a 1.4 MW heat exchanger. Its glycol is distributed via multiple pipe loops of equal length along the long side of the grass field and the supply and return distribution on the short side of the grass field. The grass conditions are characterized by the root temperature T_{root}, measured on the field side at the turn-around of the long pipe loops. By standard operational setup, the root temperature is governed by the glycol supply temperature provided to the grass field - which is controlled by a corresponding set point ($T_{G,set}$) if the heating system is switched on. The sensor and meter installations integrated with the stadium’s BMS are explained in Tab. 1 and schematically shown in Fig. 2. We collect their data from the BMS as part of its approximately 13,500 variables in 10 minute intervals via BACnet/IP using an OSGi based, distributed holistic data aggregation platform [7] designed, implemented and deployed under the umbrella of the CAMPUS21 project [8].

3.2 Grass Heating Control: Status Quo

Current Control Schemes

The stadium’s current grass field operation is characterized by two distinct control schemes which can be described as:

[2] To maintain optimal growing conditions for grass, grass root temperatures must be controlled and thus a high near surface soil temperature accuracy is desired for our work.

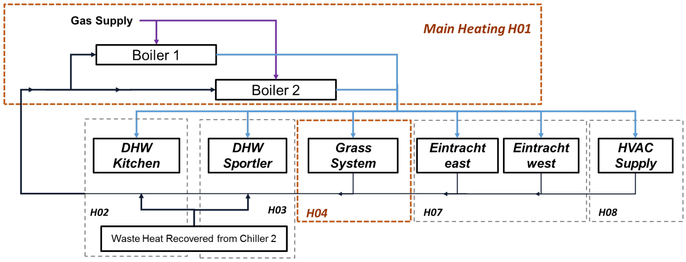

Figure 1: Heating Distribution System structured into core arena subsystems

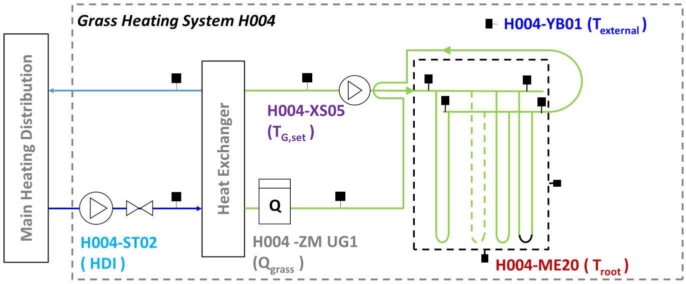

Figure 2: Grass Heating Sensor installations

- *Control 1*: Heat demand logic patterns
  $HDI = \begin{cases} 1 & \text{if } ON \\ 0 & \text{if } OFF \end{cases}$ with either

  (1.A) Threshold of $T_{external}$ at $\sim 6^oC$, or

  (1.B) Time schedule, e.g. 12 hour interval

- *Control 2*: Set-point $T_{G,set}$

These control schemes are adapted manually by the stadium's operational staff. The following analysis for different months and with different control logic combinations illustrates the limitations of these semi-supervised control schemes. Fig. 3 shows the control logic performed during 1^{st} half of November 2013. It represents a control scheme based on *Control 1* pattern only. This scheme impacts the grass field conditions in the following ways:

- *Control 1.A*: The trend of $T_{external}$ is followed by T_{root}. Note that $HDI = 0$ for a large fraction of time as $T_{external} > 6°C$ frequently and thus heating does not impact T_{root} substantially.

- *Control 1.B*: T_{root} follows a fixed HDI schedule. The schedule combined with the choice of $T_{G,set}$ apparently overcompensates $T_{external}$ and results in an upward trend for T_{root} - in particular at the time when $T_{external}$ rises above $6°C$ again.

Table 1: Grass Heating Sensor installations

Sensor ID	Description	Variable	Unit
H004-ZM UG1	Heat meter	Q_{grass}	MWh
H004-ME20	Grass Root Temp.	T_{root}	^oC
H004-YB01	External Temp.	$T_{external}$	^oC
H004-XS05	Glycol Supply Set point	$T_{G,set}$	^oC
H004-ST02	Heat Demand Indicator	HDI	1/0

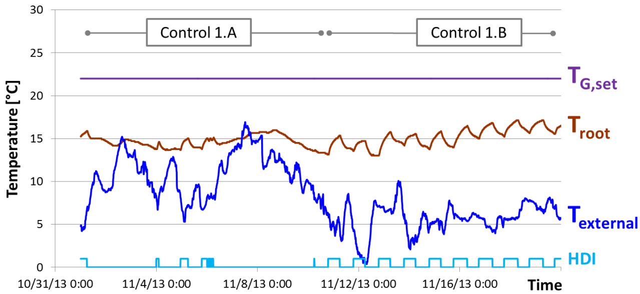

Figure 3: Control logic for November 2013

The problem of both control strategies *1.A* and *1.B* is that there is no explicit consideration of T_{root}: the control schemes do not react automatically to violations of any pre-defined T_{root} target range. We note that agronomy publications [9–11] give a variety of different optimum grass root temperatures for different types of grass. Those recommendations largely overlap between $10°C - 18°C$ in order to keep "cool grasses" growing through winter.

In Fig. 4, the control strategy applied in January 2014 is shown, which allows to observe the impact of *Control 2*. Resulting from low external temperature during December 2013, the grass heating demand has been kept on over a longer period. With increasing $T_{external}$ near $5 - 6^o$C, T_{root} started to rise considerably above $15°C$[3]. The *Control 2* related action of reducing the supply temperature set-point $T_{G,set}$ by -1K on January 14 could not stop the increasing T_{root} by itself: only the heating shut-off due to $T_{external} > 6°C$ at January 16 resulted in a cooling down of the grass roots.

During the following days, the external temperature decreased again and the system was switched to control *1.B* (time-scheduled heat demand). As $T_{external}$ fluctuated around $4 - 5^o$C, the scheduled HDI had a strong impact on T_{root}. On January 20, the manual decision was taken to increase $T_{G,set}$ by +2K. This established a strong upward trend for T_{root}, actually exceeding $15°C$ in the next heating cycle already. Even the reduction of $T_{G,set}$ by -1K on January 22 did not significantly reduce T_{root} - and the switch to continuous heating (see Fig. 4) continued to drive T_{root} further up.

[3] $15°C$ is an acceptable temperature, but [9–11] would allow lower temperatures, also.

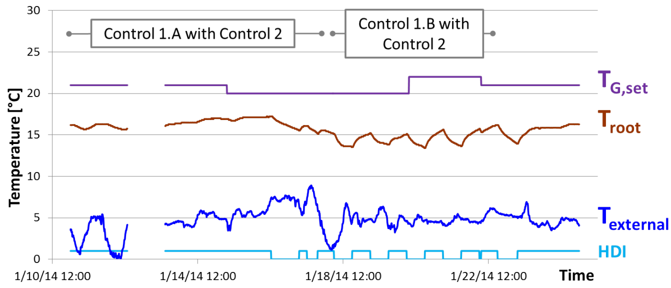

Figure 4: Control logic for January 2014

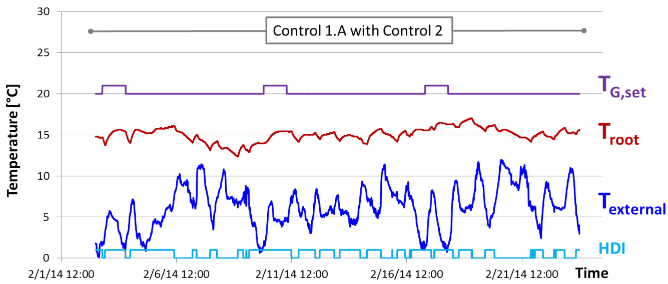

Figure 5: Control logic for February 2014

Additionally, we observe the control scheme in February 2014 in Fig. 5. The primary logic is kept on *Control 1.A*. $T_{G,set}$ was kept mainly at $20°C$. Strong variation in $T_{external}$ at the beginning of the considered period caused intermittent heating behavior and as a consequence T_{root} declined. $T_{G,set}$ set to $20°C$ could not equalize the heat loss over the grass field. With observed temporary increases of $T_{G,set}$ to $21°C$, T_{root} was led back to approximately $15°C$. When repeating this temporary set-point modification later again, T_{root} had already been at a higher temperature base, and the increased set-point caused T_{root} to rise further to relatively high values, caused by thermal energy already stored in the field.

We conclude that the motivations for the operational staff's decisions for combining particular control schemes and choosing particular parameters are not always evident in the collected data. As a result, the grass heating system frequently heats when T_{root} can be considered high when compared to literature. Therefore we see that the system presents opportunities for energetic improvements through adapting the control parameters in an algorithmic way, e.g. taking into account forecasts about $T_{external}$ and controlling T_{root} ranges more tightly.

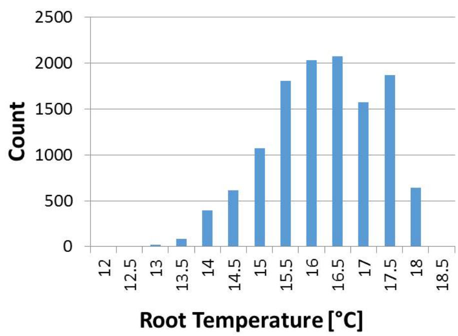

Figure 6: Root temperature distribution during winter 2013-2014

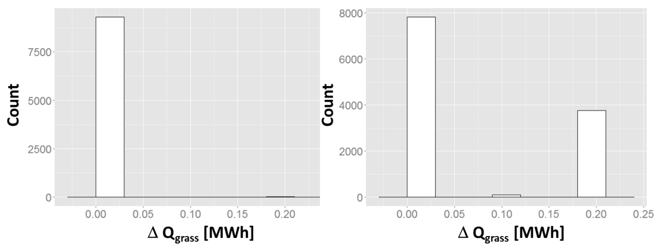

Figure 7: Number of intervals with a reported ΔQ_{grass} for $HDI = 0$ (left) and $HDI = 1$ (right).

Observed Root Temperature Behavior and Energy Demand

To illustrate the result of the observed control schemes, we show a histogram of T_{root} measurements (10 minute intervals) during the period between November 2013 and March 2014 for which the grass heating was switched on in Fig. 6. We observe that of the approximately 1956 hours the heating system was running last winter, T_{root} has been kept for more than 400 hours above $17°C$, 1600 hours above $15°C$ and 1944 hours above $13°C$. The observed mean root temperature for $HDI = 1$ was $\overline{T_{root}} \approx 16°C$.

Over the entire period, the grass heating approximately used approximately 795 MWh of thermal energy - considerably less than the average consumption in literature [1], partly caused by the very mild German winter 2013-2014. The installed heat exchanger of the grass heating system (see Fig. 1) has a capacity to deliver 1.4 MWh/h. Looking at observation intervals of 10 minutes, this translates to a maximum of about 0.23 MWh/interval. We focus on the heat volume distribution and related meter sensitivity to observe the heat energy usage for the grass field. The Fig. 7 histograms show the consumed energy ΔQ_{grass} per 10-minute-interval measurement with a bin-size of 0.03 MWh,

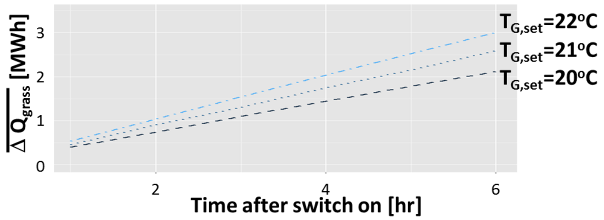

Figure 8: $\overline{\Delta Q_{grass}}$ for six hour heating period of 87 heating events in relation to $T_{G,set}[°C]$.

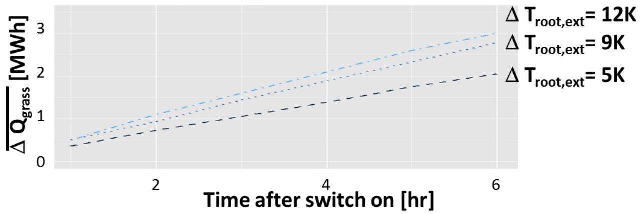

Figure 9: $\overline{\Delta Q_{grass}}$ for six hour heating period of 87 heating events in relation to $\Delta T_{root,ext}$.

covering the observation period. The diagrams represent ΔQ_{grass} for $HDI = 0$ (left) and $HDI = 1$ (right). Besides showing a large fraction of intervals below the sensitivity threshold of 0.1 MWh (populating the 0 MWh bin), the $HDI = 1$ histogram also shows that $\Delta Q_{grass} = 0.2$ MWh is much more often observed than $\Delta Q_{grass} = 0.1$ MWh. This means, that with given metering resolution in ΔQ and Δt the grass heating system mainly records to have either consumed almost all the capacity of the heat exchanger (up to 0.23 MWh/interval), or to have aggregated below the measurement threshold for one or more intervals. On average, an increase in reported energy consumption is monitored approximately every third interval.

Tab. 2 provides the average $\overline{\Delta Q_{grass}}$ of all measurement intervals with $HDI = 1$ related to $T_{G,set}$. It becomes evident that energy demand increases by more than 50% when $T_{G,set}$ will be increased from $20°C$ to $24°C$, however we also note that the speed of increase is reduced with higher $T_{G,set}$.

As thermal processes are driven by temperature relations, we derive the thermal loss over the grass field by $\Delta T_{root,ext} = T_{root} - T_{external}$, which we consider as one important factor in our analysis. Tab. 3 shows that with rising $\Delta T_{root,ext}$ from 5K up to 14K, the energy needed to compensate the effects of thermal transmission increases by 10%.[4] Investigations show

[4] $\overline{\Delta Q_{grass}}$ should be considered with caution for extreme $\Delta T_{root,ext}$ where only few intervals were recorded - the statistics may not be as robust as for the other $\Delta T_{root,ext}$ observed.

Table 2: Observed average energy consumption $\overline{\Delta Q_{grass}}[MWh]$ per interval in relation to $T_{G,set}[°C]$

$T_{G,set}$	Total # Intervals	$\overline{\Delta Q_{grass}}$
20	2926	0.052
21	3071	0.064
22	4150	0.072
23	1033	0.075
24	516	0.080

that the energetic demand jump for $\Delta T_{root,ext} = \{15, 16, 17\}$ is caused by the fact that for the observed intervals, $T_{G,set}$ was always set to the very high $23°C$ and $24°C$.

So far, our studies have considered all heating intervals equally and provided an average energy consumption per measurement interval. As we suspect that the switching-on of the heating system exhibits a higher energy use than when the system is continuously running, we now focus on 131 heat demand switch-on events that we detected during the investigation period which were preceeded by several hours of $HDI = 0$. Of these, we study the subset of 87 events for which $HDI = 1$ for six hours or longer. Fig. 8 and 9 confirm the trends we identified in Tab. 2 and 3. For prolonged heating events, Fig. 9 shows the accumulated $\overline{\Delta Q_{grass}}$ for selected $\Delta T_{root,ext} = \{5, 9, 12\}$K over time. After six hours of heating we observe:

- $\overline{\Delta Q_{grass,5K}} \approx 2.1$ MWh, i.e. 0.36 MWh/h
- $\overline{\Delta Q_{grass,9K}} \approx 2.8$ MWh, i.e. 0.47 MWh/h
- $\overline{\Delta Q_{grass,12K}} \approx 3.0$ MWh, i.e. 0.5 MWh/h

For $\Delta T_{root,ext} = 5K$, Tab. 3 captures the effects switch-on events quite accurately, whereas for 9K and 12K the switch-on events consume more than average energy.

The documented relations are important to estimate the energy consumption in different situations and control settings. Measures aiming at improved energy efficiency or load balancing will have to work with the temperature dynamics and the T_{root} temperature range to gain a significant impact on the observed energy behavior.

4 Studying Contextual Thermal Grass Field Characteristics

Our documented observations show that the current sports facility operation implements a wide range of temperature settings and heating period durations. The clear dependency on thermal loss $\Delta T_{root,ext}$ over the grass field presents energy savings potential for contextual control concepts. In order to develop improved control strategies, e.g. to dynamically set the supply temperature set-point $T_{G,set}$ and (de-)activate the grass heat system, we devote this section to analyzing the thermal behavior of the stadium's playing field, in particular we focus on:

Table 3: Observed average energy consumption $\overline{\Delta Q_{grass}}[MWh]$ per interval in relation to $\Delta T_{root,ext}[K]$

$\Delta T_{root,ext}$	# Observed Intervals	$\overline{\Delta Q_{grass}}$
5	198	0.060
6	355	0.062
7	551	0.062
8	765	0.063
9	996	0.063
10	1576	0.064
11	1678	0.065
12	1945	0.065
13	1311	0.065
14	979	0.066
15	707	0.073
16	313	0.078
17	172	0.080

- the current grass root temperature T_{root} and its trend, its heating and cooling speeds when the grass heating system is switched ON/OFF,
- the air temperature $T_{external}$ within different time frames related to heating cycles and heating/cooling speed, and
- the temperature difference $\Delta T_{root,ext}$ describing the thermal loss over the grass field in order to estimate the heat demand.

More specifically, we investigate

- the impact of weather conditions on T_{root} trends when heating is switched off,
- T_{root} cooling and heating speeds (i.e. temperature change per time interval $\Delta T_{root}/\Delta t$), and
- the impact of the supply temperature set-point $T_{G,set}$ on the heating dynamics.

These characteristics will be the starting point for a contextual time schedule for a dynamic load balancing concept by

(1) impacting the actual heating time based on $T_{external}$ (past, present and forecast)

(2) exploiting T_{root} behavior for various heat demand request periods

(3) applying a T_{root} range from historical data and literature to control dynamics

(4) considering the heat loss to heat request relationship to drive the time pattern.

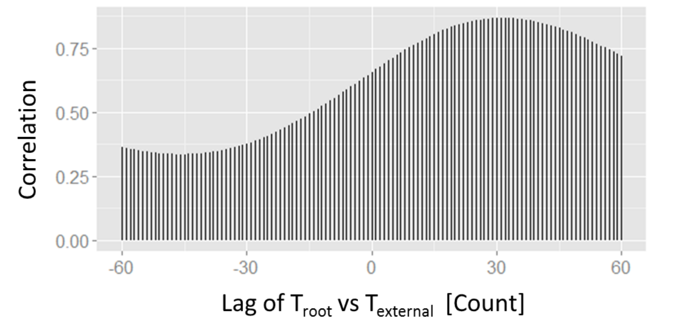

Figure 10: Cross-correlation of T_{root} with $T_{external}$.

4.1 Dependency on Air Temperature

In order to understand how weather conditions impact thermal dynamics, we analyze the air temperature's impact on T_{root}. Studies [12, 13] mention a three hour delay for a high correlation of air temperature with soil temperature at a depth of 5 cm. Additionally, the work in [13] also provides estimations for depths of 10 cm (five hours) and 20 cm (eight hours). For monitoring the grass root conditions at the Commerzbank Arena, T_{root} is measured at a depth of 15 cm[5].

To validate these time frames, we cross-correlate T_{root} and $T_{external}$ under the conditions that the grass heating system is non-operational. Fig. 10 shows the results based on the measurements from the Commerzbank Arena for a three week period in April 2014. The resulting maximum Pearson correlation value of more than 0.86 indicates a very strong linear relation for a lag of the T_{root} time series of 32 measurement intervals - approximately five hours - compared to the $T_{external}$ time series. If we consider that other factors such as lawn irrigation, rainfall, wind and solar radiation likely act as disturbance to any linear relationship between T_{root} and $T_{external}$, then it reasons that their impact is less than expected, or that their effect is largely overlapped by their impact on $T_{external}$. Due to this consideration, we neglect the effects of these externalities on T_{root} at this stage and study them in future work. Compared to [13], our observed lag of approximately five hours is less than expected for a depth of 15 cm, but we consider this to be related to possible differences in soil composition and moisture as well as the grass vegetation. To reflect this lag in our subsequent analysis, we adjust the $T_{external}$ time series by 32 intervals to assess the thermal behavior.

4.2 Cooling Speed

Investigating the operational data of the winter season from November 2013 to March 2014, we identified 132 heat demand switch-off events. From those, we investigate a subset

[5] Studies on plant grows report an average root depths for cool season grass up to 6 inches/ 15 cm [11].

of 75 events, for which the heating cycle has been switched OFF for six hours, with an optionally minimal interruption by a short heating cycle for less than 10 min. during these six hours. For this subset, we calculate for each event the change of T_{root} (denoted ΔT_{root}) for Δt_{OFF} up to six hours from the time the system was deactivated. In Fig. 11, the obtained ΔT_{root} averaged over all events is presented (denoted $\overline{\Delta T_{root}}$) together with the observed standard deviation (s).

Looking on the details, we find the dependencies to the operational (a) and thermal (b) context:

- (a) the temperature $T_{G,set}$, on which the system was running on prior to switch off (Tab. 4) and
- (b) the temperature difference $\Delta T_{root,ext}$ (Tab. 5).

In the considered set of events, $T_{G,set}$ was set to either $20°C$, $21°C$ or $22°C$. As expected, Tab. 4 shows that the cooling speed increases with higher supply temperatures as the thermal flow should be stronger. This effect could be caused either by a higher T_{root} on switch-off or by a lower $T_{external}$. While higher temperatures $T_{G,set}$ were also present in the data set, these data sets coincided with prolonged intermittent heating within the first six hours of switch off. This implies that when $T_{external}$ is low, human operators often tend to increase $T_{G,set}$ and additionally reduce switch-off periods manually.

Tab. 5 shows the cooling trends for selected $\Delta T_{root,ext}$. We observe similar behavior when the $\Delta T_{root,ext} \geq 10K$ and slower cooling when $\Delta T_{root,ext}$ is reduced. The relatively low s seems to support that temperatures (T_{root}, $T_{external}$) seem to dominate the thermal dynamics compared to rain, lawn irrigation, wind and solar radiation with less effect on T_{root}.

4.3 Heating Speed

We will now look on the thermal behavior for heating the field. For the previously discussed 87 heating events we calculate the average temperature trend $\overline{\Delta T_{root}(\Delta t_{ON})} \pm s$ (see Fig. 12).

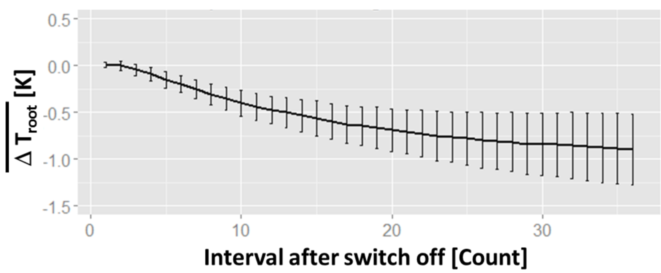

Figure 11: Cooling trend: $\overline{\Delta T_{root}(\Delta t_{OFF})} \pm s$ for six hours cooling period ($HDI = 0$).

Table 4: Cooling trend: $\overline{\Delta T_{root}(\Delta t_{OFF})} \pm s$ [K], related to $T_{G,set}$

Δt_{OFF}	$T_{G,set}$		
$[hr]$	20°C	21°C	22°C
1	-0.2 ± 0.07	-0.2 ± 0.09	-0.2 ± 0.11
2	-0.4 ± 0.10	-0.6 ± 0.16	-0.5 ± 0.18
3	-0.6 ± 0.13	-0.8 ± 0.21	-0.7 ± 0.24
4	-0.6 ± 0.17	-1.0 ± 0.27	-0.9 ± 0.29
5	-0.7 ± 0.22	-1.1 ± 0.33	-1.0 ± 0.34
6	-0.7 ± 0.24	-1.2 ± 0.38	-1.1 ± 0.36

Table 5: Cooling trend: $\overline{\Delta T_{root}(\Delta t_{OFF})} \pm s$ [K], related to $\Delta T_{root,ext}$

Δt_{OFF}	$\Delta T_{root,ext}$ [K]			
$[hr]$	8	10	12	14
1	-0.2 ± 0.05	-0.2 ± 0.06	-0.2 ± 0.08	-0.3 ± 0.05
2	-0.4 ± 0.08	-0.5 ± 0.10	-0.5 ± 0.13	-0.5 ± 0.12
3	-0.6 ± 0.12	-0.7 ± 0.14	-0.7 ± 0.15	-0.7 ± 0.21
4	-0.7 ± 0.19	-0.8 ± 0.18	-0.8 ± 0.21	-0.8 ± 0.30
5	-0.7 ± 0.23	-0.9 ± 0.25	-0.9 ± 0.25	-0.9 ± 0.39
6	-0.7 ± 0.26	-0.9 ± 0.28	-1.0 ± 0.31	-0.9 ± 0.48

As in the cooling case, $T_{G,set}$ was set to $20°C$, $21°C$ or $22°C$ in this subset. In Tab. 6, we detail the values averaged for time periods of Δt_{ON} of 1hr. The large standard deviation of measurements for $T_{G,set} = 21°C$ indicates that the data set is too small for deriving profound insights. The majority of heating cycles used $20°C$ and $22°C$ for $T_{G,set}$; showing a clear heating speed increase. The higher s appearing for $22°C$ is caused by a greater range of $T_{external}$ impacting the heating process more diversely than in the data series of $T_{G,set} = 20°C$.

Tab. 7 summarizes the heating dynamics for selected $\Delta T_{root,ext}$. Only the data for $\Delta T_{root,ext} \in [8K, 14K]$ yielded acceptable levels of s du-

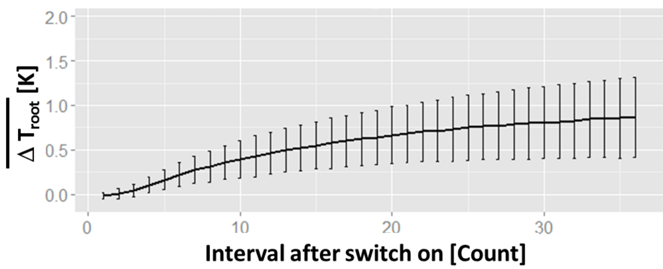

Figure 12: Heating trend: $\overline{\Delta T_{root}(\Delta t_{ON})} \pm s$ for six hours heating period ($HDI = 1$).

Table 6: Heating trend: $\overline{\Delta T_{root}(\Delta t_{ON})} \pm s$ [K], related to $T_{G,set}$

Δt_{ON}	$T_{G,set}$		
$[hr]$	20°C	21°C	22°C
1	0.2 ± 0.11	0.2 ± 0.16	0.3 ± 0.08
2	0.5 ± 0.15	0.4 ± 0.26	0.6 ± 0.15
3	0.6 ± 0.20	0.5 ± 0.35	0.8 ± 0.24
4	0.7 ± 0.23	0.6 ± 0.42	1.0 ± 0.30
5	0.8 ± 0.25	0.6 ± 0.49	1.1 ± 0.36
6	0.8 ± 0.28	0.7 ± 0.55	1.2 ± 0.39

Table 7: Heating trend: $\overline{\Delta T_{root}(\Delta t_{ON})} \pm s$ [K], related to $\Delta T_{root,ext}$

Δt_{ON}	$\Delta T_{root,ext}$ [K]			
$[hr]$	8	10	12	14
1	0.2 ± 0.12	0.2 ± 0.11	0.2 ± 0.14	0.3 ± 0.23
2	0.4 ± 0.21	0.6 ± 0.17	0.5 ± 0.16	0.6 ± 0.23
3	0.6 ± 0.29	0.8 ± 0.21	0.6 ± 0.16	0.8 ± 0.16
4	0.7 ± 0.34	0.9 ± 0.28	0.7 ± 0.14	1.1 ± 0.24
5	0.8 ± 0.37	1.0 ± 0.30	0.7 ± 0.19	1.3 ± 0.17
6	0.9 ± 0.43	1.1 ± 0.31	0.8 ± 0.15	1.4 ± 0.16

ring the observation period. For the first two to three hours, the heating dynamics are comparable across the different $\Delta T_{root,ext}$ values. The limited statistics given in this period permit a good qualitative trend understanding, but with less accuracy possible - especially due to the higher s for $\Delta T_{root,ext} \in [8K, 10K]$ caused by a higher variety of $T_{G,set}$ than for $12K$ and $14K$.

Comparing cooling and heating speed in Tab. 4 and 6, we have with $\overline{|\Delta T_{root}(\Delta t_{OFF})|} \approx \overline{|\Delta T_{root}(\Delta t_{ON})|}$ similar trend behavior. Higher $T_{G,set}$ causes in both cases stronger temperature changes for $\Delta t \geq 4$ hours. Excluding the heating statistics of $T_{G,set} = 21°C$ due to relatively large s, the heating effect after activating the heating is slightly faster than the cooling-down after switching off the grass heating. Folding in the external temperature, the heating dynamics develop a stronger trend over longer periods for larger $\Delta T_{root,ext}$ than the cooling dynamics (see Tab. 5 and 7).

5 Improved Heating Strategies

5.1 Energetic Effect of Observed T_{root}

Given the wide range of acceptable T_{root} in literature, we see substantial potential for conserving energy in the Commerzbank Arena by lowering the average T_{root} value and controlling its range closely. Energy savings of the grass heating could then either be diverted to other systems for load balancing or monetized upon through reduced energy cost. In the considered period, the average $\overline{T_{external}}$ for $HDI = 1$ reported by the stadium's BMS was $4.3°C$. From the documented $\overline{T_{root}}$ this implies an average $\overline{\Delta T_{root,ext}} \gtrsim 10.7K$. With Tab. 3 this translates into an average energy demand of $\overline{\Delta Q_{grass}} \gtrsim 0.39MWh/h$.

5.2 Alternating Heating Cooling Cycles

In the past winter, a simple improved heating strategy heating only if e.g. $T_{root} \leq 13°C$ or $T_{root} \leq 15°C$, would not only have had effects on the energy demand per hour of heating due to lowered $\Delta T_{root,ext}$, it would also have led to a reduced runtime of the heating system. Taking into account that switching states implies stress on mechanical systems, a heating strategy should not switch states too frequently. Our proposed approach exploits the observed heating and cooling speeds: the documented heating effect is faster than cooling by approximately $0.1°C$ after 6 hours, thus allowing ~ 30 minutes of additional cooling time. The resulting time ratio of heating to cooling ratio is therefore 48%. As a safe guard to hedge against too low root temperatures, the alternating pattern should only become active if an activation threshold is exceeded (denoted $T_{root,alt}$). In summary, when $T_{root} \geq T_{root,alt}$ our strategy is to heat 6 hours consecutively, followed by 6.5 hours of cooling.

While the exact value of $T_{root,alt}$ depends on the sort of grass grown on a stadium's playing field and needs the operational staff's consent, we provide rough calculations about the order of magnitude of expected savings for the considered period based on the Commerzbank Arena's measured energy data. Assuming the application of this strategy for the documented hours of $T_{root} > T_{root,alt}$, this would lead to:

- $T_{root,alt} = 13°C \Rightarrow 1944h \times 52\% = 1011h$ runtime savings
- $T_{root,alt} = 15°C \Rightarrow 1600h \times 52\% = 832h$ runtime savings
- $T_{root,alt} = 17°C \Rightarrow 400h \times 52\% = 208h$ runtime savings

As the average heat demand is larger during the first hours after heating is switched on than the overall average energy demand, we assume the maximum observed energy demand of 0.5 MWh/h [6] instead of taking the average energy consumption documented in Tab. 3. For the selected values of $T_{root,alt} = \{13, 15, 17\}$ the savings translate into:

- $T_{root,alt} = 13°C \equiv \Delta T_{root,ext} \approx 9K \Rightarrow 270MWh \equiv 34\%$ savings[7]
- $T_{root,alt} = 15°C \equiv \Delta T_{root,ext} \approx 11K \Rightarrow 240MWh \equiv 30.2\%$ savings[8]
- $T_{root,alt} = 17°C \equiv \Delta T_{root,ext} \approx 13K \Rightarrow 69MWh \equiv 7.5\%$ savings[9]

Comparing these savings to an average German household's heating energy demand of approximately 11,400 kWh[10] in 2012 reported by [14], the potential energy savings of

[6] See Fig. 9

[7] $1944h \times 0.52 \times 0.378MWh/h - 1944h \times 0.48 \times (0.5MWh/h - 0.378MWh/h) \approx 270MWh$

[8] $1600h \times 0.52 \times 0.39MWh/h - 1600h \times 0.48 \times (0.5MWh/h - 0.39MWh/h) \approx 240MWh$

[9] $400h \times 0.52 \times 0.39MWh/h - 400h \times 0.48 \times (0.5MWh/h - 0.39MWh/h) \approx 69MWh$

[10] 466 billion kWh for heating constitute $\approx 70\%$ of the total 663 billion kWh consumed. $70\% \times 16,304$ kWh (average household energy consumption) $\approx 11,400$ kWh.

this simple strategy are roughly equivalent to the annual heating energy consumption of approximately 24 average households. In the upcoming heating season we will validate the savings of this strategy experimentally.

5.3 Heat Demand Balancing

Beyond the strategy to alternate prolonged heating and cooling cycles when $T_{root} \geq T_{root,alt}$ to realize energy savings, it is also possible to exploit the heating and cooling characteristics to balance with the other stadium systems' energy demands: if thermal load patterns of other systems are known, e.g. office and domestic hot water heating cycles peaking around certain times of business days, the grass heating system can pre-heat the playing field and then switch-off to conserve energy during peak demand hours. The amount of hourly energy balancing capacity of the grass heating field follows from Tab. 3 and the maximum switch-off time follows from the minimally acceptable $T_{root,min}$ of the stadium's operational staff. In other words, based on the energy demand of the other thermal systems and the known grass cooling and heating characteristics, the grass heating system can be operated such that it reaches a required T_{root} at the planned switch-off time in order to provide enough balancing capacity.

Further analysis of the energy demand of the arena's other thermal sub-systems is required prior to estimating the energy balancing potential. However, the grass heating behavior documented in the previous sections will enable the CAMPUS21 project to experiment with balancing the grass heating system's thermal capacity against those systems in the upcoming heating season.

6 Conclusion

Our first analysis of the Commerzbank Arena's grass heating characteristics focused on understanding the thermal dynamics of its main asset - the soccer pitch - and the effect of the different control schemes used by the operational staff currently.

Our investigations show that the grass field's conditions are strongly dependent on its heating and cooling characteristics driven by operational as well as external context parameters such as $T_{external}$. The control space is defined through variations of the operational parameters *start of heat request*, *duration of heat request* and the *glycol supply temperature set-point* $T_{G,set}$. These studies of heating and cooling behavior of the arena's soccer pitch are first steps to quantify the dependence on $T_{G,set}$ and $\Delta T_{root,ext}$ in the first six hours after switching on or off the grass heating system. It shows that when the heating system is switched off for prolonged periods of time, T_{root} is strongly correlated with the $T_{external}$ of five hours in the past. Thus, near term changes of $T_{external}$ will impact T_{root} with a delay of approximately five hours. The strong linear correlation also indicates that it is very likely that impacts of solar radiation, wind, rain and lawn irrigation on T_{root} play a subordinate role, but further studies are needed to confirm this understanding. The thermal transmission differs for heating and cooling cycles depending on the considered parameter ranges. Due to the relatively warm winter of past season, the data do not cover very low temperatures possible for Frankfurt region. Nevertheless, we can conclude that studies on the thermal effects will lead to the definition of optimal T_{root} ranges depending on $T_{external}$ for an energy-efficient dynamic heating schedule and the optimal choice of $T_{G,set}$. Further studies in upcoming seasons will deepen the insights.

As result of the current studies, we provide an estimation of potential savings through a simple strategy of alternating heating and cooling patterns when T_{root} exceeds a certain threshold parameter $T_{root,alt}$. This estimation would indicate potential savings at run time of the heating system of up to 1011 operating hours as well as savings of up to 270 MWh or 34%. Extrapolating this finding to the 36 soccer club stadiums that make up the German first and second Bundesliga soccer leagues, the potential energy savings amount to at least 10,080 MWh throughout Germany - equivalent to the yearly heat demand of more than 850 average German households. Further, we also high-lighted the suitability of exploiting the grass heating system's characteristics for thermal load balancing.

The assessment of the current operational modes open a variety of options to control the heating operation which we will study further for their efficiency and effectiveness:

- constant heating with dynamically controlled supply temperatures (controlled through $T_{G,set}$) to ensure low but constant energy consumption
- heating cycles where the documented thermal dynamics of the grass field are exploited - these cycles can vary in steepness of heating curves and consequently heating on/off ratios
- overheating the grass in order to prolong the periods during which grass heating can be switched off until heating starts again for load balancing purposes.

When lowering the range for T_{root}, any energy savings occurs obvious, but the risk in such strategy lies in the under-performance for grass heat provisioning by crossing the lowest acceptable T_{root}. A control scheme based on real-time monitoring and consequent context-dynamic actuation along the thermal behaviour will enable the grass heating performance on required service level.

In the upcoming heating season, we will focus on experimentally validating the proposed strategy as well as studying the current thermal conditions, external conditions (beyond external temperature) and related operational parameters to develop an energy schedule to respect office occupancy, event schedules and other context factors for increasing the thermal comfort. Additionally, the heating operation of the warm water supply for kitchen and athlete areas will be included to understand their individual operational cycles, consumption patterns and thermal storage effects, and combine them into the grass heating schedule optimization with dynamic context awareness.

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Paper C

Energy Efficiency Gains in Daily Grass Heating Operation of Sports Facilities through Supervisory Holistic Control

Authors:
Mischa Schmidt, Anett Schülke, Alberto Venturi, Roman Kurpatov

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Energy Efficiency Gains in Daily Grass Heating Operation of Sports Facilities through Supervisory Holistic Control

Mischa Schmidt, Anett Schülke, Alberto Venturi, Roman Kurpatov

Abstract

In recent reflections on environmental impacts of buildings, medium to large scale sports stadiums have gained substantial attention. These stadiums of e.g. professional soccer teams are characterized by special system installations like grass heating systems serving the crucial commercial asset(s) and by event-driven usage patterns. Public buildings of this size imply situation-specific operational modes combined with high levels of safety and comfort requirements. In this paper we provide experimental verification of the energy savings potential of a professional soccer stadium's grass heating system during day-to-day operation. Our supervisory holistic control based on state of the art information and communication technology (ICT) is verified by seven experiments which we executed within the real operational setup of the *Commerzbank Arena* in Frankfurt, Germany. Our experiments operated different control strategies of increasing complexity. In winter 2014/2015 we achieved weather normalized energy savings of more than 56% compared to the last heating season. In an average heating season this would amount to savings of approximately 780 MWh and 150 t CO_2. At the same time we violated minimum temperature targets less than 6% of the time. These results stress the feasibility and benefits of applying holistic context-aware control strategies to large scale legacy consumption systems using supervisory ICT platforms. We demonstrate significant efficiency improvements and establish a new energy baseline that future control strategy evolutions will have to benchmark against.

1 Introduction

A modern sports stadium presents unique challenges to architects, construction companies and facility operators for energy efficient operation: the operational modes are driven by planning patterns specific to the events held in the respective stadium. This trait makes stadium operation different from conventional medium to large-scale buildings that have been studied in literature. A stadium's energy requirements are very high in order to provision all systems like floodlighting, heating, ventilation, air conditioning, lighting, catering, grass heating and supplying the event-specific media centers. The various building systems and their controls are good examples of cyber-physical systems, with varying degrees of complexity, intelligence and level of integration. Major sports arenas such as professional soccer stadiums are characterized by high safety and comfort standards to support large-scale events, including soccer games and cultural events of different types. In particular, professional soccer arenas have high lawn quality requirements - the prime commercial target for the facility operation - addressed by professional staff that waters, lights and cuts the grass throughout the year based on information collected from sensors and taking into account contextual information such as weather forecasts. To keep the soccer pitch in high-quality conditions even in winter, professional stadiums run a dedicated under-soil heating system consuming a considerable fraction of thermal energy inside a stadium. The alternative to heating is replacing the soccer pitch during the season due to wear and tear with associated cost of 100,000 EUR [1], i.e. using heating to avoid the replacement cost is a commercially viable solution.

We study the grass heating system in the concrete case of the Bundesliga soccer stadium *Commerzbank Arena* in Frankfurt am Main, Germany, a medium sized soccer stadium with space for 50,000 spectators which was completely rebuilt for the soccer world championship 2006. Its thermal system operation is set up to ensure that the grass heating demand is served with priority. The grass heating system consumes up to 50% of the peak output of the main gas boilers whereby the aggregate heat demand can exceed the capacity of the main heating supply (a gas - hydronic system) at peak times. In case of heating shortages, the operational scheme needs to sacrifice the service quality and thermal comfort conditions in other areas like offices, conference center and meeting rooms. To avoid such heating disbalance, current best practice is to run heating only during the night and rely on the soil's thermal inertia during the day.

In this paper we study the effect of relying on automated data taking and control rather than the status quo operation. We present the outcome of a series of experiments executed in winter 2014/2015 proving energy savings effects from the improved operation. The evaluation is performed under the given operational conditions of limited heating capacities coupled with high priority for the grass heating system. We assess the quality of our automated control strategies under energetic and thermal considerations. This paper provides a first quantification of the energetic impacts of lowering grass root temperatures by few degrees Kelvin without violating lower temperature target bands - something which the human driven control was not able to achieve. Our work highlights the potential automated control schemes - even those of low complexity - have, when these are applied routinely in daily operation. Further, we establish a new baseline for benchmarking the effectiveness of more complex control schemes in future work.

This paper is structured as follows: after an overview of related work in Section 2, we provide a description of the applied methodology as well as a summary of the different variables used in Section 3. The following Section 4 summarizes the stadium's grass heating system and its pre-existing control scheme as observed in last winter. In Section 5 we introduce the different experiments we executed, analyze the collected data and discuss our findings in comparison to the reference winter 2013/2014. We conclude the paper in Section 6 providing a summary of our studies and an outlook on future work.

2 Related Work

This work is to be seen in a market context affected by energy efficiency guideline 2012/27/EU [2] which requires 20% savings on primary energy usage by 2020 and 50% savings by 2050, compared to 2008. These translate into yearly savings of 1.5% for all EU member states. For Germany these targets require a reduction of energy consumption from 220.7 million tonnes of oil equivalent (Mtoe) (2008) to 194.3 Mtoe (2020). These abstract targets are supported by a related EU regulation affecting, among others, the German market landscape: starting in 2015 regular energy audits (every 4 years) are becoming mandatory for all non Small and Medium Enterprises (SME) that neither have an ISO 50001 certified energy management system nor an EU regulated Energy Management and Audit Scheme (EMAS) implemented. Further measures include the promotion of decentralized energy supply with renewable energies and support programs for energy efficiency.

In [3] we provided a first analysis of the Commerzbank Arena's different building systems's energy consumption characteristics, including the grass heating system. It became evident that the operation patterns of the grass heating system did not exhibit an expected deterministic relationship between air temperature and energy use in winter 2013/2014. In [4] we focused then on the grass heating system. We describe the system's normal best practice operation and the dynamics of the associated observables. The operation scheme was centered around human experience and based on manual adjustments of temperature set points which led to high temperature margins as human operators could not constantly supervise temperature readings and adapt control parameters accordingly. We estimated an energy savings potential of 34% when using simple automated control strategies instead of the current manual mode of operation. Also, we motivate our empiric data-driven approach instead of modeling the soil with physical models: this was not feasible in the stadium's operational setting considering the physical models described in literature.

While literature does not provide coverage of controlling under-soil heating systems, HVAC systems control is covered. In particular the *Model Predictive Control* (MPC) approach is studied extensively in current research. Here, future evolution of the system is predicted given a model describing the system dynamics, the system's state and optionally considering related (context) variables. Depending on the technique chosen, these models can be very complex and consequently MPC becomes computationally challenging, see e.g. [5, 6]. To address that, e.g. [7, 8] use data-driven models (Neural Networks) to predict and optimize HVAC operation of buildings. Similarly also [9] learns a single room Predictive Mean Vote (PMV) model for thermal comfort as input to MPC. Our experiments are a first step to developing a data-driven Model-Predictive Control (MPC) for future use with grass heating systems where we use the models learned from the observed building data directly for deciding control actions. This approach sometimes is also referred to as *model free* as no explicit system model is formulated.

In literature, stadium related energy usage studies predominantly cover renovation potential and renewable energy integration, such as e.g. [10] providing also business case considerations of the proposed modernizations. The study covers three European soccer stadiums among which also the Commerzbank Arena is presented. In particular, the modernization measures proposed for the Commerzbank Arena's grass heating system (splitting distribution circuits and lowering the feed-in supply temperature to the heat exchanger) are estimated to save annually 381 MWh or 8% of the arena's total energy consumption. Our focus however lies on enhanced operation schemes regardless of refurbishments and other modernizations, i.e. it is orthogonal to such measures.

3 Methodology

In the recent heating season of winter 2014/2015, we conducted a series of experiments with different control approaches to verify the savings we anticipated when moving to automated control. The control schemes used in the past led to unnecessarily high grass root temperatures when compared to literature recommendations ($10°C$ - $18°C$). Thus, any control strategy devised to save energy should aim first at lowering T_{root}. For our experiments the Commerzbank Arena's operational staff defined the temperature target band $T_{root} \in [12°C, 14°C]$. This band was chosen conservatively to provide sufficient room in case of control failures during the experiments without negatively affecting grass growth.

For our empiric approach to model the grass heating system dynamics in a data-driven way, we deployed a data aggregation platform [11] to *holistically* study the operational schemes and energetic profiles of the Commerzbank Arena's building systems in normal operation. We build on the existing sensors and operational data as obtained from the BACnet/IP-based Building Management System (BMS) to analyze the energy flows and the soil's thermal inertia in relation to the operational context, taking into account also external information sources, e.g. weather forecasts. To achieve the desired thermal effect, our *supervisory* control uses application interface to interact with BMS and to actively influence the grass heating system's control loops by appropriately changing set points. Further, when defining our control strategies we draw upon the operational staff's experience and the system's operational parameters observed during the winter 2013/2014 baseline period.

To account for changing weather conditions across different years, we apply the widely used standard Heating Degree Day (HDD) normalization mechanism [12] to the measured energy consumption Q: to derive the normalized daily energy use Q_{HDD} we divide the energy consumption by the heating degree days calculated from daily $\overline{T_{external}}$ [13]. By doing so, we are able to compare energy consumption across the different years as the temperature influence is normalized to some extent. The German standard HDD base temperature is $15°C$ [14] for heating systems. However, as the grass heating system is exposed to the open air and since the operational staff configured the system to become active only when the building external air temperature $T_{external}$ is below $7°C$, we deviate from the standard and use $T_{HDD,base} = 7°C$ for the grass heating system normalization. When calculating daily energy use statistics, we exclude days with $HDD = 0$ from our daily statistics as normalized energy goes to infinity.

Table 1: Overview of variables used.

Parameter	Description	Unit
$T_{external}$	Building external air temperature	$^\circ C$
$\overline{T_{external}}$	Mean air temperature	$^\circ C$
$T_{HDD,base}$	HDD norm. base temperature	^{o}C
T_{root}	Grass root temperature	$^\circ C$
$\overline{T_{root,HDI=1}}$	Mean T_{root} when $HDI = 1$	$^\circ C$
$T_{G,set}$	Grass heating supply set point	$^\circ C$
$HDD7$	HDD for $T_{HDD,base} = 7^\circ C$	DD
$HDD7_{ex.}$	Expected HDD in average winter conditions for $T_{HDD,base} = 7^\circ C$	DD
HDI	Grass heating status flag, *Heat Demand Indicator*	1/0
T_{supply}	Main thermal supply circuit temp.	$^\circ C$
Q_{grass}	Energy use of grass heating system	MWh
$Q_{grass,HDD7}$	HDD norm. grass heating energy with $T_{HDD,base} = 7^\circ C$	MWh/DD
Q_{gas}	Total arena thermal energy use	MWh
$Q_{grass,ex.7}$	Expected Q_{grass} in average winter $Q_{grass,HDD7} \times HDD7_{ex.}$ or	MWh

For analyzing the energy statistics, we rely on standard measures applicable to sampled data: 1^{st} quartile, median, mean (m), standard deviation (s) and 3^{rd} quartile. For discussing energy savings, we focus primarily on reductions in median and mean, with the quartiles and standard deviation providing information about the spread of the measurements, i.e. the consistency of results. To statistically verify the experiment impact, we select the standard two-sample Kolmogorov-Smirnov (K-S) and Anderson-Darling (A-D) tests on the daily normalized energy data samples of the winter seasons. By using these non-parametric tests, we avoid assuming normality of the underlying distributions.

Beyond purely focusing on energetic considerations when analyzing the experiments, we also consider service level Key Performance Indicators (KPI) based on the T_{root} target band defined for our experiments. Specifically, we use the measure of *Under-Performance Ratio* (UPR) representing the fraction of (operating) time a system does not meet the minimum service level requirements [15] to weigh against the normalized energy savings. From an application perspective, a low UPR is preferred.

Tab. 1 provides a summary of the different variables used in this paper.

4 The grass heating system

4.1 Grass Heating System Design

In Fig. 1, we depict a high-level view of the heating distribution system of the Commerzbank Arena.

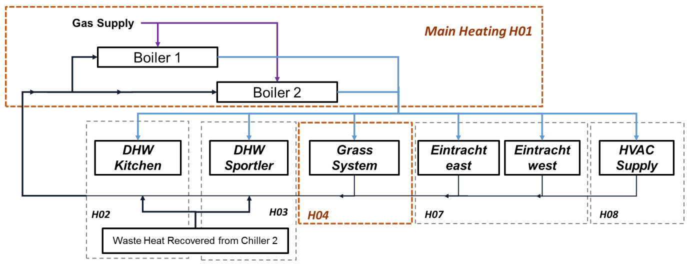

Figure 1: High-level view of heating distribution system structured into core arena subsystems [4].

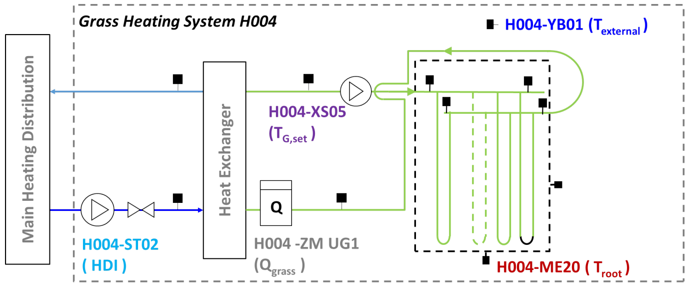

Figure 2: Grass heating sensor installations with sensor identifiers [4].

The stadium's grass heating is a glycol-based under-soil heating which is connected to the main heating network through a 1.4 MW heat exchanger. Its glycol is distributed via multiple pipe loops of equal length along the long side of the pitch and the supply and return distribution on the short side of the pitch. The grass conditions are characterized by T_{root}, measured by sensors buried in the soil at the turn-around of the long pipe loops. By standard operational setup, the T_{root} is governed by the glycol supply temperature provided to the soil - which is controlled by a corresponding set point ($T_{G,set}$) if the heating system is active. The sensor and meter installations integrated with the stadium's BMS are schematically shown in Fig. 2. We collected their data from the BMS as part of its approximately 13,500 variables in 10-minute intervals.

4.2 Current Control Schemes

We identified two aspects representing opportunities for improving the grass heating:

First, the current grass heating control system is not driven by T_{root} but by $T_{external}$, resulting in wasteful heating.

Second, the operational staff interferes manually with grass control in several ways, e.g. adjusting $T_{G,set}$ according to anticipated T_{root} ranges based on experience. Also, during very cold days, the night-time heating between 6 p.m. and 6 a.m. does not suffice and day-time heating is then used in addition. These forms of human interference with the grass heating system's control limits the ability to predict its energy consumption based on $T_{external}$ - in particular when compared to fully automated heating control systems deployed in the sports facility such as the static heating system were the operating supply temperature is determined by a function of $T_{external}$. While the different heating systems' controls work independently, the systems are inter-dependent due to the shared thermal supply capacity. It will be for future work to study the potential synergies of a combined control approach.

From the winter 2013/2014 collected data it is not always comprehensible why a change of the control scheme was decided. Consequently the status quo heating strategy frequently activates the grass heating system when T_{root} is already relatively high. This situation presents opportunities for lowering the energy consumption through adapting the control parameters in an algorithmic way, e.g. by taking into account forecasts about $T_{external}$ and tightly controlling T_{root}. This dynamic control mechanism applies the knowledge of the effect of each control configuration, and its dynamic adaption aims for better performance to maintain T_{root} in preferred temperature ranges.

5 Experiments and Results

The underlying hypothesis of our work is that the performance of the grass heating system shall be increased by

1. reducing the heating demand (estimated savings of about 34% [4]),
2. reducing the T_{root} to stay within suitable boundaries stated by the defined target temperature band, while ideally achieving 0% UPR, and
3. balancing within the entire thermal system without adversely affecting the operation of other heating systems to enable a change to an automated day-time heating paradigm.

5.1 Baseline: Winter 2013/2014 Observation Period

In our reference period (November 2013 - March 2014), the Commerzbank Arena's grass heating system consumed 795 MWh of energy. This represents 20% of the stadium's overall gas consumption, which is in line with the relationships given in [10] for the *Euroborg* stadium in Groningen, Netherlands. Based on [16], grass heating accounted for 152 t CO_2 emissions[1].

Tab. 2 provides the grass heating energy consumption statistics observed in the period of winter 2013/2014. The high standard deviation for $Q_{grass,HDD7}$ stems from warm days resulting in HDD normalization divisors close to 0.

[1] In 2012, 2,920 PJ of German natural gas consumption accounted for 155.3 Mt CO_2 emissions. → 191 g/kWh.

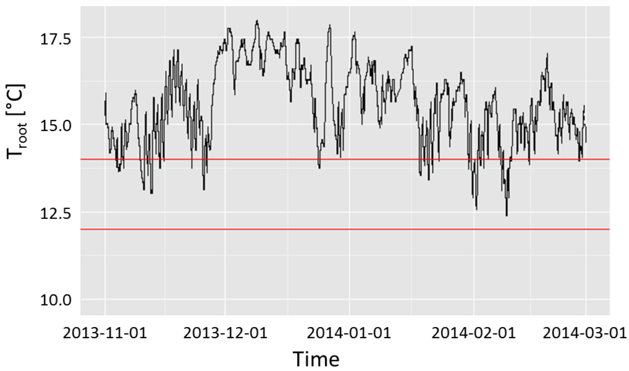

Figure 3: T_{root} of November 2013 - February 2014, red lines indicating the T_{root} target band.

Table 2: Daily grass heating energy statistics for winter 2013/2014.

Parameter	Q_{grass} [MWh]	$Q_{grass,HDD7}$ [MWh/DD]
1^{st} Quartile	0	1.8
Median	4.4	2.5
$m \pm s$	4.5 ± 3.8	4.1 ± 7.1
3^{rd} Quartile	7.2	4.0

In Fig. 3, we depict the observed T_{root} of the last heating season. Of the 17,093 measurement intervals constituting the observation period, 1,512 measurements lay within the target band. 91.2% of the time T_{root} violated the target band. This was caused by the grass heating control system being mostly driven by $T_{external}$ instead of T_{root} directly and by inconsistent control strategy changes. This resulted in the heating system being active for 10,354 measurements (60.6%) during the observation period with T_{root} above the target band. The mean HDD7 divisor was 1.80 ± 2.17 [13].

5.2 Winter 2014/2015 Actuation Experiments

In this section we document the results of the seven control strategy actuation experiments we conducted to verify the savings potential and the ability to meet service level requirements at the same time. While the heating season officially lasts from October to March, Fig. 4 shows that experiments could only start towards the end of November due to warm weather conditions. Further, the figure indicates the execution period of each experiment. The experiments' varying lengths reflect the relative importance given; in particular the pre-heating experiment *B3* and the day-time heating experiments *D* and *Dmod* were at the core of our interest this winter. Also, we note that the experiments *PA1* and *PA2* fell into a period with higher temperatures.

For each of the experiments, we executed the associated control algorithm (presented

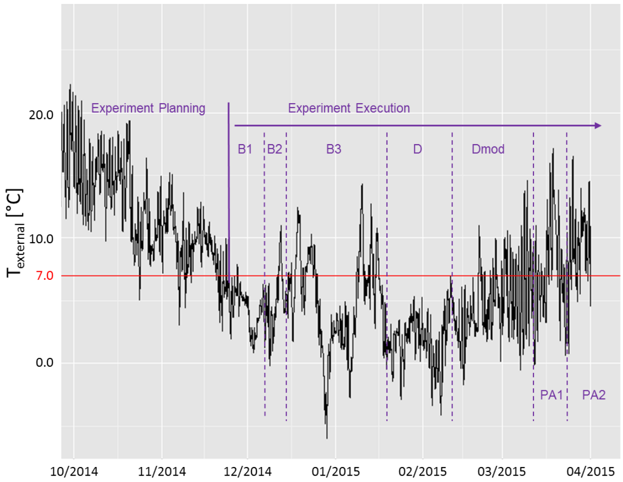

Figure 4: $T_{external}$ observed during the experimental phase, red line indicating the Grass Heating switch-on threshold temperature of $7°C$.

in the following subsections) once every minute. Figs. 5 - 13 illustrate the respective control logic - solid horizontal temperature lines indicating a trigger of actions when T_{root} exceeds them, dashed horizontal temperature lines indicating a trigger of actions when T_{root} undercuts them. After any modification to the heating system operation no modification was allowed for the duration of 10 minutes to account for the system's inertia.

Basic Strategy B1: Static Supply, On/Off

Strategy definition. In this simplest of strategies, we used a fixed supply temperature $T_{G,set}$ for 3 consecutive nights and alternated between activating and deactivating the grass heating. More specifically, we activated heating when $T_{root} < 12°C$ and deactivated heating when $T_{root} > 14°C$. This simple logic is also illustrated in Fig. 5.

To understand the thermal and energetic impacts of the supply temperature more clearly, we repeated the experiments for each $T_{G,set} \in \{18°C, 20°C, 22°C\}$. The temperature selection was chosen based on historic data from the last winter season, when $T_{G,set}$ had been predominately set within this range.

Experimental Results. We executed this experiment series in the period 2014-11-24 18:00 - 2014-12-04 06:00. In Fig. 6, we depict the recorded T_{root}. Of the 1,355 measurements 1,205 lay within the target band, i.e. UPR=11.1%. One source of recorded under-performance is the phase at the beginning of *B1* caused by a day cool-down phase prior to the experiment. The larger fraction of T_{root} target band violations happened

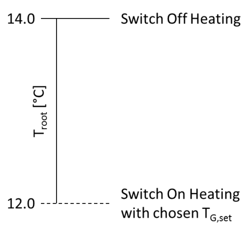

Figure 5: Static heating algorithm logic.

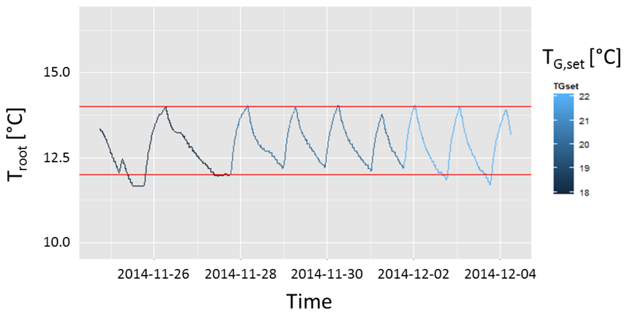

Figure 6: T_{root} of static supply temperature heating experiments B1 *for different $T_{G,set}$, red lines indicating the T_{root} target band.*

Table 3: Aggregate daily Q_{grass} statistics for experiment series B1.

Parameter	Q_{grass} [MWh]	$Q_{grass,HDD7}$ [MWh/DD]
1^{st} Quartile	2.7	0.8
Median	3.6	0.9
$m \pm s$	3.7 ± 1.7	1.2 ± 0.5
3^{rd} Quartile	4.3	1.3

at the end of the day-time phase for $T_{G,set} = 22°C$: from 2014-12-02 onwards we notice that for moderate $T_{external}$ and higher $T_{G,set}$ the simple control algorithm resulted in too steep heating curves, in turn resulting in earlier switch-off times of the grass heating. Combined with the soil's thermal inertia, this amounted to relatively low T_{root} towards the end of the respective night - on top of which the day cool-down would then lead to violating the minimum $12°C$ and requiring more heating the next night and possibly leading to increased UPR during the day.

Tab. 3 provides the aggregate energy performance statistics for the entire experiment series *B1*, which we use to compare against the other experiments using variable supply temperature set points. The mean HDD7 normalization divisor was 3.34 ± 1.46 [13].

This first experiment is proof that automated control can actively steer T_{root} towards the target band to save energy: 64% (median) to 71% (mean) of normalized grass heating energy are saved compared to last winter. Also, it provides a reference UPR for the remaining experiments.

Basic Strategy B2: Variable Supply

Strategy definition. To address the identified issue of too steep heating curves of *B1*, we now used a variable supply temperature $T_{G,set}$ for 3 consecutive nights, never completely deactivating the grass heating during any night. This way, the control should be able to react to the system's context - the weather impact on the grass root temperature. For this experiment we varied the $T_{G,set} \in [12°C, 22°C]$ in steps of $0.5°C$. We chose $12°C$ as

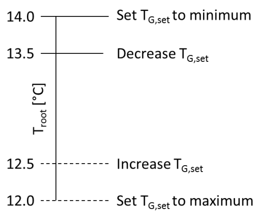

Figure 7: Variable heating algorithm logic.

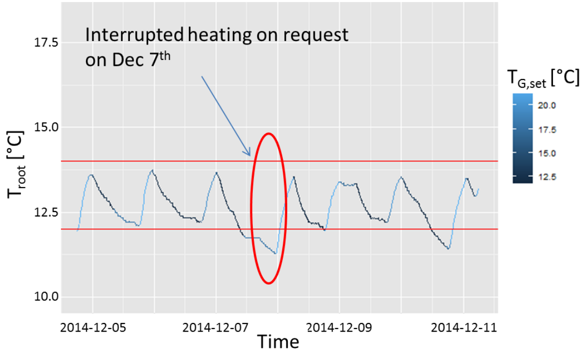

Figure 8: T_{root} of variable supply temperature heating experiment B2 *for varying $T_{G,set}$, red lines indicating the T_{root} target band.*

lower limit in order to never have $T_{G,set}$ undercut the target band. We chose $22°C$ as this was the highest supply temperature observed last winter for prolonged periods of time. In more detail, our simple control algorithm performed the following control actions, as also illustrated in Fig. 7:

1. Set $T_{G,set} = 22°C$, if $T_{root} < 12°C$
2. Set $T_{G,set} = 12°C$, if $T_{root} > 14°C$
3. Increase $T_{G,set}$ by $0.5°C$, if $T_{root} < 12.5°C \wedge T_{G,set} < 22°C$ to reduce the cooling curve steepness and avoid that T_{root} exceeds the maximum target root temperature.
4. Decrease $T_{G,set}$ by $0.5°C$, if $T_{root} > 13.5°C \wedge T_{G,set} > 12°C$ to reduce the heating curve steepness and avoid that T_{root} undercuts the minimum target root temperature.

Experimental Results. In Fig. 8, we depict the observed T_{root} of this experimental phase between 2014-12-04 18:00 and 2014-12-11 06:00. Of 933 observed measurements 787 were within the target band leading to UPR=15.6%. Fig. 8 shows that under-performance occurred mainly during day-time towards the end of the day which then had to be rectified at the start of the next heating phase. Additionally, we delayed the heating start time on request by the operational staff due to an evening match on 2014-12-07 resulting in several hours of additional target band violation. Excluding this day from the analysis, UPR drops to 12.5%, i.e. it is comparable to *B1*. The second period of violation on 2014-12-10 stems from a faster day-time cooling due to lower $T_{external}$. This motivates an evolution towards control algorithms that pre-heat the soil to reduce UPR further.

Table 4: Daily grass heating energy consumption statistics for experiment B2.

Parameter	Q_{grass} [MWh]	$Q_{grass,HDD7}$ [MWh/DD]
1^{st} Quartile	3.3	0.9
Median	4.8	1.0
$m \pm s$	4.4 ± 2.1	1.0 ± 0.4
3^{rd} Quartile	5.2	1.1

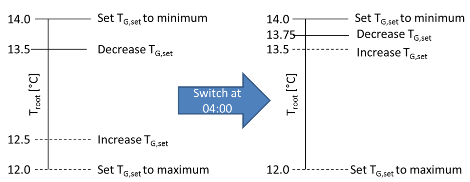

Figure 9: Pre-heating algorithm logic.

The energy statistics are documented in Tab. 4 indicating similar performance to *B1*. The majority of energy was consumed at the beginning of the night to counter day-time cool-down. During *B2* the mean HDD7 normalization divisor was 4.37 ± 1.02 [13].

Basic Strategy B3: Pre-Heating

Strategy definition. After completion of *B1* and *B2* we focused on countering day cool-down due to the operational condition that the heating is deactivated during day-time. Our aim was to ensure that T_{root} is near the upper limit of the target band at the end of the night-time heating phase. In essence, we mimicked the current best practice of night-time pre-heating the soil, but with more insight into and a higher level of control over the evolution of T_{root} than in the past season. Previous experiments *B1* and *B2* did not account for this explicitly.

Taking into account the cooling speed curves observed last winter rarely undercut $-1.0°C$ after 6 hours and flattened off, we considered it sufficient for pre-heating if $T_{root} \in [13.5°C, 14°C]$ at the end of the heating period. Therefore we started the night-time heating phase with the *B2* control algorithm and replaced its third and fourth step at the end of the night between 04:00 and 06:00 as illustrated also in Fig. 9:

1. Set $T_{G,set} = 22°C$, if $T_{root} < 12°C$
2. Set $T_{G,set} = 12°C$, if $T_{root} > 14°C$
3. Increase $T_{G,set}$ by $2.0°C$, if $T_{root} < 13.50°C \wedge T_{G,set} \leq 20°C$.
4. Decrease $T_{G,set}$ by $2.0°C$, if $T_{root} > 13.75°C \wedge T_{G,set} \geq 14°C$.

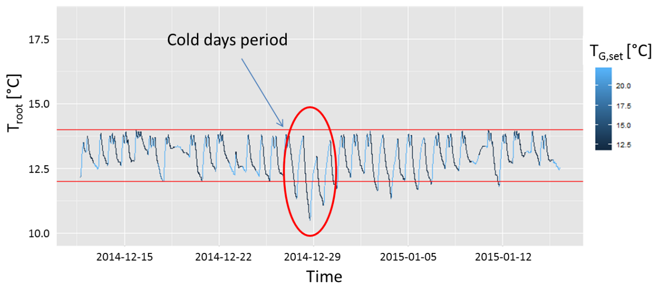

Figure 10: T_{root} of pre-heating experiment B3 *for varying $T_{G,set}$, red lines indicating the T_{root} target band.*

Table 5: Recorded energy consumption for pre-heating experiment B3.

Parameter	Q_{grass} [MWh]	$Q_{grass,HDD7}$ [MWh/DD]
1^{st} Quartile	4.4	1.1
Median	5.2	1.7
$m \pm s$	5.2 $\pm$ 1.9	2.6 $\pm$ 2.4
3^{rd} Quartile	6.2	3.3

As the variable supply temperature control algorithm is adapts better to changing weather conditions changes than the static control algorithm of *B1*, we defined the pre-heating experiment with the variable supply temperature control algorithm only.

Experimental Results.

We executed *B3* from 2014-12-11 18:00 to 2015-01-16 06:00. In Fig. 10, we depict the recorded T_{root}. Of 5,112 observed measurements 4,750 lay within the target band, i.e. UPR=7.1%. The observed violations are mainly caused by the colder days resulting in a faster-than-anticipated drop of root temperatures. On these days around 2014-12-29 (refer also Fig. 4) the system even had a hard time to get T_{root} back up to above 13.5°C during night-time heating. We consider that for phases of low $T_{external}$ higher supply temperatures should be used. Also overheating the soil during the night to counter day-time cooling is a viable option. Tab. 5 summarizes the energy consumption which approximately doubled compared to *B1*, yet it still was 30% (median) / 40% (mean) lower than in Tab. 2. During *B3*, the mean HDD7 normalization divisor was 3.67 $\pm$ 2.86 [13]. This experiment proved that the current best practice of human driven night-time pre-heating could be reproduced with higher energy efficiency at an UPR below 10%.

Advanced Strategy D: Introducing Day-time Heating

Strategy definition. Aiming to evaluate a paradigm shift from night-time pre-heating to a careful day-time heating scheme, we developed this strategy from *B2* and *B3*. Day-time heating is delicate as the heating capacity constraints are known to negatively affect

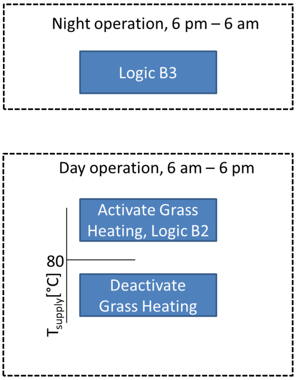

Figure 11: Algorithm to combine night-time pre-heating with day-time heating.

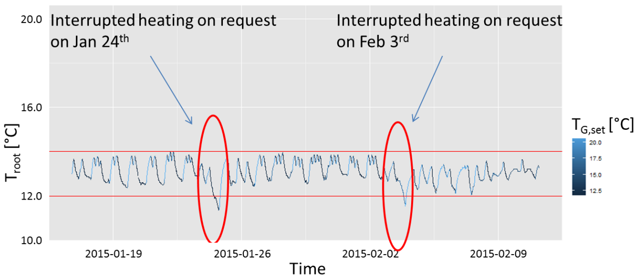

Figure 12: T_{root} of day-time heating experiment D *with varying $T_{G,set}$, red lines indicating the T_{root} target band.*

some of the attached thermal consumption sub-systems such as the office heating. This happens when the thermal output of the stadium's gas boilers is insufficient for the overall heating demand, resulting in a drop of the main thermal supply circuit's temperature denoted T_{supply}. Thus, when extending the grass heating operation beyond the night-time we had to pay careful attention to this critical parameter. To ensuring the standard operation of the other heating systems a minimum threshold value of $T_{supply} = 80°C$ was defined. When undercut, the grass heating had to be deactivated immediately.

As the heating demand of offices and other arena areas peaks at office hour start, logic *B3* was chosen to be used during night-time. This choice ends each night with a pre-heat cycle resulting in higher T_{root} giving us the option to deactivate the grass heating at the beginning of the day without risking under-performance. For day-time grass heating control operation $T_{supply} > 80°C$, we chose the variable supply logic without pre-heating (*B2*) - as also illustrated in Fig. 11.

Experimental Results. Fig. 12 illustrates the observed T_{root} between 2015-01-16 18:00 and 2015-02-11 06:00. Of 5,662 observed measurements 5,532 lay within the target band resulting in UPR=2.3%. Due to two soccer matches on January 24^{th} and February 3^{rd} the heating experiments were interrupted twice on request. In combination with relatively low $T_{external}$, these interruptions caused the observed under-performance. Excluding these interruptions from the analysis, the deployed control strategy led to UPR=0%. During day-time, the algorithm deactivated the grass heating 51 times due to violations of the back-off threshold. Due to this reactivity to peak load conditions no under-performance of other heating systems was observed. Thus, the grass heating system could be served without adversely impacting other systems. In theory, *D* should already be able to satisfactorily control the grass heating also on days with soccer events - and by integrating match plan information e.g. to result in higher night-time pre-heating temperatures, also

Table 6: Recorded energy consumption for day-time heating experiment D.

Parameter	Q_{grass} [MWh]	$Q_{grass,HDD7}$ [MWh/DD]
1^{st} Quartile	6.4	1.4
Median	10.8	1.8
$m \pm s$	9.9 ± 3.6	1.9 ± 0.7
3^{rd} Quartile	12.0	2.1

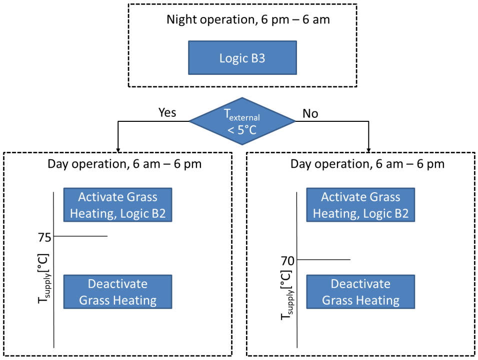

Figure 13: Aggressive day-time heating with night-time pre-heating.

pro-active load shedding should be feasible.

Tab. 6 summarizes the energy statistics that, compared to *B3*, show a slightly increased median but a lower mean energy consumption. The lower mean is related to the more consistent energy consumption (i.e. less outliers) expressed by lower standard deviation and lower 3^{rd} quartile. Thus, the change from a night-time heating paradigm to day-time pays off in more uniform daily energy consumption of the grass heating system - which is considered as advantageous. The mean HDD7 normalization divisor was 5.55 ± 1.81 [13].

Advanced Strategy Dmod: Modified Day-time Heating

Strategy definition. After introducing the paradigm change to day-time heating in *D*, we started defining a more aggressive strategy *Dmod* as depicted in Fig. 13 to increase the amount of heating energy to be used during the day. This was intended to keep T_{root} in the middle of the target band to flatten the temperature curves and reduce overall energy consumed. It differs in the day-time logic from *D* in two ways:

1. During day-time heating *Dmod* applied a lower T_{supply} threshold of $75°C$
2. If $T_{external} \geq 5°C$, an even lower T_{supply} back-off threshold of $70°C$ was used.

Experimental Results. Fig. 14 illustrates the observed T_{root} of *Dmod* 2015-02-11 18:00 - 2015-03-11 06:00. Of 3,910 observed measurements, all lay within the target band.

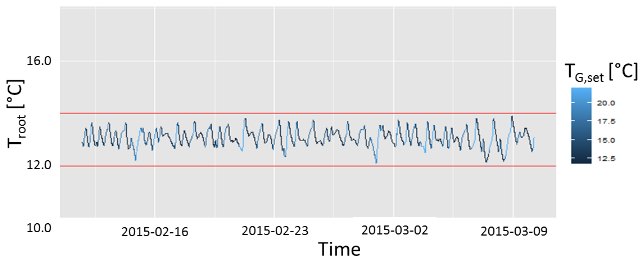

Figure 14: T_{root} of day-time heating experiment Dmod *with varying $T_{G,set}$, red lines indicating the T_{root} target band.*

Table 7: Recorded energy consumption for day-time heating experiment Dmod.

Parameter	Q_{grass} [MWh]	$Q_{grass,HDD7}$ [MWh/DD]
1^{st} Quartile	0	0
Median	2.2	0.6
$m \pm s$	2.4 $\pm$ 2.6	0.6 $\pm$ 0.6
3^{rd} Quartile	4.4	1.1

This leads to the ideal UPR=0%. During day-time, the algorithm switched off the grass heating 48 times due to violations of the back-off thresholds. Again, the grass heating system could be served without impacting adversely other systems by reacting on peak load conditions.

For *Dmod* the mean HDD7 normalization divisor was 3.56 $\pm$ 1.49 [13]. Tab. 7 summarizes the energetic results. The suspiciously low 1^{st} Quartile and mean $Q_{grass,HDD7}$ with a relatively high standard deviation led to a closer investigation. Indeed, during March $T_{external}$ was relatively high so that the Commerzbank Arena's grass heating system consumed only little energy at all. To increase the comparability of these results, Tab. 8 only reports the findings for the colder February experiment period which are close to the *B1* and *B2* experiments. The mean HDD7 normalization divisor of this sub-period was 4.13 $\pm$ 1.45 [13].

Advanced Strategy PA1: Pre-heating with Advanced Forecasting of T_{root} trends

Strategy definition. Next, we were interested in studying the effect of using weather forecast information in addition to sensor readings. To isolate the energy gains due to improved forecast accuracy, we reverted back to the night-time heating paradigm. As we identified a high linear dependency of T_{root} on $T_{external}$ in our earlier work (correlation 0.86, delay of approx. 5 hours), we focused our experiments on $T_{external}$.

During night-time (before 4 a.m.) the strategy *PA1* used an advanced non-linear *Deep Belief Network* (DBN) regression method inspired by [17] but trained on winter

Table 8: Recorded energy consumption for experiment Dmod*, February only.*

Parameter	Q_{grass} [MWh]	$Q_{grass,HDD7}$ [MWh/DD]
1^{st} Quartile	2.4	0.7
Median	3.9	1.1
$m \pm s$	3.8 ± 2.3	1.0 ± 0.5
3^{rd} Quartile	4.8	1.3

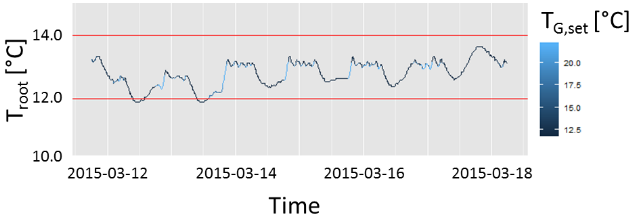

Figure 15: PA1*: T_{root} of pre-heating based on 6-hour DBN regression with varying $T_{G,set}$, red lines indicating the T_{root} target band.*

2013/2014 data to forecast a first 6 hour T_{root} trend (mean absolute error $(MAE) = 0.24 \pm 0.1K$) under the assumption no heating was in effect. Due to the time delayed impact of past and current weather conditions on T_{root}, no weather forecast information was required for this prediction. Then, combining this T_{root} forecast with weather forecast information [13] for another 6 hour T_{root} forecast led to a 12 hour T_{root} trend. If the trend violated the minimum T_{root} threshold, *PA1* predicted T_{root} for 6 hours $(MAE = 0.29 \pm 0.2K)$in different $T_{G,set}$ heating scenarios and selected the heating scenario resulting in the highest T_{root} without violating the maximum T_{root} threshold during the remaining night-time period. Note that this implies a pre-heating effect similar to *B3* as towards the end of the night, the maximum T_{root} threshold violation horizon shortens and thus higher heating scenarios are selected automatically.

Experimental Results. In Fig. 15 we depict the observed T_{root} of *PA1* between 2015-03-11 18:00 and 2015-03-18 06:00. Of 936 observed measurements, 885 lay within the target band, i.e. UPR=5.4%. The under-performance occurred during mid-day on March 12^{th} and 13^{th}. The mean HDD7 normalization divisor was 2.00 $\pm$ 0.98 [13].

Due to the mild weather conditions during the experiment *PA1* the grass heating system consumed extremely little energy (below the grass meter sensitivity) and thus no reliable conclusions on energetic behavior can be drawn. Fig. 15 shows an active control pattern on $T_{G,set}$ and acceptable UPR levels, thus we will include the experiments in our aggregate considerations. As also the reference heating season had mild phases we consider the inclusion of *PA1* in the aggregate considerations will enhance the representativeness of our results.

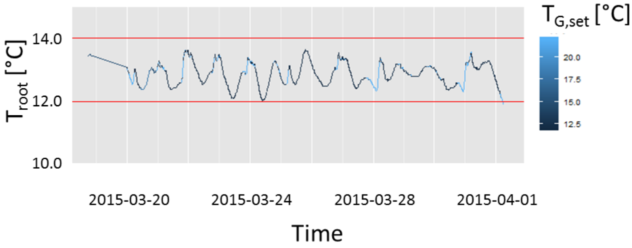

Figure 16: PA2*:* T_{root} *of pre-heating based on 12-hour DBN regression with varying* $T_{G,set}$*, red lines indicating the* T_{root} *target band.*

Advanced Strategy PA2: Pre-heating with 12 Hour T_{root} Forecast

Strategy definition. Following *PA1*, we developed a slight variation in that we directly produced a 12 hour T_{root} trend ($MAE = 0.3 \pm 0.2K$)instead of forecasting two consecutive 6 hour horizons. The night-time control of $T_{G,set}$ itself was not modified.

Experimental Results. Fig. 16 visualizes T_{root} of *PA2* between 2015-03-18 18:00 - 2015-03-31 06:00. Of 1,780 observed measurements, 1,775 lay within the target band resulting in UPR=0.3%. It becomes evident that there was a data taking complication on March 19 which we excluded from the analysis. For *PA2* the mean HDD7 normalization divisor was 1.23 ± 1.19 [13].

As with *PA1*, due to warm air temperatures experiment *PA2* did not produce meaningful energy statistics. As Fig. 16 shows an active control pattern on $T_{G,set}$ and acceptable UPR levels, we will also include this experiment in our considerations on seasonal level.

5.3 Discussion

Our series of seven experiments confirmed our hypothesis: by deploying our supervisory ICT based holistic control in the operational setup of the Commerzbank Arena we significantly reduced the grass heating system's energy consumption in the winter 2014/2015 compared to the reference winter 2013/2014. The daily energy statistics in Tab. 9 are right skewed. Both the K-S and the A-D test confirm that the data samples stem from different probability distributions (p-values $2 * 10^{-16}$ and $3 * 10^{-21}$). The effect of our control strategies is visible in $\overline{T_{root,HDI=1}}$: it was reduced from $15.98 \pm 1.04°C$ in winter 2013/2014 compared to $13.05 \pm 0.48°C$ during our experiments. The aggregate results show that this reduction of approximately 3 K saved between 60% (median) and 66% (mean) of grass heating energy. When comparing the 3rd Quartile of our experiments to the 1st Quartile of the reference period, it is evident that the ranges of measurements barely overlap.

Tab. 10 compares the different experiments. The reduction of $Q_{grass,HDD7}$ in our

Table 9: Daily $Q_{grass,HDD7}$ [MWh/DD]: winter 2013/14 compared to winter 2014/2015.

Parameter	Winter 2013/2014	Winter 2014/2015
1^{st} Quartile	1.8	0.3
Median	2.5	1.0
$m \pm s$	4.1 ± 7.1	1.4 ± 2.1
3^{rd} Quartile	4.0	1.5

Table 10: Summary of experimental results: Median $Q_{grass,HDD7}$ [MWh/DD], Mean $Q_{grass,HDD7}$ [MWh/DD] and UPR [%].

Dataset	Median $Q_{grass,HDD7}$	$\overline{Q_{grass,HDD7}}$	UPR
Baseline	2.5	4.1 ± 7.1	NA
B1	0.9	1.2 ± 0.5	11.1
B2	1.0	1.0 ± 0.4	15.6
B3	1.7	2.6 ± 2.4	7.1
D	1.8	1.9 ± 0.7	2.3
Dmod Feb. only	1.1	1.0 ± 0.5	0
PA1	NA	NA	5.4
PA2	NA	NA	0.3

experiments exceeds our estimated savings of one third: for the observed mean they range from 37% (*B3*) to 76% (*B2* and *Dmod*, February only). When considering the median, savings range from 28% (*D*) to 64% (*B1*). Unfortunately, due to mild weather conditions in second half of March, we cannot analyze the energetic impacts of using advanced T_{root} forecasts as both experiments *PA1* and *PA2* did not produce enough reliable energy data to derive meaningful statistics and we intend to repeat these experiments in the next heating season.

Pre-heating (*B3*), day-time heating (*D*, *Dmod*) and strategies relying on non-linear forecasting (*PA1*, *PA2*) outperform the experiments *B1* and *B2* in terms of UPR - which is not surprising given that the latter only focus on the nightly temperatures and neglect day-time cool-down effects.

All night-time heating experiments used the majority of energy at the beginning of the night to counter day cool-down. From *B3* we see that on colder days, pre-heating schemes would need to violate the upper temperature limit in order to ensure not dropping too low during day-time - or additional day-time heating is required to avoid excessive under-performance.

The *D* and *Dmod* experiments were conducted for approximately 2 months, stressing our priority of studying this changed operational paradigm and demonstrating the feasibility of our approach in daily routine operation. As confirmed by the operational staff, in both experiments the grass heating system could be served during day-time without adversely impacting other systems - the defined back-off thresholds appropriately modeled peak load situations. The day-time experiments outperformed the basic control scenarios in terms of UPR as spare capacity could be used during the day-time.

Table 11: Aggregate winter statistics of winter 2014/2015 and reference winter 2013/2014.

Parameter	Winter 2013/2014	Winter 2014/2015
$HDD7$	327	479
$HDD7_{ex}$	574	574
Q_{gas}	3,965	4,341
Q_{grass}	795	512
$Q_{grass,HDD7}$	2.4	1.1
$Q_{grass,ex.}$	1,396	614

The aggregate winter statistics in Tab. 11 confirm energy savings of more than half. At the same time our experiments achieved a low aggregate UPR of 6%. This UPR predominantly stems from the night-time heating experiments. Despite winter 2014/2015 was colder and had 50% higher HDD7, Q_{grass} was 36% lower than 2013/2014 and Q_{gas} only increased by 10%. Consequently, our experiments reduced the grass heating system's energy consumption share of the overall consumption from 20% to 12%. Compared to the 5 year average heating season conditions of Frankfurt both winters were mild. Extrapolating the savings to average winter conditions, Tab. 11 shows our experimental strategies would save approximately 780 MWh or 56% of $Q_{grass,ex.}$ - equivalent to 150 t of CO_2 emissions. These savings purely stem from control logic improvements and are orthogonal to e.g. refurbishment and modernization measures.

6 Conclusion

We demonstrated the feasibility and the potential of applying a closed supervisory dynamic cyber-physical control loop on top of a normal legacy BMS infrastructure. Our series of seven different experiments in a real-life demonstrator setup increased energy efficiency while keeping a satisfactory service level performance during day-to-day operation of the Commerzbank Arena in Frankfurt, Germany. By closely monitoring relevant observables through a holistic ICT platform, we saved more than half of the weather normalized energy consumed by the 1.4 MW grass heating system. At the same time, by respecting the application specific T_{root} target band we achieved a low UPR of 6%. Applied in typical winter conditions, the experimental grass heating strategies are expected to save about 780 MWh and 150 t CO_2. These figures exceed our earlier estimates. They also exceed the anticipated savings of refurbishment measures suggested in [10] by a factor of two and in principle our control strategy improvements are compatible with these measures.

We consider our work to be relevant on a global scale as there is a high number of sports arenas for soccer, rugby and American football world wide. Many of these have grass heating systems installed and these systems are prominent consumers of thermal energy. Using the Commerzbank Arena as representative example of current stadium building stock and operational practices, even simple control schemes can save several hundreds of MWh per heating season without adversely affecting the daily operational routine. Extrapolating our results to the 36 soccer arenas of the German 1. and 2. Bundesliga for which this kind of system is mandatory, about 28 GWh (exceeding the annual heating demand of 2,450 average German households [4]) or 5.4 kt CO_2 could be saved annually.

We identified several areas to extend our work - we aim

- To experimentally verify the strategies *PA1* and *PA2* reflecting weather forecast information to further reduce energy demand without increasing UPR. Incorporating additional weather parameters should further improve prediction accuracy.
- To apply online learning approaches to continuously improve the models. In particular if sufficiently different winter conditions are observed this will reduce situations of under-performance as in *B3*.
- To embed the developed models and heuristics into an optimization framework and extending control to other thermal systems will enable to realize arena wide synergies. Positive effects on future heating system dimensioning are expected.
- To verify the applicability to different stadiums and study the effect of individual stadiums' heating system equipment as well as differences in climatic environments.
- To transfer the underlying data-driven concepts to other domains, e.g. to ice rinks and green houses.

7 Acknowledgments

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Paper D

Cyber-Physical System For Energy Efficient Stadium Operation: Methodology And Experimental Validation

Authors:
Mischa Schmidt, Anett Schülke, Alberto Venturi, Roman Kurpatov, Enrique Blanco Henríquez

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Cyber-Physical System For Energy Efficient Stadium Operation: Methodology And Experimental Validation

Mischa Schmidt, Anett Schülke, Alberto Venturi, Roman Kurpatov, Enrique Blanco Henríquez

Abstract

The environmental impacts of medium to large scale buildings receive substantial attention in research, industry, and media. This paper studies the energy savings potential of a commercial soccer stadium during day-to-day operation. Buildings of this kind are characterized by special purpose system installations like grass heating systems and by event-driven usage patterns. This work presents a methodology to holistically analyze the stadium's characteristics and integrate its existing instrumentation into a Cyber-Physical System, enabling to deploy different control strategies flexibly. In total, seven different strategies for controlling the studied stadium's grass heating system are developed and tested in operation. Experiments in winter season 2014/2015 validated the strategies' impacts within the real operational setup of the *Commerzbank Arena*, Frankfurt, Germany. With 95% confidence, these experiments saved up to 66% of median daily weather-normalized energy consumption. Extrapolated to an average heating season, this corresponds to savings of 775 MWh and 148 t of CO_2 emissions. In winter 2015/2016 an additional predictive nighttime heating experiment targeted lower temperatures, which increased the savings to up to 85%, equivalent to 1 GWh (197 t CO_2) in an average winter. Beyond achieving significant energy savings, the different control strategies also met the target temperature levels to the satisfaction of the stadium's operational staff. While the case study constitutes a significant part, the discussions dedicated to the transferability of this work to other stadiums and other building types show that the concepts and the approach are of general nature. Furthermore, this work demonstrates the first successful application of Deep Belief Networks to regress and predict the thermal evolution of building systems.

1 Introduction

Throughout the world, buildings are major consumers of energy producing significant amounts of Green House Gas emissions. According to [1], residential and commercial buildings jointly accounted for 41% of the US' primary energy use in 2010. Fossil fuels served close to 75% of this consumption, with space heating (37%), water heating (12%), space cooling (10%), and lighting (9%) jointly accounting for more than two-thirds of the building consumption. In conventional buildings, irrespective of the type of construction, up to 90% of energy is used during their operational phase [2]. There are two complementary approaches to address the lion's share of building lifetime energy consumption: (i) refurbishments with better materials, components, and systems and (ii) improving operational strategies. Buildings already equipped with some level of automation infrastructure are particularly suitable for the latter approach by adopting a Cyber-Physical Systems (CPS) approach. In this approach "computers and networks monitor and control the physical processes, usually with feedback loops where physical processes affect computations and vice versa" [3].

This work studies the energy savings potential of intelligent control strategies when applied to a commercial soccer stadium. Concretely, this work shows how the CPS concept can improve the operation of a special-purpose stadium system: the grass heating system of a German Bundesliga soccer stadium, the *Commerzbank Arena* in Frankfurt am Main. This stadium was completely rebuilt for the FIFA World Cup 2006 ™. Its age, installations, and capacity (≈50,000 spectators) make it a typical representative of German stadiums. The stadium's grass heating system keeps the soccer pitch in high-quality condition throughout the winter season. Systems of this type account for a considerable share of the stadium's total thermal energy demand, but current natural gas prices in the range of €0.05/kWh make them commercially viable. The alternative to heating the soccer pitch is to replace it during winter due to wear and tear with associated costs of €100,000 [4].

Based on the holistic analysis of data obtained from the Commerzbank Arena's automation system, we build a closed loop CPS controlling the grass heating system. This work documents the outcome of a series of experiments executed in two consecutive winters to validate the methodology applied in daily operation. The automated control strategies realize substantial savings in energy, associated cost, and CO_2 emissions while meeting requirements for grass growth to the staff's satisfaction. While the case study demonstrates the methodology's viability and the strategies' effectiveness, we also discuss the transferability of this work to other stadiums and other buildings.

The remainder of the paper is organized as follows: Section 2 introduces the problem statement, formulates the hypotheses underlying this work, and discusses related work. Section 3 presents the methodology and the concrete methods applied. Section 4 introduces the Commerzbank Arena's heating system, derives the requirements specific to grass heating, and describes the communication platform deployed to interact with the stadium. Section 5 details the analysis of operational heating system data that makes predictive control possible. Section 6 introduces seven heating strategies of various levels of complexity. Section 7 quantifies the experiments' impacts based on collected data. It also discusses the results and the potential limitations of this study, as well as the transferability to other stadiums and buildings in general. The paper concludes with a summary and an outlook on future work in Section 8.

2 Problem Statement and Hypotheses, Related Work and Contribution, Terminology

2.1 Problem Statement and Hypotheses

A modern sports stadium has high energy requirements to provision systems like flood lighting, interior lighting, and catering, as well as supplying the event-specific media centers. Heating, ventilation, and air conditioning (HVAC) systems serve lounges and meeting spaces. Specific to lawn sports such as soccer, professional staff waters, lights, and cuts the grass throughout the year to meet the high pitch quality requirements - the stadium's prime target. For this purpose, the staff has access to information from sensors, the building systems, and services such as weather forecasts. In colder regions, it is common to heat the soccer pitch to maintain the grass at growth conditions throughout winter. Grass heating offers business value as it helps to avoid (i) pitch replacement during the season and (ii) costly match cancellations due to low pitch quality. As the heating also reduces the risk of player injuries, the German soccer regulations mandate the use of grass heating systems in the two top leagues [5]. There are installations in other countries, e.g. France, Russia, the UK, and the US in soccer, rugby, and American football stadiums.

During the heating season (October - March), the Commerzbank Arena's total heat demand can exceed the capacity of the main heating supply (a gas boiler-based hydronic system). As the grass heating system consumes up to 50% of the peak output of the supply, it is the chief cause of heating shortages. When these occur, the stadium's heating distribution circuit serves the grass heating system with priority and sacrifices the service quality and thermal comfort of other areas like offices, the conference center, and meeting rooms. The current best practice to avoid shortages is to run the grass heating system only during nighttime and rely on the soil's thermal inertia during the day. However, on cold days that does not suffice and the stadium has to resort to daytime grass heating to ensure grass quality, causing the described shortages.

The objectives of this work are to improve energy efficiency, to maintain grass quality, and to mitigate heating shortages. In the status quo operation, staff monitors the soccer pitch's quality visually and by using spot checks of the pitch's soil temperatures. Occasionally, staff adjusts heating system parameters manually. The frequency of checking varies with the workload, but usually, there are daily checks. In times of leave or of high workload, system operation is set to conservative settings to ensure grass growth even in the case of adversely changing weather conditions. This work explores the automation of adopting the staff's supervisory control decisions through reactive, predictive, and context-aware strategies by developing data-driven CPS capabilities, that leverage the stadium's Building Management System (BMS).

In summary, this work has two hypotheses:

1. *The automation of currently manual supervisory control decisions improves efficiency in daily operation as less conservative operational settings are needed.*

2. *Predictive and context-aware control strategies can mitigate heating shortages and further improve the building's operational efficiency.*

2.2 Related Work, Relation to Earlier Work

In theory, the grass heating system and the associated soil can be modeled based on physical parameters. However, [6] argues that the standard soil temperature models [7–9] are not sufficiently precise to estimate the soil temperature near the surface. For this reason, the meteorology and geoscience communities provide several works on data-driven approaches for soil temperature prediction at different depths. Unfortunately, their focus lies on meteorological influences without discussing the possibility of under-soil heating systems. For example, [10] concentrates on day-ahead mean temperatures, whereas [11] and [12] predict monthly mean temperatures. These works show that the daily mean air temperature is the dominant meteorological parameter impacting the soil temperature - solar radiation, relative humidity, wind speed, and precipitation play minor roles. Several studies focus on estimating soil temperatures at different depths by using either nearby weather stations' soil temperatures [13] or local meteorological data [14–16]. All of the cited works study neural networks for predicting soil temperatures. In [10, 13, 14] neural networks achieve higher regression accuracies when compared to linear or non-linear regression. Further, [15] shows that neural networks outperform an adaptive inference system-based regression approach. The cited works focus on forecasting soil temperatures on timescales of one day or larger. However, to predictively operate the grass heating system, an intra-day prediction horizon is crucial.

Stadium operation strongly depends on scheduled events, making it distinct from other medium or large-scale buildings studied in the building energy efficiency literature. Also, to the best of our knowledge, the recent research addresses neither the modeling nor the optimization of under-soil heating systems. However, the literature provides guidance on the methods and techniques to apply, as well as magnitudes of effect sizes to expect. As outlined in the following, current research on predictive building control strategies achieves high increases of performance by relying on predictive models learned from sensor data.

[17] optimizes the operation of a multi-zone Heating, Ventilation and Air Conditioning (HVAC) system for room temperature and energy consumption, taking relative humidity, room temperature and indoor CO_2 levels as the input. Compared to seven other regression models, a neural network ensemble performed best. A modified Particle Swarm Optimization algorithm solves for Pareto-optimal solutions of indoor air quality, comfort, and energy consumption by controlling the supply air's static pressure set-points. Different weightings of these objectives lead to different Pareto-optimal trade-offs. Regression models created from a recorded two week period indicate average estimated electricity savings of 12-17%.

[18] uses neural networks and multi-objective optimization for HVAC operation to minimize economic cost while ensuring user comfort. The study takes into account indoor temperatures, schedule information, cost, and weather variables. It documents energy

consumption for three out of a total of six experiments conducted in winter and summer seasons at University of Algarve, Portugal. The experiments' lengths are relatively short with a maximum of two days. The results suggest financial savings while spending more energy to ensure minimized comfort violation: "savings in the order of 50% are to be expected".

Starting from a thermal building simulation, [19] proposes to use neural networks to learn building behavior regarding energy and comfort subject to control actions. The Genetic Algorithm then derives building control rules. A knowledge base stores these, enabling facility managers e.g. to strive for energy savings targets. The approach is verified in a care home in the Netherlands where heating supply, window opening, the degree of shading, and light levels can be controlled by using three months of simulation and two months of experimentation. Energy savings are normalized for weather influences using the Degree Day method and reach 25%.

[20] uses an ensemble of neural networks to assist Reinforcement Learning in creating an HVAC demand response controller able to control on-off decisions. A simulation of 40 days with different temperature regimes validates the approach. A shorter experiment in a living lab verifies the findings qualitatively.

The references indicate that neural networks are a popular regression technique in the meteorological, the geoscience, and the building optimization communities. The energy efficiency works show that validation is typically computational, or in case experimentation is used, it usually is limited to short periods of a few days or weeks. Furthermore, of the referenced works only [19] uses weather normalization. None of the works uses methods of statistical inference. That, however, limits the generalizability and robustness of the results. The work in this paper relies on a prolonged observation and experimentation period spanning across three winters, accounts for weather influences on collected energy data, and applies methods of statistical inference to draw robust and reliable conclusions.

The lack of literature on intra-day soil temperature predictions subject to grass heating systems and the absence of accurate physical models advocate the application of a data-driven approach to the stadium's operational data. To extract the operational data needed and to also communicate control decisions to the grass heating system, this work creates a CPS leveraging the existing building instrumentation as much as possible. In larger facilities such as the Commerzbank Arena arena, staff typically relies on automation systems to operate building systems efficiently. Usually, the automation system architecture is three-layered [21]:

1. The lowest layer, the *Field Layer*, consists of sensors and actuation devices.

2. The middle layer, the *Automation Layer*, consists of controllers implementing control loops to meet configured set-points.

3. The top layer, the *Management Layer*, usually consists of the computer hosting the BMS. That allows monitoring building system operation and configuring set-points. Typically, these BMS provide basic means of configuration, e.g. simple supervisory control rules and schedules.

We develop a CPS by extracting information from the Commerzbank Arena's automation infrastructure via the stadium's BMS and by accessing an internet weather forecast service. The information provides insights into the building operation and the associated physical processes of concern. That enables predictive or reactive control of building system operation parameters. The CPS issues appropriate control commands to the BMS to enact these using the lower automation infrastructure layers.

This paper builds on earlier findings in [22, 23] and extends these as follows:

- The present work describes the overall methodology that guided earlier work. Over the course of three years, its application formed an efficient and effective data-driven CPS integrating the Commerzbank Arena's BMS and enabling flexible execution of different supervisory control algorithms.

- [22] provides a description of the arena and its heating system. It provides the first analysis of data collected from the Commerzbank Arena's grass heating system captured in winter 2013/2014 by data aggregation platform deployed on top of the stadium's BMS. The analysis confirms literature in that air temperature is the primary meteorological parameter of interest impacting the soil temperature evolution in the absence of under-soil heating systems. The strong effect size allows reducing the number of the predictive models' input variables by neglecting other meteorological parameters than air temperature.

  Based on the collected operational data, the current work contributes the intervals of 95% confidence for the grass heating system's energy consumption. Further, this work provides the accuracies of neural networks trained with the data to predict grass root temperature evolution in response to the heating system operation.

- [23] formulates the seven different algorithms to control the stadium's grass heating system and provides their experimental validation - the winter 2014/2015 experiments. It provides descriptive statistics of weather-normalized energy use and grass root temperatures, demonstrating significant savings compared to the status quo operation.

  This work documents an additional experiment executed in winter 2015/2016 to quantify the effect of lowering the target soil temperature band. Further, for robust interpretation, it infers intervals of 95% confidence of median normalized daily energy consumption for all Commerzbank Arena experiments and also infers the pairwise differences among the strategies' energy impacts. That allows the robust quantification of the differences in the strategies' effect sizes, i.e. to reliably identify the most effective strategies.

2.3 Notation

Table 1 summarizes the different variables used in this paper.

Table 1: Variables used. The column BMS ID *specifies the BMS variable available to the CPS, if any.*

Param.	Description	BMS ID	Unit
h	A specific dimension of $\vec{\hat{y}}$. Identifies a specific T_{root} point estimate, h time steps in the future		$\{1, .. H\}$
H	Prediction horizon, depends on time resolution, defines dimensionality of $\vec{\hat{y}}$		$\in \mathbb{N}_+$
$HDD7$	HDD for base temperature of 7°C		DD
HDI	Grass heating system *Heat Demand Indicator*, indicates if system operates or not	H004-ST02	1/0
Q_{grass}	Measured energy use of grass heating system	H004-ZM UG1	MWh
$\tilde{Q}_{grass}$	Median of Q_{grass}		MWh
$Q_{grass,HDD7}$	HDD7-normalized Q_{grass} using Equation 1		MWh/DD
$\tilde{Q}_{grass,HDD7}$	Median of $Q_{grass,HDD7}$		MWh/DD
RMSE	Root Mean Squared Error		K
$T_{external}$	Air temperature measured at time t	H004-YB01	°C
$\overline{T_{external}}$	Daily mean air temperature		°C
T_{Gset}	Grass heating supply temperature set-point	H004-XS05	°C
$\Delta\ T_{Gset,root}$	$T_{Gset} - T_{root}$		K
t_{now}	Current time		Time
t_{OFF}	Time of grass heating system deactivation		Time
t_{ON}	Time of grass heating system activation		Time
T_{root}	Grass root temperature measured	H004-ME20	°C
$\Delta\ T_{root}$	Root temperature difference, e.g. since t_{ON}		K
$\Delta\ T_{root,ext}$	$T_{root} - T_{external}$		K
T_{supply}	Main arena supply circuit temperature	WMZ01-ME3	°C
$\vec{\hat{y}}$	Predictions of grass root temperatures in defined forecast horizon		°C, $\in \mathbb{R}^H$

3 Methodological Approach

3.1 Methodology

This work develops a data-driven CPS to improve grass heating operation within its normal operational environment. The proposed approach makes sure to understand the requirements a control strategy needs to address and describes the process to build, deploy, and validate the CPS. The following steps form an understanding of the system encountered and the current best practice operation:

1. *Understanding the overall system, its operation, and data available.* Discussions with the arena's operational staff lead to a technical understanding of the grass heating system, its purpose, the thermal supply system, the ways of controlling operation, and the relevant data points available.

2. *Identification of requirements.* By literature review and discussions with expert

staff, a thorough understanding of the use case specific requirements is formed.

3. *Establishment of communication for data extraction and actuation.* This work pursues a data-driven approach relying on a data aggregation platform that supports the appropriate communication protocols to provide BMS access. That allows extracting building operation data and enacting actuation commands. As these influence the physical process, they impact future operational data and affect the future computational representation. Hence, this step creates a closed-loop CPS.

4. *Data analysis and modeling of system characteristics.* Monitoring the system in routine operation establishes a reference baseline and allows analyzing current control strategies to reveal inefficiencies. Moreover, the data allows modeling the soil characteristics for use in predictive control strategies.

5. *Development of improved control strategies.* Based on discussions with staff, the analyzed data, and the operational insights, control strategies are formulated.

6. *Validation by experimentation.* These experiments execute the different control strategies via the deployed platform within the real operational environment for prolonged periods of time. Data is recorded, analyzed, and discussed to extrapolate and generalize the results.

3.2 Methods for Analysis and Inference

This subsection provides information about the methods to be applied in the presented methodology steps 4 and 6. Sections 5 and 7 document their application.

Weather Normalization

This work uses the Heating Degree Day (HDD) normalization technique to account for changing weather conditions across different years. It normalizes energy consumption Q by dividing it by a normalization factor HDD that captures the extent to which the measured outside air temperature $T_{external}$ is below a use case specific *base temperature* $T_{HDD,base}$. This work follows the German standard [24] by relying on daily mean air temperature ($\overline{T_{external}}$) for approximating HDD:

$$HDD \approx \begin{cases} T_{HDD,base} - \overline{T_{external}} & T_{HDD,base} > \overline{T_{external}} \\ 0 & T_{HDD,base} \leq \overline{T_{external}} \end{cases} \tag{1}$$

Usually, $T_{HDD,base}$ is defined as the outside air temperature below which the studied building requires heating. As the grass heating system is outdoors and the Commerzbank Arena's standard system configuration activates it only when $T_{external} \leq 7°C$, this work uses $T_{HDD,base} = 7°C$ for normalization. When calculating daily energy statistics, days with 0 HDD are excluded.

Degree-day-based calculations are especially sensitive to the choice of $T_{HDD,base}$ as it has a big effect on the proportional difference between different periods' HDDs (e.g. days or winter seasons). Additionally, on days where $\overline{T_{external}}$ is close to the building's $T_{HDD,base}$, the building will often require little or no heating possibly leading to misleading or erroneous energy consumption statistics. We choose $T_{HDD,base}$ equal to the grass heating activation temperature. The stadium operations team, which is responsible for the arena's energy consumption, confirms this choice as appropriate. For robustness against multiplicative effects of HDD values close to 0, this work discusses energy-related effects using the median, not the mean, as described in the next section.

Situations of intermittent heating, e.g. around occupancy hours or as in the case of nighttime-only heating, are another aspect requiring consideration when applying HDD normalization. In these situations, the HDD value covering the full period (e.g. a day) may not be a suitable representation of the air temperatures most relevant to the energy consumption. However, the thermal energy stored in and lost from the soccer pitch over the day is a result of $T_{external}$ and the soil's thermal inertia, i.e. a multi-hour period. In particular, on days without daytime heating, i.e. the days with mild temperatures on which best practice relies on nighttime-only heating, the grass heating system needs to counter daytime cool-down effects when the nighttime starts. Thus, considering the full-day HDD is appropriate for describing the grass heating system's behavior even on days with nighttime-only heating.

Descriptive Statistics and Statistical Inference

For robustness against outliers, this work discusses effects on energy consumption and thermal behavior based on the *median*. This measure of descriptive statistics describes the properties of the observed data but does not assume that the observations are samples of a larger population. However, this work interprets a change to control strategies as changing the underlying population's characteristics. Hence, to derive generalizable results from measured data, *statistical inference for a single median* is used to characterize the data sets of the individual control strategies. This work uses statistical inference for *two medians* to calculate a robust estimate of the pairwise differences between two strategies' effects while accounting for stochastic uncertainty.

Specifically, this work applies inferential statistics using the Student's t-distribution to construct intervals of 95% confidence in those cases that satisfy the underlying requirements of independence and normality of the collected data samples. While the former condition requires careful reasoning, the latter is tested using the Shapiro-Wilk test of normality. Where this test rejects the normality assumption, common statistical bootstrapping is used to construct the confidence intervals, using the percentile method with 10,000 bootstrap replicates. This work explicitly points out the situations of applying bootstrapping.

Assessing Grass Quality

After discussions with staff, the control problem is to keep the grass root temperature T_{root} within defined temperature bands as much as possible. For this work, violations of minimum temperature levels are particularly critical as these affect the grass quality negatively. Thus, we assess the extent to which the control strategies fail to keep T_{root} above a defined minimum temperature by relying on the service level Key Performance Indicator *Under-Performance Ratio* (UPR). It represents the fraction of (operating) time the system does not meet minimum service level requirements. Other environmental parameters such as the soil's humidity are not monitored and thus unavailable for automated grass health monitoring. Throughout the three winters, spot checks by experts ensure that the pitch quality stays satisfactory. Section 7 incorporates the experts' feedback into its discussions.

3.3 Methods for Data-Driven Grass Root Temperature Prediction

[22] identifies the dominant influencing variables for short term T_{root} prediction. These are T_{root} itself, $T_{external}$, information whether the heating system is being active (HDI), and the grass heating system's supply temperature (controlled by the corresponding setpoint T_{Gset} when the system is active). That study also characterizes the T_{root} heating and cooling trends as non-linear, resembling a saturation curve. The current work applies the following two non-linear regression techniques, using fivefold cross-validation during model training.

- We focus on neural networks as [17] indicates that they outperform other non-linear standard regression techniques for thermal predictions. Section 2.2 shows that in particular, the feed-forward *Multi-Layer Perceptron* (MLP) is popular when modeling thermal characteristics.

- For comparison, this work also applies a *Deep Belief Network* (DBN) [25]. As shown in [26] and the references therein, DBNs have been applied successfully to visual object recognition, natural language processing, information retrieval, and robotics. This category of neural network consists of multiple stacked Restricted Boltzmann Machines that can be composed into deep network structures. During an unsupervised initialization phase, DBNs learn feature representations from inherent characteristics of the input data before learning to regress in a supervised way. To the best of our knowledge, these networks have not been applied to the field of predictive control of building systems, yet.

As not only a point estimate of the future is of interest, but also the temperature trajectory until that point, a vector $\vec{\hat{y}}$ of T_{root} predictions is regressed. With a given time resolution, the length of prediction horizon H defines the dimensionality of $\vec{\hat{y}}$.

Both methods are implemented in Python with Theano [27]. For both, the input data is standardized by shifting each feature datum by its training data mean and dividing by its training data standard deviation. 60% of the data serves as the training set. The validation set and the validation set each use 20% of the data. By using the same periods to train, validate, and test the regression models, weather parameters affect all

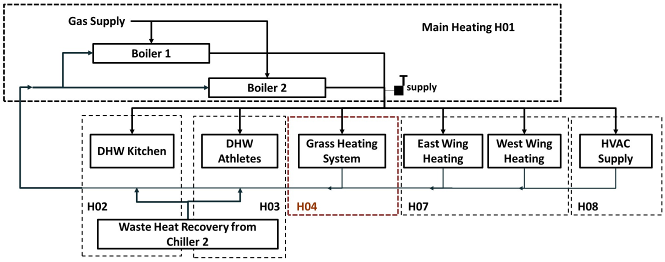


Figure 1: The Commerzbank Arena's thermal distribution system, including the grass heating system H04.

models equally. A grid search identifies the different models' hyper-parameter combination (e.g. number of neurons, data history length, learning rate) performing best on the test set to tune the models to best performance. The standard Root Mean Squared Error (RMSE) metric assesses for each dimension of $\vec{y}$ the regression model performance on the test set. $RMSE^h = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i^h - \hat{y}_i^h)^2}$, where n is the number of predictions, $\hat{y}_i^h$ is the i^{th} value predicted by the model for the h^{th} time step into the future, and y_i the i^{th} true value.

4 Commerzbank Arena: The Thermal System, Requirements, and Communication Aspects

4.1 Methodology Step 1: System Understanding and Available Data

Fig. 1 depicts the Commerzbank Arena's hydronic heating distribution system. Two gas boilers with a total capacity of 2.4 MW supply the stadium with thermal energy. The main distribution circuit serves hot water to six different sub-systems. These are two domestic hot water systems (athletes' showers and kitchen); two radiator-based static heating systems for east and west offices, lodges, and meeting rooms; the HVAC to supply warm air to all spaces with air conditioning; and the grass heating system. Waste heat is recovered from cooling machines and supplied to the hot water systems, primarily in summer. In the event of heating supply bottlenecks, the main circuit's temperature T_{supply} drops below required levels.

A 1.4 MW heat exchanger connects the stadium's grass heating system shown in Fig. 2 to the main heating distribution network. Its multiple pipe loops distribute the water-glycol fluid under the playing field longitudinally. As indicated in Section 3.2, T_{root} is the primary variable of concern to monitor the grass conditions. The corresponding sensor measures this variable in a depth of 15 cm. The BMS also monitors $T_{external}$, but it does not monitor other soil parameters such as humidity. When the heating system is active

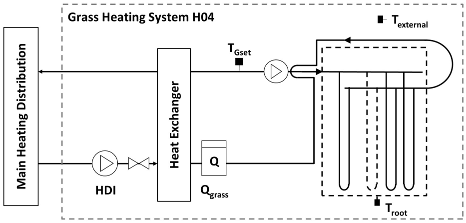


Figure 2: Grass heating system H04 with sensor installations.

($HDI = 1$), T_{Gset} controls the temperature of the fluid pumped through the pipe loops. That affects T_{root} and consumes energy Q_{grass}. The system has a configurable fail-safe to protect the grass from overheating: the system deactivates if the fluid's temperature exceeds $40°C$ to avoid damaging the grass roots. Table 1 indicates the stadium's relevant BMS variables. [28] provides weather forecasts for a nearby weather station (Frankfurt airport).

4.2 Methodology Step 2: Grass Root Temperature Requirements

To identify the requirements for grass heating, botanical literature and discussions with the arena's green keepers provide an understanding of the biological needs that drive the target T_{root}. In Germany, the Landscape Development and Landscaping Research Society e.V (Forschungsgesellschaft Landschaftsentwicklung Landschaftsbau e.V.) defines standard seed mixtures ("Regel-Saatgut-Mischungen", RSM) for use in landscaping. German DIN 18035 [29] recommends RSM categories 3.1 and 3.2 for sports use, consisting of a mixture of *Lolium perenne* and *Poa pratensis*. For these weeds, [30] recommends $10°C \leq T_{root} \leq 18°C$ for optimal growth. In coordination with the arena's experts, the T_{root} target band for the winter 2014/2015 control experiments is defined as $12°C$ to $14°C$. This choice leaves a safety margin of 2K to the recommended minimum. For winter 2015/2016, the T_{root} target is lowered to $10°C$ to $12°C$ to study the effects associated with removing the safety margin.

Note that in Germany, the different stadiums' staff meets several times per year to exchange experiences and best practices. Thus, we consider the Commerzbank Arena's best practice for T_{root} regimes as representative.

4.3 Methodology Step 3: Establishment of Communication for Data Extraction and Actuation

The data aggregation platform [31] addresses Step 3 of the presented methodology. The distributed and modular platform interacts with the Commerzbank Arena's BMS through the BACnet/IP protocol, enabling the development of data-driven CPS while maximally reusing the building automation infrastructure. The platform is designed to *holistically* study the operational schemes and energy profiles of buildings by unifying data from different sources. A harmonized application interface serves the modules analyzing the data and implementing the control strategies. The BMS manages approximately 13,500 variables. These include readings from sensors and meters, as well as values of set-points, status flags, and internal values, providing a detailed snapshot of the entire building state and its operation. Since August 2013, the platform accesses the BMS every 10 minutes. Table 1 indicates the subset of BMS variables relevant for this work.

5 Methodology Step 4: Data Analysis, Modeling of System Characteristics

5.1 Current Control Schemes

In winter 2013/2014 the status quo grass heating operation consumed 795 MWh. Fig. 3 depicts this reference period's recorded air and grass root temperatures. The status quo strategy is driven by manual operation as illustrated in Fig. 4.4(a):

1. For days with mild temperatures, $T_{external}$ and time define the heating control. Heating is active only during nighttime (18:00 and 06:00) when $T_{external} \lessapprox 7°C$. That operation schedule is best practice to avoid the reported shortages.

2. Staff manually adjusts control parameters in several ways. For example, the data of February 2014 shows a regularly alternating T_{Gset}. On freezing days, staff changes from nighttime-only to daytime heating causing heating shortages in offices.

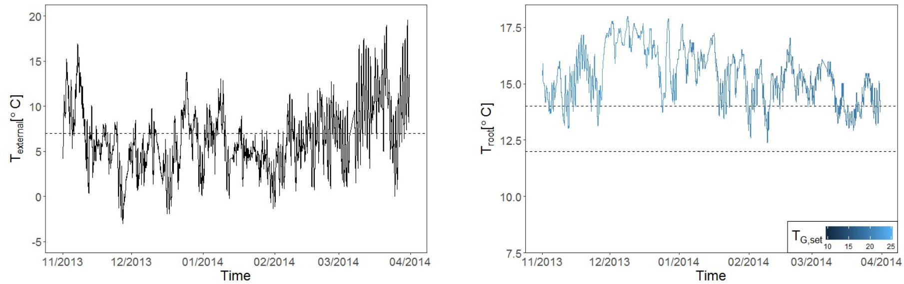
3. Staff tends to choose conservative values for T_{Gset}, i.e. higher values than necessary, as it cannot constantly monitor the system operation nor the grass conditions.

The observed control schemes' effects are visible in Fig. 4.3(b) showing higher than needed T_{root}. Fig. 4.4(b) focuses on T_{root} for active grass heating only. Out of the total 1956 hours operating time, $T_{root} \geq 17°C$ for more than 400 hours and $T_{root} \geq 15°C$ for more than 1,600 hours. That presents an opportunity for significant savings.

5.2 The Effects of Heating Activation

Statistical Considerations, Defining Heating Events

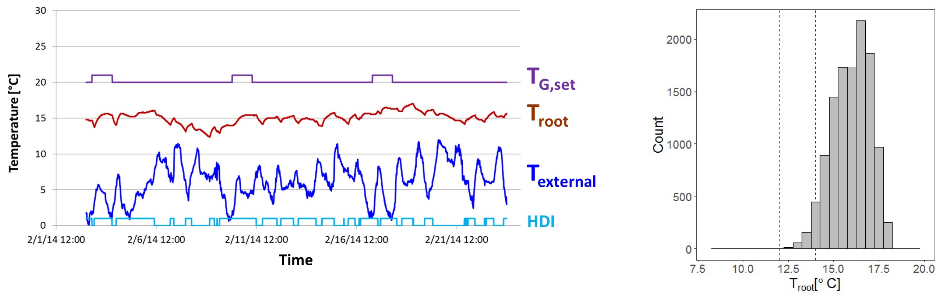
The intention of this subsection is to understand the effects associated with an extended operation of the grass heating system. Its energy consumption, as well as its effect on T_{root}, are bigger after a prolonged cooling period than when the system had been heating shortly before. That establishes a time dependency among the data samples of T_{root} prohibiting to apply statistical inference techniques to the samples directly. To establish independence among the samples and to capture prolonged heating effects, this work focuses on heating activation events at time t_{ON} meeting the following criteria.



(a) $T_{external}$, the dashed line indicates $T_{HDD,base} = 7°C$.

(b) T_{root} evolution, T_{Gset} decided by stadium staff. Dashed lines indicate the first experiments' target band of $12°C \leq T_{root} \leq 14°C$.

Figure 3: Air and root temperatures observed in the stadium in reference winter 2013/2014.



(a) Grass heating control in February 2014: temperature variables and grass heating operation indicator HDI.

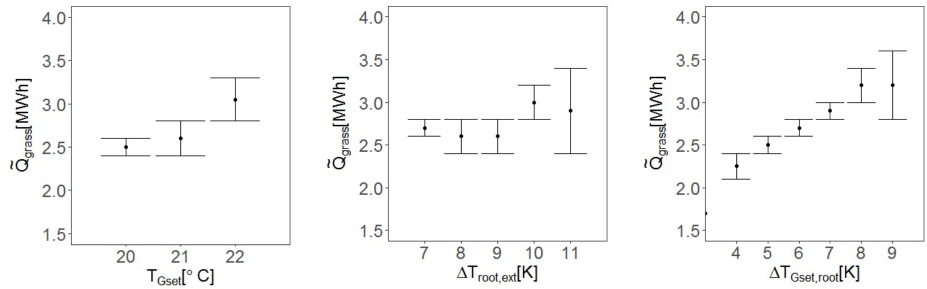
(b) T_{root} distribution when grass heating active. Dashed lines indicate the target band of $12°C \leq T_{root} \leq 14°C$.

Figure 4: Status-quo operation resulted in wasteful heating in reference winter 2013/2014.

- The events start a period of active grass heating of 6 hours or longer.
- A period of inactive heating precedes the events, so that heat from the earlier heating cycle has been lost. That allows viewing the events as mutually independent.

Considering the second aspect, this work considers two alternatives of defining the period preceding t_{ON}. Both ensure heating event independence to study the effects on predictive accuracy. Definition 5.1 is more restrictive than Definition 5.2. While Definition 5.1 selects 87 heating system activation events during winter 2013/2014 (resulting in regression model training sets of 52 events), Definition 5.2 selects 117 events (leading to a training set size of 70 events).

Definition 5.1. Uniform Cooling History*: The grass heating system was inactive the full 6 hours before t_{ON}.*



(a) In relation to T_{Gset}. (b) In relation to $\Delta\ T_{root,ext}$. (c) In relation to $\Delta\ T_{Gset,root}$.

Figure 5: Confidence intervals of median energy consumption for 6 hour heating events using Definition 5.1.

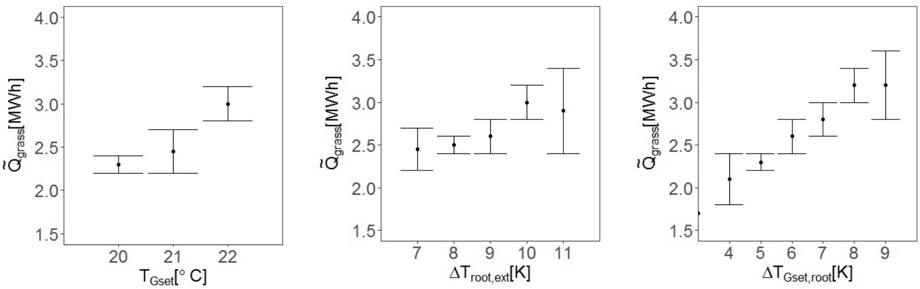
Definition 5.2. Intermittent Cooling History*: The grass heating system was intermittently active for at most 3 hours during the 6 hours before t_{ON}.*

Energy Consumption

Using the heating events of each definition, Fig. 5 and 6 depict the intervals of 95% confidence for the estimate of the true median energy consumption ($\tilde{Q}_{grass}$) per heating activation event derived by bootstrapping. Overall, Definition 5.1 yields slightly narrower confidence intervals than Definition 5.2 as the corresponding data set is more uniform. The figures exhibit a clear increase of energy for higher T_{Gset} and higher $\Delta\ T_{Gset,root}$. For both event history definitions, there is significant overlap of the confidence intervals. Thus, while the intervals are suitably narrow for heating control strategies to take informed heating operation decisions, numerical optimization cannot be applied to select T_{Gset}. The underlying trend of the confidence intervals concerning $\Delta\ T_{root,ext}$ is less pronounced. The application of regression models (MLP, DBN) to heating event energy data did not produce satisfactory results. The corresponding analysis is omitted for brevity.

Thermal Effects

Statistical inference for the evolution of T_{root} (denoted $\Delta\ T_{root}$) related to heating system activation at time t_{ON} does neither produce sufficiently narrow confidence intervals for Definition 5.1 nor for Definition 5.2 to formulate control strategies. This section omits the associated analysis for brevity and focuses on MLP and DBN trained with the available heating activation events for both definitions. Under the assumption that weather forecast information helps regression accuracy, the effect of a perfect forecast of $T_{external}$ is studied for the MLP and DBN models. That leads to a total of 8 different combinations of the conceptual choices. For each concept ($\{\text{MLP}, \text{DBN}\} \times \{\text{uniform}, \text{intermittent}\} \times \{\text{perfect forecast}, \text{no forecast}\}$), the grid search results in several regression models with similar performance. Fig. 7 presents results of an MLP of two hidden layers with 50 nodes each, and of a DBN with two hidden layers of 100 and 50 nodes, respectively. The MLP



(a) In relation to T_{Gset}. (b) In relation to Δ $T_{root,ext}$. (c) In relation to Δ $T_{Gset,root}$.

Figure 6: Confidence intervals of median energy consumption for 6 hour heating events using Definition 5.2.

learning rate is 0.1. The DBN pre-training learning rate is 0.001, the learning rate 0.1. Both models rely on the 36 preceding T_{root} and $T_{external}$ measurements to predict the next 36 Δ T_{root} from t_{ON}. The models taking weather forecast information into account use the next 6 hours of $T_{external}$ (downloaded from [28], interpolated to 10-minute intervals) as additional input features. The figure illustrates the regression accuracies for uniform and intermittent cooling histories and whether or not using perfect forecast information. From Fig. 7 follows:

- the DBN consistently outperforms the MLP over H, but by less than $0.1K$;
- the lowest RMSE for a 6-hour heating point estimate ($h = H = 36$) is $0.4K$ using uniform cooling history data;
- the delayed impact of $T_{external}$ on T_{root} limits the effect of using accurate air temperature forecasts on the RMSE, hence the small accuracy improvements;
- even for small h all $RMSE > 0K$, which we attribute to (a) the fact that potentially interesting soil parameters such as humidity are not measured and (b) the temperature sensor's measurement resolution;
- using uniform cooling history improves regression accuracy as the data is more uniform despite reducing the data sets' sizes.

As the DBN exhibits a slightly lower and less variable RMSE than the MLP, the predictive heating strategies use a DBN with 6 hours of uniform cooling history, taking into account weather forecast information. Relative to the temperature target band's width of 2K, the resulting RMSE is acceptable - especially the first 3 hours of predictions ($h \leq 18$) exhibit a relative RMSE $\lessapprox 10\%$ compared to the target band's width. Moreover, it is feasible to execute the regression models each time step (10 minutes), which mitigates possible prediction errors of earlier time steps.

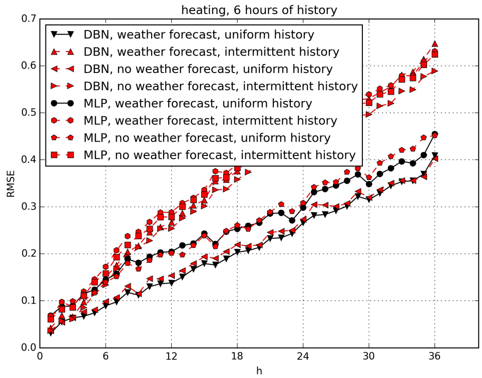


Figure 7: $RMSE^h$ for up to 6 hours (H=36) of heating for MLP (circle, hexagon, pentagon, square) and DBN (triangles), with and without using perfect weather forecast, in relation to cooling history definition. Black solid lines represent the best performing MLP (circle) and DBN (triangle down): using weather forecast and uniform cooling history. The red dashed lines represent the MLPs and DBNs achieving lower accuracies.

5.3 The Effects of Heating Deactivation

Statistical Considerations, Defining Cooling Events

Similar to Section 5.2, the intention of this subsection is to build an understanding of the soil temperature dynamics when heating deactivates at t_{OFF}. The following characteristics establish independence among data samples of heating deactivation events.

- t_{OFF} marks the start of a period with inactive grass heating of 6 hours or longer.
- A period of active heating precedes t_{OFF} to mitigate any previous cool-down period. That allows considering the events as mutually independent.

Considering the second aspect, this subsection studies two alternate ways of defining the period preceding t_{OFF}, both ensuring event independence. Definition 5.3 selects 72 heating system deactivation events (the regression model training set contains 43 events). Definition 5.4 selects 99 events (leading to a training set size of 60).

Definition 5.3. Uniform Heating History*: The grass heating system was active the full 6 hours before t_{OFF}.*

Definition 5.4. Intermittent Heating History*: The grass heating system was intermittently inactive for at most 3 hours during the 6 hours before t_{OFF}.*

Thermal effects

Statistical inference for $\Delta\ T_{root}$ in relation to t_{OFF} does neither produce sufficiently narrow confidence intervals for Definition 5.3 nor for Definition 5.4 to formulate control

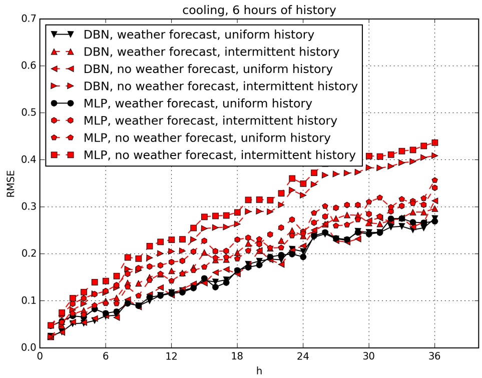


Figure 8: $RMSE^h$ for up to 6 hours (H=36) of cooling for MLP (circle, hexagon, pentagon, square) and DBN (triangles), with and without using perfect weather forecast, in relation to heating history definition. Black solid lines represent the best performing MLP (circle) and DBN (triangle down): using weather forecast and uniform heating history. The red dashed lines represent the MLPs and DBNs achieving lower accuracies.

strategies. The associated analysis is omitted for brevity. In analogy to the scenario of heating activation, this subsection describes the performance of MLP and DBN models for predicting $\Delta\, T_{root}$ under the assumption of a heating switch-off event. The parameter grid search returned several models of similar performance. Fig. 8 presents the results of an MLP consisting of two hidden layers with 60 and 50 nodes, and a DBN with two hidden layers of 90 and 55 nodes. The MLP learning rate is 0.13. The DBN's pre-training learning rate is 0.001, its learning rate 0.08. Both models rely on the 36 preceding T_{root} and $T_{external}$ measurements to predict the next 36 $\Delta\, T_{root}$ from t_{ON}. Analogous to Section 5.2, the models relying on weather forecast information additionally use 6 hours of $T_{external}$ prediction. The figure presents the accuracies for predicting 6 hours of continuous cooling using both Definition 5.3 and Definition 5.4 for heating history data, with and without taking perfect $T_{external}$ forecasts into account. It shows that MLP and DBN models are comparable in accuracy. Moreover, the figure illustrates that

- accurate air temperature forecasts tend to reduce the RMSE, in particular when using intermittent heating history data;
- using uniform heating history data leads to the best cooling predictions for $h = H = 36$ ($RMSE \approx\ 0.28K$);
- similar to Section 5.2, even for small h all $RMSE > 0K$ for both model types;
- compared to heating predictions (Fig. 7), cooling predictions exhibit a lower RMSE.

Considering the temperature target band's width of 2K, the resulting RMSE is sufficiently small to predictively take heating system deactivation decisions - especially the first 3 hours of predictions ($h \leq 18$) exhibit a relative RMSE below 10% compared to the target band's width. As the best MLP and DBN models are of similar performance, the predictive strategies use the latter. The DBN relies on uniform heating history data and takes weather forecast information into account.

6 Methodology Step 5: Heating Strategies

This section summarizes the different control strategies developed in [23] for reference. As mentioned in Section 5.2 neither the statistical inference models nor the neural networks achieved satisfactory accuracy for heating event energy predictions. Therefore, we avoid using computational optimization methods in the heating strategies. Every 10 minutes, the CPS control strategies have access to the past and current BMS variables of Table 1 and to the forecast of $T_{external}$ provided by [28]. The strategies control whether the grass heating system should be active or inactive, as well as the value of T_{Gset}.

In coordination with staff, based on the ranges of glycol supply temperatures observed in the reference winter, the strategies are allowed to choose $T_{Gset} \leq 22°C$. The lower T_{root} target temperature defines the minimum T_{Gset} permissible. This approach is implemented by a failsafe mechanism in each control strategy after e.g. executing the predictive regression models of Section 5. That software failsafe ensures that regression model errors do not cause excessively high or low T_{Gset} choices. The grass heating system's failsafe described in Section 4 provides an additional level of protection against overheating and consequently damaging the grass.

6.1 Basic Control Strategies

Basic Strategy B1: Static Supply, On/Off

This simplest of strategies uses a fixed T_{Gset} during the nighttime. It activates heating when $T_{root} < 12°C$ and deactivates heating when $T_{root} > 14°C$.

Basic Strategy B2: Variable Supply

Strategy *B2* continuously heats during the nighttime with varying T_{Gset}. This way, it can gradually react to the system's environmental context - the weather impact on T_{root}. The strategy relies on the empiric findings of thermal behavior [22] to vary $T_{Gset} \in [12°C, 22°C]$. Specifically, steps 3 and 4 modify the steepness of the heating and cooling curves to avoid violating the target band due to the heating system's (and the soil's) thermal inertia:

1. Set $T_{Gset} = 22°C$, if $T_{root} < 12°C$
2. Set $T_{Gset} = 12°C$, if $T_{root} > 14°C$
3. Increase T_{Gset} by $0.5K$, if $T_{root} < 12.5°C \wedge T_{Gset} < 22°C$
4. Decrease T_{Gset} by $0.5K$, if $T_{root} > 13.5°C \wedge T_{Gset} > 12°C$

Basic Strategy B3: Pre-Heating

This strategy focuses on countering day cool-down due to the operational condition that the heating is inactive during the daytime. The intention is to ensure that T_{root} is near the upper limit of the target band at the end of each nightly heating phase. The strategies *B1* and *B2* do not explicitly account for this. In essence, *B3* mimics the current best practice of nighttime pre-heating, but with a much faster reaction time than the human control during the reference period. The strategy reuses *B2* during the first hours of heating. Taking into account the cooling speeds observed, *B3* modifies the third and fourth steps of *B2* between 04:00 and 06:00 based on empirical observations about the heating system's inertia, resulting in the desired pre-heating at the end of each night: $T_{root} \in [13.5°C, 14°C]$.

(3) Increase T_{Gset} by $2.0K$, if $T_{root} < 13.50°C \wedge T_{Gset} \leq 20°C$

(4) Decrease T_{Gset} by $2.0K$, if $T_{root} > 13.75°C \wedge T_{Gset} \geq 14°C$

6.2 Advanced Control Strategies: Operational Context and Predictive Control

Strategy D: Introducing Daytime Heating

Daytime heating is delicate as the heating capacity constraints are known to negatively affect some of the attached thermal sub-systems such as the office heating. That happens when the output of the stadium's gas boilers is insufficient for the overall heating demand, causing the main supply circuit's temperature T_{supply} to drop. As a consequence, the Commerzbank Arena's physical heating distribution system prioritizes the grass heating system over other heating systems. Therefore, the control strategy must take into account the grass heating system's *operational context*, i.e. the operational situation of other systems to avoid thermal supply scarcity when changing the grass heating paradigm to include the daytime. In this specific setting, T_{supply} is a good indicator for situations of thermal peak demand, and thus, the grass heating system's operational context is sufficiently well captured by that single variable. Discussions with staff defined a threshold value of $T_{supply} = 80°C$, which ensures the standard operation of the other heating systems. When T_{supply} undercuts the threshold during the daytime, the strategy deactivates the grass heating immediately and reduces T_{Gset} to the minimum. After this kind of deactivation, when $T_{supply} \geq 80°C$, T_{Gset} is slowly increased again. This slow ramp up mechanism in response to peak demand prevents oscillations of grass heating system operation that would unnecessarily stress the system. In other words, the control strategy addresses a limitation of the physical heating distribution system in case T_{root} is sufficiently high: it reacts to scarcity and limits the grass heating consumption accordingly. As the heating demand of offices and other arena areas peaks at office hour start, the strategy reuses *B3* during the nighttime. That ends each night with a pre-heat cycle resulting in higher T_{root}, enabling a safe deactivation of the grass heating at office day start without risking under-performance. For daytime operation when $T_{supply} > 80°C$, the variable supply logic *B2* is reused.

Strategy Dmod: Modified Daytime Heating

After introducing the paradigm change to daytime heating in *D*, this subsection describes a more aggressive strategy *Dmod*. Its aim is to increase the amount of heating energy used during the day even further to keep T_{root} in the middle of the target band. That flattens the temperature curves and relieves nighttime operation from mitigating cool-down effects, which reduces overall energy consumed. During daytime, it differs from *D* twofold:

(a) *Dmod* applies a lower T_{supply} threshold of 75^oC.

(b) If $T_{external} \geq 5°C$, it uses an even lower T_{supply} back-off threshold of $70°C$.

Strategy PA1: Predictive Pre-heating

This strategy is intended to study the effect of using weather forecast information in addition to sensor readings. The heating approach is reverted to the nighttime heating paradigm to isolate the energy gains due to improved forecast accuracy. During nighttime, *PA1* uses the trained DBN cooling model of Section 5.3 to predict a first 6-hour $\Delta\ T_{root}$ trend. The combination of this first $\Delta\ T_{root}$ forecast with another subsequent 6-hour $\Delta\ T_{root}$ forecast leads - due to the saturation effect of cooling curves - to a pessimistic 12-hour $\Delta\ T_{root}$ prediction. If this prediction indicates T_{root} undercutting the required minimum temperature, *PA1* uses the heating DBN of Section 5.2 to predict T_{root} for 6 hours in different T_{Gset} heating scenarios. *PA1* selects the heating scenario resulting in the highest T_{root} without violating the maximum temperature during the next 6 hours. If the remaining time of the nightly heating phase is shorter, *PA1* considers only the first h T_{root} predictions, where $t_{now} + 10\text{min} \times h \leq 06{:}00$. This strategy implies a pre-heating effect similar to *B3*: as the prediction horizon shortens towards the end of the night, *PA1* checks less of the predicted T_{root} for violating the target band's upper threshold. Therefore, higher T_{Gset} are selected automatically. In winter 2015/2016, another experiment with a T_{root} target band lowered by 2K was executed (denoted *PA1**).

Strategy PA2: Predictive Pre-heating with Longer Forecast Horizon

Based on *PA1*, the slightly varied strategy *PA2* directly produces a 12-hour T_{root} cooling trend with a single trained DBN ($RMSE = 0.65 \pm 0.2K$, not presented in Section 5 for brevity) instead of forecasting two consecutive 6-hour horizons.

Table 2: Confidence Intervals (95% level) for median daily grass heating energy consumption and with median normalized daily grass heating energy consumption for HDD7 > 0. As the Shapiro-Wilk test rejected the normality hypothesis for most of the data series, bootstrapping was applied to all cases for consistency. For experiment Dmod*, only the February 2015 data is used for confidence interval calculations due to warm weather. This warm weather also prevented* PA1 *and* PA2 *to be interpreted from an energy perspective.*

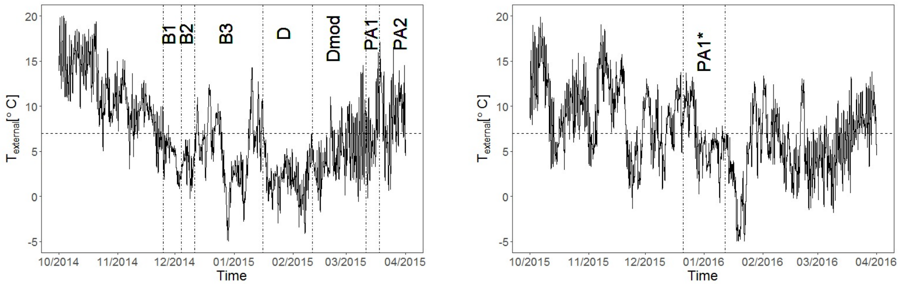
Data Set	$\tilde{Q}_{grass}$ [MWh]	$\tilde{Q}_{grass,HDD7}$ [MWh/DD]	# Experiment Time Frame	UPR	$\overline{\text{HDD7}} \pm s$ [DD]
Reference Period	[5.70,6.60]	[2.12,2.88]	2013/11/01-2014/02/28	0%	2.17 ± 1.92
B1	[2.60,4.60]	[0.83,1.48]	2014/11/24-2014/12/04	11.1%	3.34 ± 1.46
B2	[3.00,5.20]	[0.91,1.11]	2014/12/04-2014/12/11	12.5%	4.37 ± 1.02
B3	[4.60,6.20]	[1.17,3.01]	2014/12/11-2015/01/16	7.1%	3.67 ± 2.86
D	[5.80,6.80]	[1.02,1.41]	2015/01/16-2015/02/11	2.3%	5.55 ± 1.81
Dmod*	[4.80,6.10]	[1.00,1.29]	2015/02/11-2015/03/11	0%	4.13 ± 1.45
PA1	NA	NA	2015/03/11-2015/03/18	5.4%	2.00 ± 0.98
PA2	NA	NA	2015/03/18-2015/03/31	0.3%	1.23 ± 1.19
(B1,B2,B3,D,Dmod*)	[4.60,5.60]	[1.06,1.33]	2014/11/24-2015/03/11	5.2%	4.07 ± 2.40
(D,Dmod*)	[4.80,6.10]	[1.00,1.28]	2015/01/16-2015/02/28	1.5%	5.02 ± 1.81
PA1*	[1.09,1.40]	[0.57,0.77]	2015/12/21-2016/01/12	4.5%	2.03 ± 1.63

7 Methodology Step 6: Experimental Validation and Discussion

7.1 Experiments' Impacts

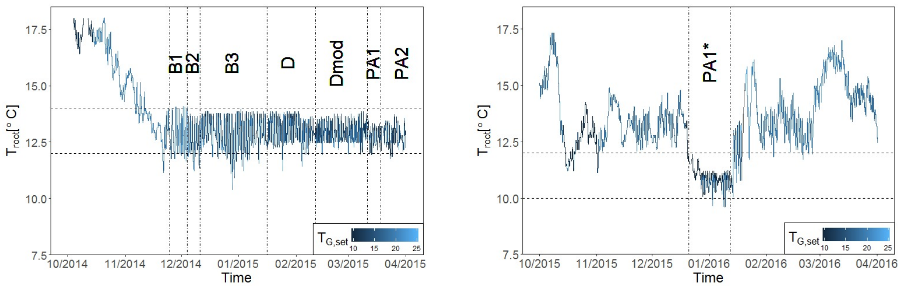
Reference winter 2013/2014 accumulated HDD7 = 327 DD, while the 5-year average HDD7 = 574 DD [28]. Fig. 3 shows the reference period's $T_{external}$ and T_{root}. During this time, the Commerzbank Arena's grass heating system consumed 795 MWh, representing 20% of the stadium's overall gas consumption. That is equivalent to 152 t CO_2 emissions [32]. Fig. 4.3(b) shows that 85.9% of the time T_{root} violated the target band by exceeding $14°C$. According to Fig. 4.4(b) there was much wasteful heating operation presenting savings potential. The wasteful operation stems from the grass heating control system being mostly driven by $T_{external}$ instead of T_{root}, by inconsistent control strategy changes, and by the staff's preference for conservative operation settings as it cannot continuously monitor and adapt the heating system operation. However, throughout the reference winter, the minimum temperature was not violated, i.e. UPR=0%.

Fig. 9 and 10 depict the measured $T_{external}$ and T_{root} during the winters 2014/2015 and 2015/2016. Further, they indicate each experiment's execution period. While the heating season officially lasts from October to March, Fig. 4.9(a) shows that experiments of winter 2014/2015 could only start towards the end of November 2014 due to warm weather. In Winter 2014/2015, pre-heating (*B3*) and daytime heating (*D*, *Dmod*) were prioritized and received more experimentation time as indicated in Fig. 4.9(a) and 4.10(a). With HDD7 = 479 DD the experimental period 2014/2015 was colder than the reference period



(a) Winter 2014/2015. (b) Winter 2015/2016.

Figure 9: Recorded $T_{external}$ of experiment winters. The dashed horizontal lines indicate the grass heating switch-on threshold temperature of $7°C$.



(a) Winter 2014/2015 T_{root} evolution, T_{Gset} decided algorithmically. (b) Winter 2015/2016 T_{root} evolution, T_{Gset} decided algorithmically.

Figure 10: Grass root temperatures during experiments. The dashed horizontal lines indicate the temperature target bands.

but still warmer than the average Frankfurt winter. Fig. 4.9(b) and 4.10(b) show the *PA1* re-execution between 2015-12-21 and 2016-01-12 to confirm the UPR results of using predictive heating and also to quantify the effect of lowering T_{root} on energy consumption. For this experiment, the T_{root} target band was lowered by 2K to $10°C \leq T_{root} \leq 12°C$.

Table 2 summarizes the collected data. It details energy consumption confidence intervals inferred for a single median for reference winter 2013/2014, the experiments of winter 2014/2015, and for *PA1**. Experiments *Dmod*, *PA1*, and *PA2* suffered from warm weather in February and March 2015. That precludes an interpretation of the energy consumption of experiments *PA1* and *PA2*, as well as the second half of experiment *Dmod*. Thus, the table presents *B1*, *B2*, *B3*, *D*, and the February sub-period of *Dmod* (indicated by *) as the seasonal aggregate statistics (denoted (*B1,B2,B3,D,Dmod**)) of winter 2014/2015. The table also singles out the effect of the heating paradigm change towards daytime heating by aggregating *D* and *Dmod**. Table 2 also provides the UPR observed, the HDD normalization factor (mean and standard deviation) from [28], and the

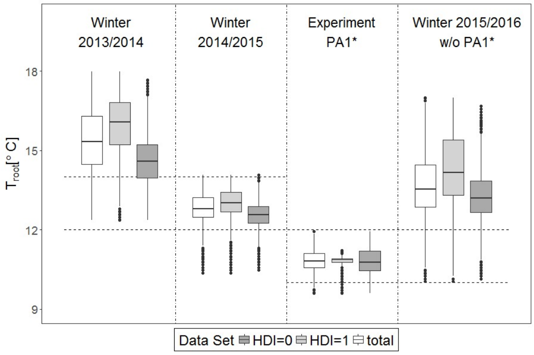


Figure 11: Boxplots of T_{root} regardless of HDI status flag ("total"), for active grass heating ("HDI=1") and for inactive grass heating ("HDI=0") of reference period (first group), experimental winter 2014/2015 (second group), of experiment PA1* *(third group), and of winter 2015/2016 excluding* PA1* *(fourth group). Dashed horizontal lines indicate the respective T_{root} target ranges.*

different experiment execution periods. As days with switching experiments do not affect UPR statistics, these are calculated by taking the accurate experiment activation and deactivation times. As the energy considerations rely on the median daily consumption, days with experiment switch-over are excluded from the confidence interval calculations as well as from the statistics of HDD7.

Fig. 10 confirms the low UPR values in Table 2 for the experiments: most of the time, the supervisory control strategies met the grass root temperature bands. Fig. 11 supports this by presenting T_{root} during the reference period and the two experimental winters. The boxplots show that the supervisory control experiments (second and third groups) kept T_{root} in a much tighter band than the staff-controlled heating operation (leftmost and rightmost groups). For the experiments, T_{root} is predominantly inside the respective target band. Both the aggregate of winter 2014/2015 experiments (*B1,B2,B3,D,Dmod**), as well as the winter 2015/2016 experiment *PA1** achieve a low UPR of approximately 5%. The subset of experiments implementing the paradigm change to daytime heating, enabled by being aware of the grass heating system's operational context, reported even lower UPR: the strategies combine nightly pre-heating with the ability to draw on unused thermal supply capacity during the day.

Experiment *B3* demonstrates that the current best practice of human-controlled nighttime pre-heating is reproducible with higher energy efficiency while keeping UPR below 10%. Similarly, experiments *D* and *Dmod** prove that control strategies being aware of a systems operational context can have extremely positive effects. They save energy and exhibit a more consistent consumption (i.e. fewer outliers), expressed by narrower confidence intervals of normalized median energy than the reference pre-heating strategy. Additionally, this context awareness enables a heating paradigm change while avoiding well-known operational problems of heating bottlenecks negatively affecting other arena heating systems.

While Fig. 10, Fig. 11, and Table 2 show that the experiments mostly met the grass root temperature bands, it is important to understand the reasons for its violation:

- Strategies B1 and B2 do not implement pre-heating. Thus, daytime cool-down increased these experiments' UPRs. In particular, *B1* produced too steep heating curves for higher T_{Gset} at the beginning of mild nights. That resulted in early heating deactivation during the nights so that at the respective night-ends T_{root} was too low for the soil's thermal inertia to keep $T_{root} \geq 12°C$ over daytime.

- On request of operational staff, experiments were partially interrupted on match days: 2014-12-07, 2015-01-24, and 2015-02-03. That could be addressed reflecting the match schedule in the pre-heating strategy. For example, *D* achieved UPR=0% when excluding the days with a delayed start from the analysis.

- On freezing days, e.g. during the period of several days around 2014-12-29, the nightly pre-heating towards 14°C did not suffice. This situation could be remedied by switching to daytime heating, or by increasing the permissible target band's upper limit depending on weather forecast information.

- In some cases, the temperature predictions of *PA1** underestimated cool-down effects for the coming day - partly because of inaccurate weather forecasts, but also due to the DBN models' RMSEs.

Feedback from the Commerzbank Arena's staff on the *PA1** experiment with a 2K reduced temperature target band indicated that due to a very wet winter 2015/2016, grass health worsened despite satisfactory levels of UPR. To reduce the high levels of moisture by evaporation, *PA1** was stopped and temperature targets were increased in January 2016 (see Fig. 4.10(b)). That shows that UPR may not suffice as grass quality indicator in certain environmental conditions.

Statistical inference on *two population medians* allows studying the experiments' effect sizes by quantifying the pairwise differences. Bootstrapping establishes the following findings with 95% confidence.

1. Compared to the winter 2013/2014 period's median daily normalized energy consumption:

   (a) The winter 2014/2015 experiments aggregate of *(B1,B2,B3,D,Dmod*)* reduced $\tilde{Q}_{grass,HDD7}$ by 1.13-1.35 MWh/DD (39.2-63.7% compared to the reference period's confidence interval bounds). In an average winter, savings are expected to amount to 648.6-774.9 MWh, confirming earlier findings. The equivalent of CO_2 emissions saved is 123.9-148.0 t.

   (b) The nighttime pre-heating strategy inspired by the status quo operation (*B3*) reduced $\tilde{Q}_{grass,HDD7}$ by 0.44-0.83 MWh/DD (15.3-39.2%). That highlights the positive impacts of algorithmic control mimicking best practices. In an average winter, savings of 252.6-476.4 MWh (48.2-91.0 t CO_2) can be expected.

(c) The daytime heating *(D,Dmod*)* reduced $\tilde{Q}_{grass,HDD7}$ by 1.19-1.40 MWh/DD (41.3-66.0%). That demonstrates the power of a paradigm change to daytime heating, enabled by taking system operational context into account. 683.1-803.6 MWh (130.5-153.5 t CO_2) of savings can be expected in an average winter.

(d) The predictive nighttime pre-heating with lowered T_{root} target band *PA1** reduced $\tilde{Q}_{grass,HDD7}$ by 1.57-1.80 MWh/DD (54.5-84.9%). In an average winter, savings are expected to reach 901.2-1,033.2 MWh (172.2-197.3 t CO_2). That provides a quantification of the effect of a lowered temperature target band while using only predictive nightly pre-heating. Even stronger effects are anticipated when used in combination with daytime heating.

2. Compared to a simple automated best practice strategy (*B3*), the benefits of a daytime heating strategy aware of the grass heating system's operational context *(D,Dmod*)* can also be inferred. The inference shows the change of heating paradigm towards daytime heating reduced $\tilde{Q}_{grass,HDD7}$ by 0.53-0.76 MWh/DD (17.6-65.0%, 304.2-436.2 MWh, 58.1-83.3 t CO_2 in an average winter). These savings are comparable to the savings of *B3* over the current status-quo operation. Additionally, daytime heating improved the UPR.

3. Experiment *PA1** provides an indication of the magnitude of the additional energy savings potential associated with lowering the target temperature band by 2K. *PA1** reduced daily $\tilde{Q}_{grass,HDD7}$:

   (a) by 0.37-0.52 MWh/DD, compared to *(B1,B2,B3,D,Dmod*)* ;

   (b) by 0.33-0.45 MWh/DD, compared to *(D,Dmod*)*;

   (c) by 0.90-1.16 MWh/DD, compared to *B3*.

During the daytime heating experiments *D* and *Dmod*, the control strategies deactivated the grass heating 51 and 48 times due to violations of the T_{supply} threshold. Because of this reactivity to peak load conditions no other stadium heating system suffered from heating shortages. Thus, the grass heating system could be served satisfactorily without adversely impacting other systems. In theory, these strategies should already be able to control the grass heating also on days with soccer events satisfactorily. By integrating match plan information e.g. to result in higher nighttime pre-heating temperatures, also pro-active load shedding should be feasible.

The reported experimental results are of practical and statistical significance. The energy savings have been achieved consistently in two consecutive winters by applying data-driven strategies using a cyber-physical system that integrates existing building automation infrastructure. The control strategies activated neither the software nor the system's failsafe. The achieved savings are complementary to refurbishment measures. For example, [33] suggests two measures for the Commerzbank Arena's grass heating system to save energy:

1. serving the heat exchanger by the arena wide thermal return circuit instead of the supply circuit; and

2. dividing the grass heating system into four sub-circuits for higher temperature control resolution of the soccer pitch.

In combination, these could save approximately 8% of annual thermal energy (381 MWh/year). While the first measure is fully compatible with the presented CPS approach, the second would require a minor adaptation of the control strategy definitions to operate all four grass heating system circuits individually.

7.2 Hypotheses

The experiments confirmed the formulated hypotheses in Section 2.1 as follows:

1. *The automation of currently manual supervisory control decisions improves efficiency in daily operation as less conservative operational settings are needed.*

   Statistical inference of two medians shows with 95% confidence that experiment *B3* reduced energy consumption by 15.3-39.2%.

2. *Predictive and context-aware control strategies can mitigate heating shortages and further improve the building's operational efficiency.*

   The experiments with predictive and context-aware control strategies mitigated negative effects of heating shortages on other heating sub-systems, saved energy, and achieved satisfactory UPR.

7.3 Limitations

The grass heating system's energy meter could not be modeled with satisfactory accuracy, preventing the use of optimization techniques in control strategies. It remains for future work to evolve the strategies using optimization.

As a result of prior work, the strategies account for weather through $T_{external}$. Additional studies are needed to identify possible efficiency improvements by reflecting other parameters such as humidity, solar radiation, or wind speed. Also, more investigation is required whether to use additional soil parameters in the algorithmic consideration of grass quality.

As mentioned in Section 4.2, the German best practice stadium operation does not account for the biologically required T_{root} range. However, comparing the reference period's energy consumption to the experiments may be considered inappropriate because the biggest share of the experiments' savings stems from lowering T_{root}. Therefore, the comparison to *B3* provided in Section 7.1 provides valuable insights: the daytime heating experiments *(D,Dmod*)* show substantial savings of 300-400 MWh in an average winter. That quantifies the additional benefit of moving from an automated best practice control strategy to a control strategy aware of the system's operational context. The associated additional savings are as large as those of moving from manual best practices to automating these.

The available data for training, validating, and testing the MLP and DBN is small due to the event definition used in sections 5.2 and 5.3. Hence, the models' test set performances might improve with access to more data. However, the potential of increasing energy efficiency associated with improved regression performance is considered small, because the achieved RMSE relative to the T_{root} target band's width is below 10% for the first hours of prediction. Moreover, as the data sampling time (10 minutes) exceeds the regression model execution time (sub-second) by orders of magnitude, inaccurate model predictions and control strategy actions can be rectified in the next time step. Besides, the control strategies could also be evolved to take the predicted $\Delta\ T_{root}$ trajectory into account to increase the stability of control decisions. Hence, tuning the model performance is of low priority.

7.4 Transferability

The presented methodology is transferable to other buildings equipped with BMS that can be enabled with standard communication protocols as required. The approach to leverage existing building automation infrastructure and develop CPS control strategies on top is feasible, flexible, and economically as well as ecologically appealing. The preparatory steps to understand the wider system context and the requirements paved the way to identify savings potential and to formulate suitable control strategies. These strategies lead to lower, yet suitable temperature regimes while accounting for operational context to address limitations and shortages intrinsic to the arena's heating system encountered. Depending on the building and its BMS, the appropriate protocols may need to be added to the communication platform [31].

Typically, heating supply systems are dimensioned based on the *coincidence factor* at design time, i.e. by estimating the fraction of total sub-system peak demand expected to coincide. When usage patterns change, sub-systems are upgraded, or control strategies are modified, heating shortages may be the unintended consequences. The approach of CPS control strategies *(D,Dmod)* being reactive to operational context information is an effective means to address this.

The German soccer grass mixture is standardized. Hence, the control strategies' concepts and their target bands are easily transferable. The target temperature range needs adaptation when encountering other mixtures, e.g. due to different regions' climatic conditions. As the current best practice of stadium operation does not rely on automated control of root temperatures (Section 4.2), this work's savings is considered as potential savings for other arenas subject to local climatic conditions. For the daytime heating strategies, the T_{supply} thresholds depend on the individual thermal distribution system. However, they are straightforward to adjust based on operational experience or system specifications.

Assuming similar grass heating system dimensioning (1.4 MW), a similar thermal exchange between piping and soil, and similar grass root temperature targets as in the Commerzbank Arena, it should be possible to reuse the trained regression models. However, it should be verified that the climatic parameters other than $T_{external}$ have little influence on T_{root}.

8 Conclusion

Experiments executed in two winter seasons in the Commerzbank Arena in Frankfurt, Germany, yielded results of statistical significance and practical relevance. They present a strong case study validating the concept of developing a CPS that integrates pre-existing building instrumentation. That concept enables the realization of a range of different strategies on top of the stadium's BMS to control the major heat-consuming system and assess the associated impacts. The experiments were integrated with daily stadium routine operation and produced high levels of weather-normalized energy savings while maintaining satisfactory grass root temperature levels. In relation to the status quo operation, winter 2014/2015 experiments saved 39.2-63.7% energy. In average weather conditions, these savings are expected to amount to 650-775 MWh - an equivalent of 124-148 t CO_2 emissions. Out of these experiments, daytime heating enabled by the awareness of the heating system's operational context achieved the best results - from the perspective of UPR, energy consumption (savings of 41.3-66.0%), and from the operational perspective as these experiments mitigated the adverse effects of heating supply shortages. Another branch of strategies focusing on predictive nighttime-only heating control is to our knowledge the first application of Deep Belief Networks to a building's operational data. In this work, these networks outperform standard feed-forward Multi-Layer Perceptrons in heating prediction accuracy and allow formulating predictive grass heating control strategies that operate satisfactorily. Compared to the human controlled status quo operation, the bulk of this work's savings stems from lowered and tightly controlled grass root temperatures. However, when compared to a strategy mimicking human best practice heating, smarter strategies still reduce consumption significantly: in average winter conditions savings of 304.2-436.2 MWh (58-83 t CO_2) are expected. Lowering the grass root temperature targets by 2K in winter 2015/2016 increased savings to 54.5-84.9%. These savings are anticipated to reach 0.9-1.03 GWh (172-197 t CO_2) in an average heating season.

Beyond saving energy, the experiments also provide evidence for the proposed methodology's feasibility. The approach of deploying reactive and predictive control strategies for thermal system operation using a data-driven CPS approach leveraging existing building instrumentation applies to a wide range of other thermal systems and buildings. The analysis of the wider heating system, the application's requirements, and the appropriate definition of a suitable Key Performance Indicator enabled energy savings even in cases where strategies merely mimic the current human operation. The savings stem from the faster reaction times and regular temperature monitoring intervals. When control focuses on individual building systems, aggressive strategies can achieve savings while avoiding adverse effects on other systems - provided that the strategies appropriately take the operational context into account. Taking the Commerzbank Arena as representative soccer stadium, grass heating system operation has a significant savings potential. It is possible to reduce consumption while meeting temperature targets most of the time and keeping the soccer pitch's grass quality at satisfactory levels. In Germany and Austria, professional stadiums are required to use grass heating systems. On an international scale, several stadiums for soccer, rugby, and American football are also known to use grass heating systems. The crucial parts of this work are transferable to these with little or no adaptation.

It is for future work to study the combined effects of daytime heating with lowered target temperatures and predictive nighttime pre-heating. Further, a flexible adaptation of the target band's upper limit should be studied to account for very low-temperature weather forecasts. Another promising direction is to evolve the strategies to using optimization techniques when choosing set-points. That, however, requires further study to improve the heat meter regression accuracies. Finally, novel ways to monitor the grass quality directly rather than exclusively focusing on the root temperature should ensure optimal grass quality at lowered temperature levels.

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Paper E

Context Sensitive Indoor Temperature Forecast for Energy Efficient Operation of Smart Buildings

Authors:
M. Victoria Moreno, Antonio F. Skarmeta Gomez, Alberto Venturi, Mischa Schmidt, Anett Schülke

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Context Sensitive Indoor Temperature Forecast for Energy Efficient Operation of Smart Buildings

M. Victoria Moreno, Antonio F. Skarmeta Gomez, Alberto Venturi, Mischa Schmidt, Anett Schülke

Abstract

This paper analyzes the potential of knowledge discovery from sensed data, which enables real-time systems monitoring, management, prediction and optimization in smart buildings. State of the art data driven techniques generate predictive short-term indoor temperature models based on real building data collected during daily operation. The most accurate results are achieved by the Bayesian Regularized Neural Network technique. Our results show that we are able to achieve a low relative predictive error for each room temperature in the range of 1.35% - 2.31% with low standard deviation of the residuals.

1 Introduction

There are many factors that affect the energy needs of buildings, such as ambient weather conditions, building structure and characteristics, the operation of sub-level components like lighting and Heating, Ventilation and Air Condition (HVAC) systems, occupancy and user's behavior, etc. This complex situation makes to accurately predict the building energy consumption very difficult. The main energy loads considered in buildings are related to heating/cooling systems, hot water and electricity consumption. In this sense, for example, the impact of HVAC on the energy usage of a building in European countries represents 76% of the total consumption [1].

Optimizing energy efficiency in buildings should be carried out in an integrated way, i.e. covering the whole lifecycle of the building [2]. During these phases it is necessary to continuously adapt the operation of its subsystems to optimize energy performance indexes. However, this process is a complex task with a lot of variables and constraints. Due to the complexity of the problem, precise consumption prediction associated to services like thermal comfort provision is quite difficult.

In recent years, a large number of approaches to predict building status, either elaborated or simplified, have been proposed and applied to a broad range of problems like energy efficiency and indoor comfort. Methods addressing this issue include engineering, statistical and artificial intelligence (AI) methods. In the context of artificial intelligence many new and more powerful technologies are bringing alternatives or even breakthroughs in the prediction of building energy consumption associated to thermal comfort [3].

Furthermore, the rapid development of smart instruments, digital communication networks and computer techniques make the data acquisition much easier. Internet of Things (IoT) paradigm represents a radical evolution of the current Internet into a Network of interconnected Objects that not only harvests information from the environment (sensing) and interacts with the physical world (actuation/command/control), but also leverages existing Internet Standards to provide services for information collection, storage, analytics, dissemination and exploitation [4].

Nevertheless, the amount of the collected data is too much to be fully and effectively utilized by most existing management systems of infrastructures like buildings. As a result, "large volumes of data with very little information" is a quite common problem in today's industrial automation. For instance, when monitoring non-residential buildings there are various databases each with data and statistics, but it is difficult to get an overall picture of the exact impact of different aspects in indoor comfort or energy consumption [5].

The work in this paper studies data collected during the daily operation of a Spanish public school, one representative example of current building stock. Based on this data we generate short-term indoor temperature models which can be used in a future step to optimize the energy consumption under consideration of thermal comfort.

The structure of this paper is as follows: Section 2 contextualizes the problem presented in this work. Section 3 analyzes the main parameters affecting indoor temperature in the building studied. Section 4 reviews relevant work in literature dealing with the problem of comfort prediction in indoor spaces and describes the selection process of the most appropriate AI techniques to be applied to our problem. Section 5 presents our approach to generate optimal temperature models as well as the results obtained from them. Finally, main conclusions and future work are tackled in Section 6.

2 Problem statement

The work presented in this paper is framed in the context of the EU project BaaS [6], which aims at providing services to optimize energy performance (associated to HVAC system and user actions) of buildings along with a generic platform for delivering such services. As part of this project, we analyze what are the main factors impacting the energy consumption associated with provisioning thermal comfort, taking into account the operational and commercial constraints of the individual buildings studied.

Upon verification of component interoperability, and development of a measurement and verification plan, the BaaS system will be demonstrated in real buildings and will be validated as an energy conservation measure with energy services companies as the end-user. One of the buildings used as reference scenario of the BaaS project is the Sierra Elvira School, located in the city of Granada, Spain. In this building the aim is to reduce the fuel consumption associated to the heating system subject to temperature constraints. The final goal of this work is to manage the heating system in the best way possible. This paper is focused on generating the thermal profile of the building, which will be part of the new heating system management.

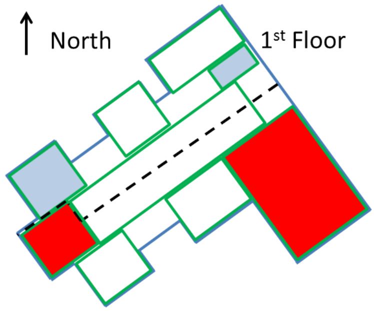


Figure 1: Distribution of the monitored rooms in the different floors of the Sierra Elvira School (zone 1 rooms red, zone 2 rooms light blue).

The heating system management in this building has not been efficient: there have been areas of the building with overheating while other areas have not reached a temperature high enough. This heating divergence among areas is due to a static heating control scheme that does not appropriately take into account some of the factors affecting the temperature in the different building areas. These factors, e.g. peoples' behavior and outdoor environmental conditions, impact the different building areas to varying degrees. For this reason it is necessary to make a complete characterization of the different building areas which can be assumed a priori to have relevant differences in their heating behavior, i.e. building rooms located on different floors, with different geographical orientation, etc.

The heating system of this building has the following schema: a biomass boiler, two heating distribution circuits each serving a different building zone, and a different number of radiators installed in each room. The current heating strategy is static, driven by an outdoor temperature controlled supply boiler temperature set point and the school's schedule. Different kinds of sensors have been distributed along the building to collect data about indoor temperature, flow temperature of the heating distribution circuits, energy consumption, etc. In addition, outdoor environmental conditions such as solar radiation, outdoor temperature, humidity and wind speed are collected from a weather station on the school compound.

To make the characterization problem of the whole building manageable, a sub-set of six rooms for each building zone (i.e. 12 rooms in total) are monitored, measuring their indoor temperature each 15 minutes. These rooms are located in different corners of the building as well as on different floors (see Figure 1). For both building characterization and analysis we use data collected from September 2014 until April 2015.

3 Analyzing context-dependent thermal effects

Our analysis of the collected data from system operation aims at the following questions: *what are the main variables affecting the temperature of each room? are there relevant differences between the heating behavior of each room along days?*. The answers to these

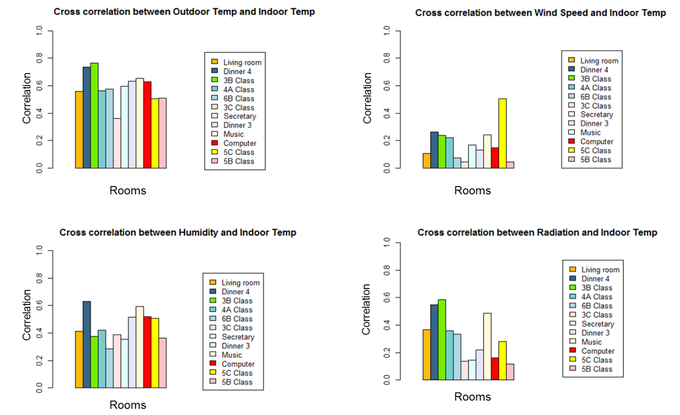


Figure 2: Maximum value of the cross-correlation between the outdoor environmental conditions and the indoor temperature of each room.

questions let us decide if it is possible to generate a unique predictive model of the whole building for forecasting its thermal conditions, or if it is necessary to model each room separately.

We start by studying the cross-correlation between the outdoor environmental conditions and the indoor temperature of each room when the heating is *inactive* to study the influence due to external context. As cross-correlation measures the degree of linear correlation and the time delay between two signals, we get an indication of the rooms' inertia and their sensitivity to outdoor conditions. For this calculation, we selected data collected during days in which the heating system was not operating and there were not people in the building (i.e. data associated to weekends, holidays, etc.). Figure 2 shows the results of this study, indicating that outdoor temperature and humidity have the strongest impacts. To a lesser degree radiation has also a notable impact on some rooms, less on others. The 3B classroom is the most affected by the outdoor temperature and solar radiation due to its high exposure to the sun as it is located in the south-east corner of the second floor. Wind speed only affects the 5C classroom notably indicating a lower air-tightness than the other rooms. Ambient factors (outdoor temperature and humidity) have a more uniform impact on the different rooms than the directed forces of radiation and wind. This indicates the effects of the rooms' different orientation.

After this first analysis, we study the impact of actively heating the building. To do so, we calculate the cross-correlation between the flow temperature of each heating circuit and the indoor temperature of each room. From this analysis we can identify the rooms most affected by the heating system. For this calculation, we select the data associated to the first hour of operation of the heating system which is prior to the school starts according to the schedule information. This way, peoples' impact on the indoor temperature of each room is excluded from the analysis. Figure 3 shows the maximum

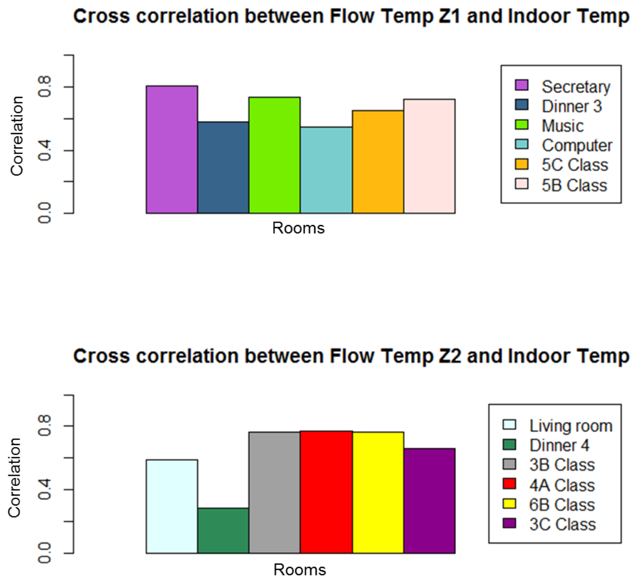


Figure 3: Maximum value of the cross-correlation between the flow temperature and the indoor temperature of each room.

value of the cross-correlation results. We can see how there are some rooms that, due to their position inside the building heating circuits, are affected in a different way by the heating system. Thus, for example, while the strongest correlation result from the flow temperature corresponds to the Secretary, which is the first room in which the hot water circulates, the lowest correlation result corresponds to the Dinner 4 room, which is located in the opposite corner from where the hot water starts circulating.

Now we analyze the impact of occupancy on the heating speed of each room. For this, we calculate the heating speed (in [K/h]) for each hour the heating system was active on the different week days. Taking as example the 5B classroom, Figure 4 shows the results of this calculation as well as the increasing of the outdoor temperature. Knowing the pupils' expected arrival time for the school rooms is 09:00 A.M. this day (based on the official schedule's first hour - in general is weekday dependent), we see the superposition of the factors occupancy, heating and outdoor conditions from 09:00 A.M. onwards only. As we have already analyzed outdoor and heating impact, we are able to derive the occupancy impact on the indoor temperature evolution with some degree of uncertainty. Ultimately, we are interested in conserving energy by reducing heating times and thus we focus on identifying the strongest impact of occupancy on the heating speed - i.e.

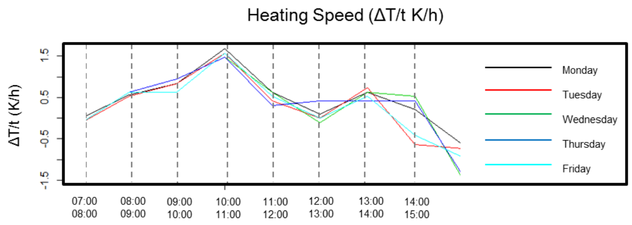


Figure 4: Hourly heating speed of the 5B classroom for different days.

the first scheduled school hour of each school day. We then are able to calculate the mean heating speed of each room in the first school hour. Figure 5 shows the results of this calculation for different weeks in December and January, and highlights that there are differences in the occupancy impact among the rooms within the same week. The rooms with the lowest occupancy impact in their heating speed are the Living room, usually occupied only at lunch time, and the computer classroom, which is sporadically occupied (highlighted in red in Figure 5). On the other hand, we see that there are some rooms uniformly impacted by the occupancy across the weeks, for example the Dinner 3 room, the 5B classroom or the 4A classroom, which means that the occupancy level of these rooms is similar every week. Consequently, occupancy level of each room should be included in a predictive temperature model as it is a factor affecting each room in a different way. As we see varying heating speeds of the same room in different weeks we are aware that this form of occupancy modeling is sub-optimal and will introduce uncertainty in our temperature regression models.

Finally, we analyze if depending on the day the indoor temperature of the rooms progresses in a different way. Looking at the daily indoor temperature evolution of each room during different weeks we could see how depending on the day the indoor temperature progresses within a different interval. Figure 6 shows an example of the daily indoor temperature evolution of the 3B classroom. In this we see how after the heating stops during the weekend, Monday (black line) is the day with the lowest indoor temperatures and how the building insulation allows the indoor temperature to grow along the week (cyan line).

Given the results of these analysis, we can confirm that all parameters selected for analysis are affecting the temperature of all rooms. However, the impact of each one of these parameters on the temperature of a specific room depends on the room considered. Consequently, in order to represent the best relationship between each input and the indoor temperature, we propose to generate a different temperature model for each room. Therefore, as factors affecting the indoor temperature of each room we will consider the outdoor environmental conditions (temperature, radiation, humidity and wind speed), the flow temperature, the occupancy level and the day. In order to generate the temperature models of the rooms that are not being monitored currently in the target

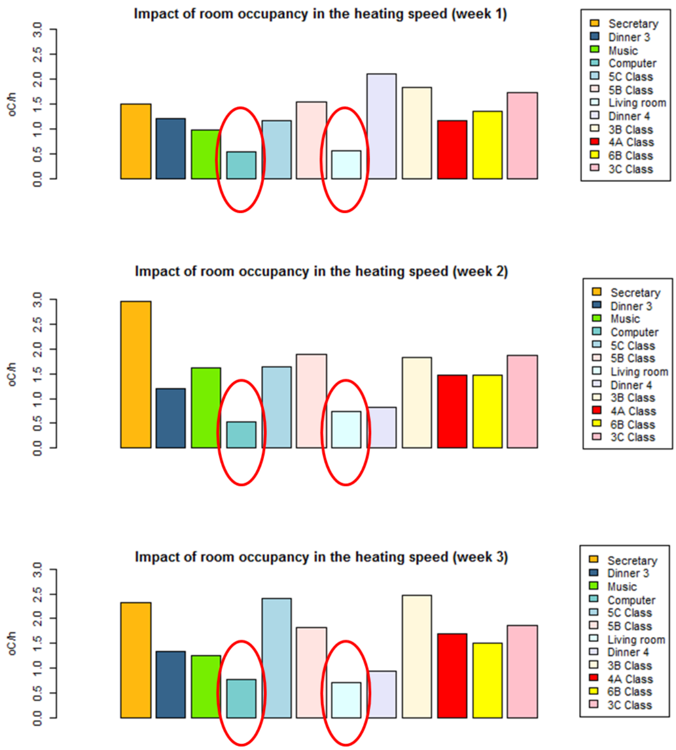


Figure 5: Impact of the occupancy in the heating speed of each room.

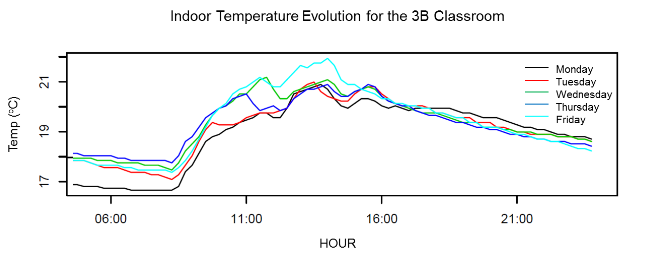


Figure 6: Daily indoor temperature evolution for the 3B classroom.

building, we interpolate the temperature models associated to the monitored rooms.

4 Room temperature models based on Artificial Intelligence regression

AI techniques in computer science have been introduced to deal with the processing of huge amount of data to extract useful information (or termed by knowledge) [7] [8]. These techniques mimic human abilities of logic reasoning by numeric computing and connections. Typical examples of data driven AI techniques are neural networks and fuzzy logics [9].

For the problem presented in this paper, our approach is to generate knowledge-based models of the building through the application of data driven regression techniques. From literature we select the methods to test in a supervised regression setting, applying a grid search for optimal parameter selection.

In [10], a backpropagation neural network is proposed to deal with the prediction of the energy requirements of different building samples associated to the thermal comfort. As conclusion of this work, it is proven that Artificial Neural Networks (ANN) are a powerful tool and helpful for designers for increasing the building energy efficiency. Reviewing the conclusions of [3], the authors state that ANNs and Support Vector Machines (SVMs) are suitable for solving non-linear problems, making them very applicable to building energy prediction associated to thermal comfort. Another common technique for non-linear regression are Gaussian Processes with Radial Basis Function Kernel (RBF) [11] which can impose a general smoothness constraint without being tied to a limited number of basis functions. This is a beneficial characteristic for our regression problem as it is possible to carry out a regression using Gaussian Processes (GPs) where only the width (σ) of the RBF is a parameter to tune, the number of RBFs to use for regression is chosen automatically. The last technique we select to analyze, the Bayesian Regularized Neural Network (BRNN) [12], is a powerful technique which fits an ANN consisting of two layers by making use of regularization to optimize the output function. This technique improves the generalization of the learned predictive model. The estimation of model parameters (α and β) is done by standard methods of Bayesian optimization and the Gauss-Newton algorithm. According to literature, the trained network tends to avoid overfitting.

We train these four techniques looking for their optimal parameters with the best results. For this, we use the CARET package (short for Classification And REgression Training) [13] for data modeling of the R software [14]. This package is a set of functions that attempt to streamline the process for creating predictive models. The four techniques implemented in R enable us to adjust their tuning parameters through the train function provided by the caret package. The configuration of the final technique implemented for each model and the associated results are described in next section.

5 Regression performance

We generate predictive temperature models for each room individually based on the regression techniques. To find the best configuration for each of the regression techniques considered, we perform a parameter grid search for the techniques' tuning parameters. After carrying out various analysis of the performance of each selected technique considering different configuration of their tuning parameters, we delimit the grid search space to the following:

- Multi-Layer Perceptron (MLP - a common form of ANN)
  - Function in R: mlp
  - Tuning parameter: size (number of neurons in the hidden layer)
  - Values for tuning: 10, 20, 30, 40, 50, 60
- Support Vector Machines with Radial Basis Function Kernel (SVM)
  - Function in R: svmRadialCost
  - Tuning parameter: Cost (the parameter Cost controls the tradeoff between margin maximization and error minimization)
  - Values for tuning: 1, 15, 18, 20, 22, 25
- Gaussian Process with Radial Basis Function Kernel (Gauss)
  - Function in R: gaussprRadial
  - Tuning parameter: sigma (radius of the RBF)
  - Values for tuning: 0.1, 0.5, 1, 1.5, 1.8
- Bayesian Regularized Neural Networks (BRNN)
  - Function in R: brnn
  - Tuning parameter: neurons (number of neurons)
  - Values for tuning: 10, 20, 30, 40, 50

The following steps were carried out for generating the room models able to predict the temperature of each room at the next 15 minutes considering the inputs associated to such time.

- Transformation: based on the parameters mentioned to be considered as inputs of our model, we transform them into representative features in order to help techniques like NN to generalize during the training model. Some examples of features are the increasing of each parameter each 15 minutes, the historical values for each variable, etc.

- Normalization: all values in the given dataset of features are normalized during this phase. The resulting values are in the [0,1] interval for every feature extracted from the initial dataset.

- Learning function: backpropagation. This function is a common method of training artificial neural networks used in conjunction with an optimization method such as gradient descent.

- Evaluation metric: RMSE (Root-Mean-Square Error) and R-Squared. The former yields the values in the same units as the output of the estimators, i.e. in ^{o}C, so we can interpret the results easily. Regarding this metric, we consider both the mean and the standard deviation of RMSE. The latter represents the percentage of the response variable variation that is explained by a linear model.

- A common technique applied to data is the transformation of the data space using the so called Principal Components Analysis (PCA) [15]. PCA is a widely used technique for reducing dimensionality, identifying the directions in which the observations mostly vary. It is not always beneficial to solving AI problems, thus we experimentally verified that generalization of the regression is improved on selected rooms. For instance, the RMSE obtained using PCA for the 3B classroom - 0.23^{o}C, see Table 1 - was lower than for a regression model with identical parameters without using PCA (0.43^{o}C). Thus for each of the temperature models we decided to process the data with the PCA method retaining 95% of input data variability.

- N samples: 192

- Samples for training: 1440

- Samples for test: 480

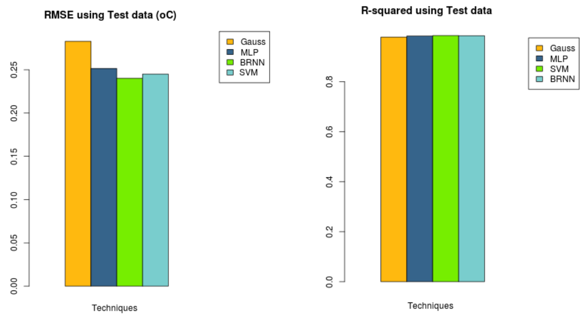
- Validation method: 10-fold cross validation and 5 repetitions over the training data set.

For all 12 rooms, we studied each of the techniques and experimented with varying input parameter set sizes. For all of them, we achieved the most accurate results using the BRNN technique with an input set containing 25 variables - the 4 most recent readings of the outdoor temperature, the 4 most recent readings of the humidity, the 4 most recent readings of the radiation, the 4 most recent readings of the wind speed, the 4 most recent readings of the flow temperature, the 3 most recent readings of the indoor room temperature, the occupation and the weekday. Exemplarily, we show in a comparison between the RMSE (Figure 5.7(a)) and the R-Squared (Figure 5.7(b)) for each technique applied to the 3B classroom model, and Figure 8 shows the statistics (RMSE and standard deviation of the RMSE) obtained for each technique and different inputs sets.

Table 1 summarizes the best BRNN temperature model test results for each room. We can see that the values obtained for the R-Squared of all rooms model are higher than 0.95, which means that the model is able to explain most of the linear variability of

Table 1: Optimal temperature model for each room.

Room	Neurons	RMSE (^oC)	R-Squared	RMSE SD (^oC)	CVRMSE (%)
Living room	10	0.25	0.97	0.05	1.58
Dinner room (4 age)	20	0.26	0.98	0.03	1.50
3B classroom	30	0.23	0.98	0.05	1.35
4A classroom	20	0.28	0.97	0.05	1.59
6B classroom	20	0.27	0.98	0.06	1.68
3C classroom	40	0.33	0.97	0.05	2.31
Secretary	30	0.35	0.97	0.06	2.05
Dinner room (3 age)	20	0.34	0.97	0.06	2.31
Music classroom	20	0.33	0.97	0.05	2.10
Computer classroom	10	0.22	0.98	0.07	1.37
5C classroom	10	0.38	0.96	0.05	2.28
5B classroom	30	0.28	0.98	0.05	1.88



(a) RMSE (b) R-Squared

Figure 7: Exemplary results for the 3B classroom model considering different regression techniques for 25 inputs

the response data. Furthermore, the standard deviation of the RMSE obtained for each temperature model is lower than 0.08, which means that the error obtained from each model is consistent. Finally, the last column collects the coefficient of variation of the RMSE (CVRMSE), which expresses the error proportion related with the mean of the temperature of the respective room.

The results obtained for each room temperature model reflect the suitable performance of the proposed approach, in which applying a regression technique based on BRNN lets us obtain RMSE values between 0.22^oC and 0.38^oC with standard deviation between 0.07^oC and 0.05^oC, respectively. Relative to the indoor temperature, the RMSE of all models is between 1.35% and 2.31%. The difference between the accuracy obtained in the models of different rooms is due to the varying uncertainty of some of the inputs like the aggregate occupancy level and occupant behavior.

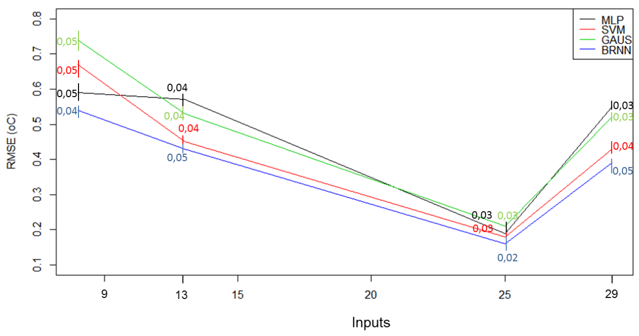


Figure 8: RMSE and standard deviation of the RMSE obtained for the 3B classroom temperature model for different regression techniques with their optimum tuning parameter and different input sets.

6 Conclusion and Future Work

This paper presents a study of the context sensitivity of the thermal characteristics of different building areas, and derives conclusions for context-aware thermal models predicting indoor room temperatures. More specifically, we analyzed real operational data of the Sierra Elvira School in Granada (Spain) as part of the EU BaaS project.

After contextualizing the problem, we generated accurate building models which will be used to reason based on them, and then make the optimum decisions to improve the building performance. As a result of this work, we are able to predict short-term indoor temperatures of individual school rooms with a low relative error (1.35% - 2.31%).

In future work, we will apply the developed regression models to a day-ahead heating planning to provision indoor temperature while minimizing the energy consumption. The derived heating strategy will be implemented in the target building to experimentally validate the performance both in terms of energy usage and thermal comfort.

7 Acknowledgment

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Paper F

Smart Buildings as Cyber-Physical Systems: Data-Driven Predictive Control Strategies for Energy Efficiency

Authors:
Mischa Schmidt, Christer Åhlund

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Mischa Schmidt, Christer Åhlund

Abstract

Due to its significant contribution to global energy usage and the associated greenhouse gas emissions, existing building stock's energy efficiency must improve. Predictive building control promises to contribute to that by increasing the efficiency of building operations. Predictive control complements other means to increase performance such as refurbishments as well as modernizations of systems. This survey reviews recent works and contextualizes these with the current state of the art of interrelated topics in data handling, building automation, distributed control, and semantics. The comprehensive overview leads to seven research questions guiding future research directions.

1 Introduction

1.1 Motivation

This survey focuses on the topic of energy efficiency in buildings by improving operations using information and communications technologies (ICT). That approach is complementary to building stock refurbishment and modernization. In 2010, buildings accounted for 41% of the primary energy use of the US with close to 75% of this consumption being served by fossil fuels [1]. In the EU-28, fossil fuels are also responsible for almost 75% of the total energy consumption [2]. Buildings used more than two-thirds of their energy consumed for space heating (37%), water heating (12%), space cooling (10%) and lighting (9%) purposes [1]. For the US, residential buildings used slightly more than half of the total building energy consumption [3]. [4] shows that in 2013, 60% of New York City's emissions stemmed from buildings in general - residential buildings as the largest source accounted for 37%. In Europe, the ODYSEE and MURE databases indicate that buildings accounted for 40% of the EU-28 final energy use in 2012, with residential buildings being responsible for two-thirds of the total building consumption [5]. Various building life-cycle analysis (LCA) case studies reveal that for typical buildings, irrespective of the type of construction, the building operational phase "dominates the life cycle energy use, life cycle CO2 emissions" [6]. For conventional buildings, the operational phase accounts for up to 90% of the life cycle energy consumption, for low energy buildings up to 50%. These figures confirm earlier findings in [7].

1.2 Political Context and Survey Focus

Recognizing the contribution of human-made greenhouse gases (GHG) to climate change, the 2015 UN conference on climate change held in Paris, France, developed an unprecedented climate framework agreement that was signed by 180 countries. The UN agreement marks a significant step towards globally coordinated efforts to reduce humankind's contribution to climate change [8]. Even before that agreement, e.g. the EU issued its energy efficiency guideline 2012/27/EU [9] which requires 20% savings on primary energy usage by 2020 and 50% savings by 2050, compared to 2008. These targets translate into annual savings of 1.5% for all EU member states. In 2016 more than the required minimum of 55 individual nations that jointly account for at least 55% of GHG emissions formally ratified the agreement, including China and the US. Now being in effect, each country ratifying this agreement will develop individual action plans that detail how it intends to reduce its GHG emissions. The agreement formulates the aim to keep global warming below $2K$ compared to pre-industrial temperature levels - ideally even keeping warming below $1.5K$. Regularly, each country will report its progress on these plans, and will also develop further plan amendments.

As buildings account for a major fraction of the total energy consumption politics aim to improve buildings' energy efficiency levels by issuing appropriate regulations. Typically, these rules target newly constructed buildings or modernization measures. Building labels and certifications such as EPBD (EU) and LEED (US) do value the presence of building automation systems positively. However, macroscopic works targeting building stock energy efficiency such as [3, 10–14] do not explicitly discuss energy efficiency potential in light of the possibilities offered by predictive techniques as surveyed in Section 3. This survey specifically targets buildings equipped with some level of building instrumentation and with sensors installed at strategic points to improve the efficiency of building operation - the lion's share of lifetime building energy use. It reviews recent studies that apply computational methods to implement predictive control strategies integrated into the daily building operation. Efficiency gains by these predictive methods are complementary to possible modernization and refurbishment measures. The surveyed works lead to research questions to guide future advances in this field. Other approaches rooted in analyzing building data, e.g. along the lines of [15], which analyzes data offline in regular intervals to infer operational inefficiencies and enable building staff to adapt operation schemes manually, are not covered by this survey. Similarly, studies that purely focus on improving modeling accuracies such as [16–18] are beyond its scope - while they may become relevant as tools in predictive control work, there is no energetic impact by these studies per se.

1.3 Structure

This work is structured as follows: Section 2 provides background information to contextualize Section 3, which summarizes recent literature on data-driven predictive control applications for buildings. Section 4 formulates open questions guiding future research. Section 5 summarizes and concludes the survey.

2 State of the Art in Buildings as Green Cyber-Physical Systems

2.1 Building Energy Application Key Performance Indicators

For any building energy application to act sensibly, appropriate key performance indicator (KPI) definitions are required. In an attempt to allow benchmarking of Energy Service Company (ESCo) efficiency measures and service contracting, [19] defined several KPIs of relevance, among which:

- *CO_2 emissions.* Reducing these emissions is an intuitive target for buildings, considering the discussions surrounding GHG emissions. However, in the building domain, CO_2 is only measured for monitoring Indoor Air Quality (IAQ, see below), not in the context of the energy supply. Therefore, this KPI is usually derived from the energy consumption by a conversion factor related to the energy source as e.g. provided in [20].

- *Comfort*: This term expresses how well a control application can create conditions in which human occupants feel comfortable. As this concept is very generic, the literature covers several different aspects:

  For *thermal* comfort, the current practice typically treats maintaining indoor air temperature or operative temperature ranges [21,22] as a proxy to meeting comfort targets. However, these parameters do not reflect the actual thermal sensation of an individual due to a set of other factors, such as solar radiation or humidity [23]. For example, the solar radiation effect on comfort has been studied in [24] and the references within. Industry and research communities express the need for appropriate thermal comfort definitions for the purpose of building control [25–27]. To date, the most common thermal comfort index adopted by international standards is Fanger's *Predictive Mean Vote* (PMV) model [28]: ISO 7730 [23], and the adaptive standards EN 15251 [29] and ASHRAE 55 [30] rely on it. Derived from PMV, the *Predicted Percentage Dissatisfied* (PPD) expresses dissatisfaction of occupants due to poor thermal comfort. The suitability of these comfort indexes and standards is subject to debate: studying classroom thermal environments [31] concludes that these indexes are "mainly found to be inappropriate for the assessment". To overcome questionnaire-based methods traditionally used to assess thermal discomfort, [32] investigates an alternative form of data collection in addition to temperature sensors: by observing occupants' activities (e.g. activating heating, pouring a hot drink, changing clothing level).

  Despite thermal sensation also *Indoor Air Quality* (IAQ) can be a source of (dis-)comfort. CO_2 and humidity levels, as well as the concentration of different pollutants, are the main parameters of concern. For example, [33] models the impact of air conditioning in an office room in Panama City from measured temperature, humidity, and CO_2 levels. [34] provides a more extensive discussion of air quality and thermal comfort.

Discomfort has a substantial socio-economic impact: based on the data of 3766 pupils taught in more than 150 different classrooms of 27 schools, [35] identified a significant impact of the environmental factors light, sound levels, IAQ, and temperature on the academic progress. [36] used online surveys to analyze the self-reported work performance of 114 office workers over a period of 8 months about perceived thermal comfort, lighting comfort and noise of their offices. Discomfort in one or more of these factors acts as stress that reduces work performance by 2.4%-14.8%. For a more comprehensive overview, we refer to [37], a recent survey on how building occupants' discomfort affects productivity.

- *Energy.* Measured during a period of concern, typically in kilowatt-hours [kWh], kilojoules [kJ] or tonnes of oil equivalent [Toe]. Depending on the context of comparison and benchmarking, often the energy consumption of a period (e.g. one year) is normalized per visitor (e.g. public buildings), employee (e.g. office buildings), or floor area. When considering heating and cooling systems, weather normalization by Heating/Cooling Degree Days [38] is appropriate. That allows comparing consumption across climatic zones and years. As indicated in [13], there is a crucial difference of perspective between assessing energy efficiency from a *primary* energy (i.e. the total energy of the natural resource used) or a *final* energy viewpoint (i.e. the final use form, e.g. used for electricity or space heating). Studies and surveys targeting political frameworks and policies usually reason about the primary energy effects whereas studies on building equipment or operation strategies typically take the final energy perspective. So-called primary energy factors (PEFs) establish a connection between both energy notions. However, there are variations in the definition and calculation of PEFs that can have significant consequences e.g. when comparing different heating systems regarding primary energy use [13].

- *Exergy* measures the maximum available energy for doing work. A thermodynamic system's exergy depends on the distance to the system's equilibrium. Unlike energy, exergy is not conserved. According to the Second Law of Thermodynamics, exergy is related to the quality and quantity of energy. Thus, a control scheme around exergy must address energy quality in addition to quantity [39]. In theory, using boilers as the heat source in buildings creates a mismatch between exergy supply and demand, which should be avoided. For example, low-temperature floor heating outperforms other (high-temperature) space heating systems regarding exergy [40].

- *Green factor.* The fraction of the energy used from renewable energy sources divided by the total energy consumption.

- *Light* levels, measured in lux, are relevant for applications of smart blinds and lighting control, often as part of a comfort KPI assessment.

- *Temperature*, measured in the controlled zone or system, can be used as an absolute reading or put in relation to an application specific target temperature. Often, temperature is part of comfort KPI assessment.

- *Underperformance Time (UPT).* Building systems have a defined range of indoor conditions related parameters, e.g. temperature, CO_2 levels, relative humidity or lux levels. Often, this range may only be in effect during a distinct period, e.g. office hours. UPT measures the time the system did not meet the target range when it should have.

- *Underperformance Ratio (UPR).* The UPT in relation to the amount of time the target range was in effect.

2.2 Buildings as Cyber-Physical Systems

Following [41], "Cyber-Physical Systems (CPS) are integrations of computation and physical processes. Embedded computers and networks monitor and control the physical processes, usually with feedback loops where physical processes affect computations and vice versa". Actions taken by CPS are not reversible [42]. A delineation from the related field of *Ambient Intelligence* [43] is that the physical processes controlled are not always subject to human interaction. The CPS concept as "co-engineered interacting networks of physical and computational components" contributes to advances in the field of Smart Buildings among others [44]. Newly constructed as well as already pre-existing buildings are often already equipped to a certain degree with building automation infrastructure. Typically, the current automation and control strategies are simplistic, e.g. heating system supply temperatures being chosen based on current outside air temperature or system operation run based on fixed schedules. While the CPS definition of [41] allows for simple rule-based mechanisms, this work interprets CPS as using computational representations of the underlying physical processes to implement *predictive* control strategies effectively.

Figure 1 illustrates the concept adopted in this survey:

1. Sensors and other information sources collect information on the building and its surroundings. This step is related to a number of fields: Wireless Sensor Networks (WSN) [45], the Internet of Things (IoT) [46], Machine-to-Machine communications (M2M) [47–49], Sensor and Data Fusion for increased accuracy and temporal resolution [50], Pervasive Sensing as discussed in [51], and Building Automation [52]. The scope of this survey is to use the information obtained for *predictive* control. However, also *reactive* strategies benefit from the information: e.g. [53] combines occupancy detection with schedule-based HVAC operation to increase energy savings.

2. To predict the evolution of the controlled building's physical processes within a defined time horizon computational representations of these processes are used. These predictions allow optimizing control decisions. Without loss of generality, this work builds on the usage of sensor data and other information sources in the optimization as well as in the continuous tuning of the representations. This step comprises multiple aspects:

(a) *Pre-processing*, converting, cleaning, selecting, and standardizing data. Many data-driven techniques are designed to operate on numeric features. This requires mapping categorical features to numeric values - a typical example is e.g. the day of the week when integer values represent the weekdays. Cleaning numerical data from outliers with statistics-based data mining approaches as e.g. documented in [15, 54, 55] often helps to achieve satisfactory performance of the subsequent applications. The field of feature selection is a prominent research area surveyed in e.g. [56–58]. Regarding numerical stability, many techniques benefit from standardizing each input feature. There exist different procedures to standardize data, e.g. shifting each feature datum by the feature's mean and dividing by its standard deviation. This approach centers each feature around the origin with a standard deviation of 1. Also, applying techniques such as Principal Component Analysis (PCA) [59] and the field of representation learning [60] can boost accuracy and prediction performance of the cyber-representations. On top of that, recent advances have shown the suitability of Deep Learning [61] for "discovering intricate structures in high-dimensional data" [62] - which allows the unsupervised discovery of highly non-linear, abstract, and meaningful feature representations from training data. Building data usually accumulates as time series data, for which [63, 64] provide overviews of different deep learning and more general machine learning approaches, respectively.

(b) Cyber-representation for *prediction*. Section 3 outlines recent works categorized into two broad categories: *theoretical approaches* and *data-driven approaches*. Over time, the accuracy of a cyber-representation may deteriorate as a building's environment is in constant flux. For example, occupants' preferences, as well as their behavioral and occupational patterns, change gradually or abruptly; building systems degrade, become repaired or replaced; refurbishments and modernizations take place; spaces are redecorated, and the weather changes with the seasons and among the years. Therefore, the representation requires regular updates to ensure satisfactory performance. For the theoretical approaches in Section 3, the models need to be maintained by experts or, in case digital building models are used for building simulations, by computer tools. For the data-driven models, the field of *concept drift*, surveyed in [65, 66], investigates the handling of changing environments in machine learning.

(c) *Optimization*. A wide variety of well-known analytic optimization techniques can be applied, e.g. linear programs, if a given building's problem formulation and cyber-representation are tractable. Considering that several stochastic events influence building operations in daily life, optimization is required to operate in an environment with aspects of uncertainty. For example, [67] shows in the field of HVAC control several studies focused on improving control robustness by accounting for uncertainty. A more general review of research in the field of *Robust Optimization* is provided by [68]. We refer to [69], describing a practical guide on how to apply robust optimization to specific problems. When optimization problems become intractable, nature-inspired heuristics such as the following can be applied to find (nearly) optimal solutions.

- *Simulated Annealing* is a popular heuristic for optimization. Its primary operation consists of a local search to minimize a problem-specific cost function. As local search methods are prone to getting trapped in local optima, Simulated Annealing attempts to avoid entrapment in local optima by sometimes proposing a move to candidate solution that increases (worsens) the value of the cost function. A configurable acceptance probability determines the acceptance or rejection of this uphill move. Focused on single objective optimization [70] uses a Genetic Algorithm's solution (see below) as the initial parameter configuration of a simulated annealing algorithm modified to avoid uphill exploration. Then it applies the proposed hybrid optimization scheme to a facade optimization planning problem in different climates validated by a building simulation. The case studies in [70] show that the combination both methods achieves robust optimization results. Further, their combination reduces computational complexity compared to a repetitive use of the Genetic Algorithm to verify the optimization outcome.
- The *Particle Swarm Optimization* (PSO) is another popular heuristic. It relies on a population (denoted *swarm*) of candidate solutions (*particles*). The heuristic is based on a gravitational metaphor to iteratively update the particles according to simple rules of attraction and inertia. Various variants and applications exist as illustrated in [71], e.g. [72] extends it with the ability to address multiple objectives by calculating the Pareto front of HVAC operation. This ability allows specifying a trade-off between saving energy and addressing comfort aspects.
- While many more nature-inspired heuristics for optimization exist, [73] argues most of these only differ marginally from PSO. For example, the *Firefly Algorithm* [74] is for specific parameterizations equivalent to PSO. This algorithm, inspired by the flashing behavior of fireflies aiming to attract other fireflies (configurations of decision variables) by means of brightness (the cost function to be optimized), is applied in [75] to optimize multi-zone HVAC operation in a dedicated HVAC test facility outperforming standard PSO. To improve the balance between exploration and exploitation [76] modifies the Firefly Algorithm's attraction equation with Gaussian distributions to avoid premature convergence to local minima.
  Cuckoo Search is another heuristic similar to PSO that identifies problem solutions with bird nests and decision variable selections as eggs within the nests [73,77]. The algorithm draws on cuckoos placing eggs at random in the nests and an evolutionary aspect in that the best nests (containing high-quality eggs) will carry over to the next generation. However, for bad nests, the host bird owning the nest may discover the cuckoo egg and

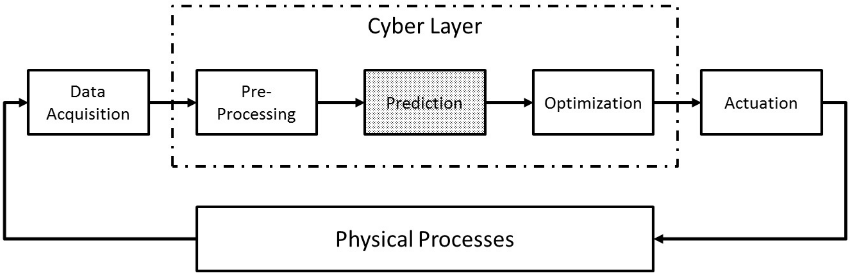

Figure 1: Block diagram of the predictive optimization CPS control loop. Recent works use different types of approaches for the prediction step (shaded) as presented in Section 3.

throw it away. With a configurable probability, it may even abandon the entire nest and build a new nest. This concept is extended by [78] with a differential approach that lends a mutation operation inspired by the Genetic Algorithm to avoid that local search gets stuck in local minima. [78] applies the concept to slightly different case studies than [76] but achieves qualitatively similar results.

- According to the survey [79], the single most widely used nature-inspired heuristic in the building optimization field is the *Genetic Algorithm* [80]. This heuristic is a stochastic technique inspired from genetic recombination found in the process of natural selection. This iterative approach mimics biological evolution, searching a population of candidate solutions (represented by *chromosomes* consisting of *genes* - choices for optimization variables) for its fittest members. A problem-specific cost function expresses this fitness, and during the evolutionary process only the fittest members' genes are mutated and exchanged stochastically to improve the solution. For example, [81] demonstrates its use for scheduling HVAC operation decisions: validation by simulation indicates system operation cost savings of 56% and improvements in thermal comfort.

3. Control decisions are communicated to the building infrastructure to steer the physical processes as desired. In this step, again IoT and M2M aspects apply. Potentially, the decisions may be in the form of set-points that are communicated to lower layer control loops of the building automation infrastructure. This case resembles the approach of *supervisory control*, typically executed by experts supervising plant operations. The decisions, however, may also be directly communicated to actuators, which effectively constitutes a control loop.

4. Actuation impacts the physical process, affecting the sensor information after a process dependent time delay.

2.3 Relation to Building Automation

In building automation, hierarchical system structures are very common, typically designed in a three-layered architecture [52]:

1. The lowest layer, the so-called *Field Level*, consists of sensors and actuation devices.

2. The middle layer (*Automation Level*) consists of controllers implementing control loops to meet configured set-points.

3. The top layer, the *Management Level*, usually consists of the computer hosting the Building Management System that offers a user interface and allows configuring static set-points as well as rules and schedules to change these set-points.

Communication protocols encountered at the different levels are M-Bus, Modbus, BACnet, EIB/KNX, LON and more recently also OPC. Traditional building automation systems that follow this structure are reactive Cyber-Physical Systems. The delineation to this survey is the aim to improve building control by *predictive actions*, e.g. by appropriate set-point manipulation to address anticipated situations ahead of time. The advocated approach of operating buildings with predictive control strategies benefits from integrating pre-existing building automation infrastructure. Ideally, the BMS supports this by acting as a single gateway to the automation infrastructure enabled by the protocols mentioned above. Depending on the cyber-representation and the optimization goals, additional field level and automation level devices may be necessary. Also, the integration of other data sources e.g. provided via the Internet, may improve the efficiency of predictive control strategies. For example, [82] deployed its cyber-representation for predictive control actions on a separate server by using the BACnet/IP protocol for BMS integration and accessed additional weather information provided by [83]. Figure 2 illustrates this concept.

2.4 Control Mechanisms

Cyber-Physical Systems require real-time control, traditionally implemented in one of the three forms [42] ordered by increasing sophistication:

- open loop control: based on only the desired value as an input signal, the CPS calculates control actions but lacks a feedback mechanism;

- feed-forward control: the CPS takes into account additional environmental information collected from sensors and decides on actuation commands based on the anticipated relation between the physical system and its environment;

- closed loop or feedback-based control: the CPS receives as feedback the difference between the input and the output signals, enabling it to adjust its control decisions - both the physical and the cyber parts of the system affect each other.

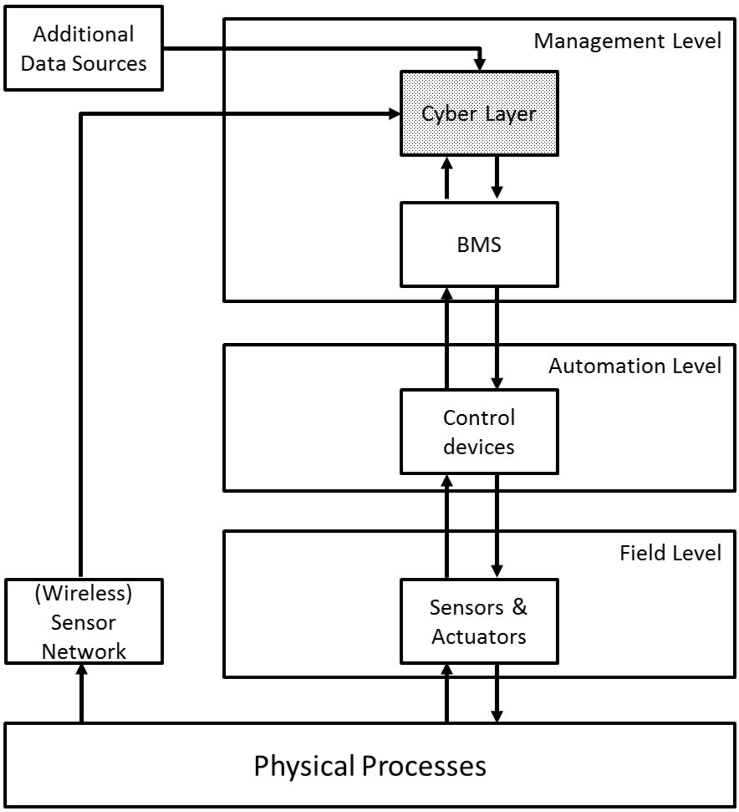

Figure 2: Integration of the predictive CPS concepts of Figure 1 (shaded) with the common three layer BMS structure described in [52].

Assuming a smart building equipped with sensors and automation infrastructure, predictive control of a building is a prime example of a closed loop CPS: actuation decisions will be reflected in future building data, which has the potential to affect future actuation decisions.

2.5 Distributed Building Control and Conflicts

The interplay of various systems with individual characteristics characterizes building operations. Some of these systems have diametric effects, e.g. heating and cooling. In large facilities, typically the coordination of these systems is configured by human experts based on their experience and operational know-how. The literature explores methods to optimize building performance according to KPIs while freeing staff from the need to monitor the routine operation closely. In principle, when moving to automated building control, a centrally formulated constrained optimization problem could accommodate and balance the systems' effects. However, for large facilities, this centralized approach is computationally complex. When facing such complex problems, it is common to split them into multiple smaller, easier to solve problem formulations. In these settings, the *Multi-Agent System* (MAS) design paradigm is popular as it is scalable, distributed, and manageable [84, 85]. Several surveys in the domains of power networks [85], microgrids [86], and smart buildings [84] underline the concept's adoption across sectors. The popularity of MAS in the building control community is evident in [79].

Agents are entities that autonomously interact with their environment (and other agents) according to agent-internal rules. When implementing an entire building control as a multi-agent system, conflicts of the agents' decisions may arise in certain situations: distributed control "contributes to the rise of organizational conflicts due to goal or perception difference between agents" [87]. Based on work on inter-personal conflict resolution [88], [89] categorizes the different types of conflict handling based on the specific agents' levels of assertiveness and willingness to cooperate:

- Avoidance: when agents have low levels of assertiveness and willingness to cooperate
- Accommodation: when agents have a low level of assertiveness but a high willingness to cooperate
- Compromise: when agents have medium levels of assertiveness and willingness to cooperate
- Competition: when agents have a high level of assertiveness and but a low willingness to cooperate
- Cooperation: when agents have high levels of assertiveness and willingness to cooperate

The capability to resolve possible conflicts in distributed building control is key to efficient and reliable operation in everyday life. As identified by [84], a survey of multi-agent systems in commercial and residential buildings, agents that use so-called *Utility* functions can weigh among different conflicting options, the likelihood of success, and goal importance. However, to accommodate conflicts with other agents, additional means, such as dedicated mediating agents or negotiation protocols, are required. In general, [86] categorizes MAS architectures in *centralized*, *distributed* and *hierarchical* describing the interactions and the distribution of responsibilities among agents. Focused on the particular setting of distributed model predictive control (DMPC) [90] defines settings where agents optimize their individual cost functions as *non-cooperative* and settings in which each agent optimizes a shared cost function as *cooperative*.

2.6 Smart Grid Interactions, Renewables, and Storage Capacity

Existing buildings' service systems may receive energy from a variety of grids: electricity, gas, district heating, or district cooling grids feed buildings worldwide. Traditionally, grid infrastructure goes hand in hand with centralized generation and distribution, which suffers from energy losses along the distribution network and potentially from supply-demand imbalances. In particular, the electricity grid is recently evolving towards a decentralized architecture with an increasing amount of distributed generation sources. The decentralized feed-in of electricity has considerably increased in recent years due to the unbundling of the energy supply chain, the technological advancements of renewable energy sources (RES), and political support promoting renewable installation. Therefore, electricity distribution system operators (DSO) have to cope with bidirectional energy flows in their networks. Furthermore, the variability of wind and photovoltaics is decoupled from energy demand, which causes a supply-demand-imbalance in the electricity network [91]. Therefore, DSOs have to manage the fluctuating energy supply, for example by shedding renewables during times of high production, increasing the electricity network's transmission, installing additional capacities of energy storage, and by managing demand intelligently. For the latter, Demand Response (DR) is actively pursued by grid operators [92]. DR requires communication capabilities between the electricity grid and the consumers [93]. DR may result in an increased energy demand to take up surplus energy from the grid due to high RES generation. However, that higher demand is "green" as it is associated with low GHG emissions and can serve time-flexible loads that otherwise would be served by fossil fuels.

Buildings with the capacity to store energy, in batteries (or connected electric vehicles), in hot or cold water tanks, or in their thermal mass are particularly well suited to leverage this energy buffering capacity to flexibly manage their demand and offer DR potential to the grid. Section 3 discusses several studies that demonstrate the feasibility of DR in data-driven building control, such as [94, 95]. Embedded in a bigger smart city context international big scale research projects [96, 97] currently investigate energy demand-side management as one aspect contributing to higher energy efficiency in addition to other interventions, such as increasing citizens' awareness of energy efficient behavior. Apart from DR settings, predicting a building's renewable energy generation (e.g., rooftop solar panels' power output) to increase local RES consumption within the building, i.e., avoiding feed-in into the electricity grid, is another, though related, goal of efficient building operation. In the context of this survey, the CPS approach to predictive building control benefits from combining buffering capacity, demand prediction, and DR signals to manage demand flexibility and increase building operation energy efficiency by deciding on optimal control strategies.

2.7 Building Information and Semantics

Ontologies conceptualize domain knowledge by establishing semantic relationships between classes and their properties. This form of knowledge representation enables applications to apply logical reasoning and inference. Several data models and ontologies suitable to inform predictive building control applications exist:

- The *Industry Foundation Classes* (IFC) describe building and construction industry data in an object oriented model defined by buildingSMART [98] and adopted by ISO [99]. The IFC exchange format definitions suit various disciplines, such as the facility management, during the different life cycle phases of buildings. An XML schema definition, as well as an OWL ontology of the IFC standard, exist.

- *Green Building XML* (gbXML) [100] facilitates the transfer of building information stored in CAD building information models, enabling interoperability between building design models and various engineering analysis tools and models. It covers the planning phase as well as systems operational data. [101] transforms gbXML into an ontology for use with semantic web technologies.

- With [102], ETSI SmartM2M endorses the *SAREF* ontology describing Smart Appliances in residential environments. While SAREF focuses on appliances, it also models devices that control building spaces such as windows or doors. To cover building construction related aspects, ETSI SmartM2M relies on the FIEMSER data model and ontology [103, 104].

- Avoiding to model building physics or construction data, Project Haystack [105] defines an ontology focused purely on building system operational data.

- Furthermore, the literature provides also a multitude of information models targeted at enabling smart home automation services, e.g. DomoML [106], DogOnt [107], and BOnSAI [108]. Several works extended these to address energetic aspects in the home: e.g. [109] attaches an energy profile ontology for devices to [107]. Beyond that, [110] defines energy semantics in a multi-agent smart home automation system modeling that not only cover device energy consumption but also the home's energy supply facilities and energy sources. However, these domotics information models, even with energetic extensions, are typically not used for predictive control scenarios but rather for convenience services.

The survey [111] summarizes 180 research publications in the building information model (BIM) field dating back until 2002. For the existing building stock, [111] shows that BIM still is rarely used due to the challenges of high effort, BIM maintenance, and the question of handling of uncertain data, objects, and relations. It identifies as one major challenge for research the BIM creation for already existing buildings. Inspired by [112], one possible application of BIM is described in [113]: a translation between BIM and Building Energy Modeling (BEM) using Modelica [114], an object-oriented, equation-based language to model complex physical systems. The work demonstrates the feasibility of reusing original BIM data in a BEM simulation. Another useful application is e.g. WSN topology planning [45], i.e. supporting one particular aspect of the approach presented in Figure 2 that enriches the information available to the predictive control strategies.

3 Building Energy Performance by Predictive Control

3.1 Building Energy Modeling Surveys

Building energy efficiency is a multi-disciplinary field of ongoing research since decades. Surveys [115, 116] review literature modeling building energy behavior. Their focus lies mainly on documenting the different fields and approaches to modeling buildings and their critical components, i.e. energy systems, for building control and operation. From [115] it becomes evident that despite considerable savings of energy or cost are envisaged, these have been validated in building simulation only, not in controlled experiments in routine operation. While [116] does not provide any energy savings figures, it reviews modeling approaches documented in literature since the 1980s, as well as the relevant parameters considered, the methods of validation, and available building simulation software packages. Survey [79] analyzes 121 works on the optimization parameters of concern in the field of building energy and comfort control. Its focus lies on assessing the publication trends and the techniques employed, rather than quantifying the effects achieved. The survey provides the insight that most published studies are US based and that Model Predictive Control (MPC), MAS approaches, fuzzy control, and the Genetic Algorithm are commonly applied in studies.

3.2 Classification of Studies

The remainder of this section surveys recent works on data-driven control of buildings: Table 2 documents the method of validation (simulation or experiments) as well as the effect sizes achieved. Table 1 provides a list of abbreviations. This sub-section provides the taxonomy used to categorize the different approaches.

- *Theoretical approaches*. These are based on either the physics of buildings or suitable approximations thereof. Works of this category often apply building (energy) simulation programs such as *Modelica* [114] or *EnergyPlus* [117]. In the literature, these kinds of approaches are commonly referred to as *white-box* or *model-based* approaches. As this survey puts emphasis on predictive control aspects rather than the modeling, both terms are used synonymously in this survey.

- *Data-driven approaches* train linear or non-linear regression models such as Neural-Networks (NN) based on observed (BMS) data. In the literature, these approaches are commonly referred to as *black-box* approaches. Sometimes they are also called *model-free* to express the absence of a theoretical model. If information on the problem nature, e.g. time-scales, effect sizes, linearity or non-linearity of the regression problem are taken into account to improve the training of these data-driven approaches, it is common to denote these approaches as *gray-box* approaches.

- Combinations of data-driven methods with theoretical models are referred to as *hybrid approaches*.

- Studies that experiment with approaches of different categories are classified as *mixed*. In these cases, we focus on the best performing approach.

3.3 Theoretical

Focused on the day-ahead planning of hourly HVAC set-points, [81] combines thermal building simulations in EnergyPlus [117] with a Genetic Algorithm implemented in Matlab to calculate the Pareto front of operation concerning energy and comfort (PPD). Considering a typical day of the heating season in Naples, Italy, the simulations demonstrate savings of heating cost of up to 56% compared to a standard control strategy when target user comfort allows a maximum of 25% PPD. This result still improves the maximum observed PPD by 8%. When targeting higher PPD (20%), energy savings amount to 42%.

Optimizing HVAC scheduling with model predictive control for buildings with several hundreds of zones becomes computationally intractable. For this reason, [118] divides the problem into three smaller, but logically linked sub-problems: knowing their characteristics and target indoor temperatures, controllers for individual zones compute the minimum required energy demand and request this amount from a central scheduling instance. That takes the building's chillers' characteristics as well as information of the building's chiller sequencing to decide on providing cooling energy to the zones. For each zone, this allocated cooling energy is required to meet the demand requested by the zonal controllers, but may also exceed the demand to exploit beneficial chiller characteristics. This way the central scheduler decides the appropriate ventilation fan stages and damper positions (expressed by desired duct pressures) to distribute the cooling energy through the ventilation ducts. A building simulation demonstrates that the distributed approach is close to optimality for a small number of zones and is also able to scale to hundreds of zones. Compared to an often used standard pre-cooling strategy, the awareness of each zone's thermal demand saves 17% energy.

[119] proposes a novel modular MPC approach that explicitly models non-linear building dynamics. The concept allows approximation of the globally nonlinear optimization problem to solve the decoupled sub-problems efficiently: first, based on measured room temperatures, TABS temperatures, and weather prediction a trajectory of temperature evolution of the building is estimated. Second, required thermal flows of the building are calculated to adjust temperatures to desired ranges. Third, corresponding set-points are derived. The approach's effectiveness is demonstrated in a co-simulation controlling an Austrian low energy office building's thermal flow. However, no energy savings are quantified.

Given a cost budget for energy and using a linear indoor temperature evolution model, [120] proposes a Comfort Prioritizing Greedy (CPG) algorithm to schedule appliances under consideration of their nature ((non-) deferrable and (non-) interruptible)). Validation is simulation-based and focuses on a single day. The CPG algorithm performs "slightly better" than both the standard bin-packing algorithm as well as a linear program to optimize the scheduling.

Focused on minimizing exergy destruction by HVAC use, [39] shows in simulations that exergy destruction and energy consumption are reduced by up to 22% and 36% compared to traditional control. Compared to an energy-focused MPC, the simulations show 4% exergy savings and 12% energy savings.

In a Demand-Response (DR) setting [121] combines a building's maximum demand with DR incentives in a single equation, constrained by appliances' characteristics. The approach combines rolling optimization of a multi-hour prediction horizon with minute-based real-time control strategies. A fuzzy logic controller controls appliances focusing on cost reduction: simulations demonstrate cost reductions of 16%-19%. A lab experiment using Zigbee illustrates the operational potential. The same authors focus in [122] on the real-time scheduling of appliances using the conditional value at risk metric from economics to express uncertainty. Fuzzy logic decides on participating in a given DR instance, computation time amounts to 30-40 seconds per 30 minute planning interval. The forecasting of conditions, e.g. prices or PV generation, is considered given. Validation is based on simulating a single day, which indicates an electricity bill reduction by 18%.

Studying six small and medium-sized commercial buildings in the cities of Boston, Chicago, and Miami [123] demonstrates energy cost savings of 20%-60% for HVAC operation on five days in August when compared to a pre-cooling night-setback strategy using three-year average weather data. The savings depend on the individual building and its location as well as the relative weight of comfort compared to energy cost. The study applies PSO to identify the Pareto front of PMV versus energy costs in EnergyPlus [117].

3.4 Data-driven

Neural Networks

[75] optimizes multi-zone HVAC operation using NN to predict room temperatures and energy consumption. The study uses relative room humidity and room temperature as input to minimize energy subject to comfort conditions by controlling the supply air's temperature static pressure set points. The work proposes to perform the optimization by a Firefly algorithm. Validation is purely computational, based on data of a single day for which the Firefly algorithm outperforms PSO. Energy savings range between 2% (most strict comfort constraints) and 17% (most relaxed). [72] extends the energy optimization to consider also indoor CO_2 levels. Compared to seven other regression models, a NN Ensemble performed best. A modified PSO solves for Pareto-optimal solutions of IAQ, comfort, and energy consumption. Different weightings of these objectives create different Pareto-optimal trade-offs. Computational results on the recorded two week period indicate average estimated electricity savings of 12%-17%. Both works use expert input and feature selection algorithms to reduce the several hundred parameters sampled in 1-minute intervals (and averaged per 30 minutes and 60 minutes respectively) but do not elaborate on this aspect.

As an evolution of [124] that trades off HVAC energy consumption and user comfort using NN and multi-objective optimization, [125] builds a data-driven predictive model for HVAC operation to minimize economic cost while ensuring comfort. The approach takes into account indoor temperatures, schedule information, cost, and weather variables. Exploration of lag times, i.e. the length of history to consider in the models, is explored by a search heuristic. The work is validated in three lecture rooms of the University of Algarve, Portugal, in several experiments spanning a period of two weeks in June 2015. The results show financial savings while spending more energy to ensure minimized comfort violation for the HVAC unit under control: "savings in the order of 50% are to be expected". Unfortunately, the work does neither normalize for room characteristics nor weather.

Studying a more exotic heating system, [82] demonstrated weather-normalized thermal energy savings of 56% over a winter season operating a soccer stadium's grass heating system - a major heat sink. This study experiments with a variety of control heuristics, e.g. simple statistics-based methods as well as more advanced NN to predict the soil temperature evolution - the latter achieving better results. Best results are obtained by extending the control concept with awareness of operational context, i.e. the status of other heat consuming systems to avoid bottleneck situations. Notably this work is the only work applying methods of statistical inference, enabling it to quantify confidence intervals for the different strategies' savings.

Starting from a thermal building simulation, [126] proposes - after a pre-processing stage of sensitivity analysis and PCA - to use NN to learn building behavior regarding energy and comfort subject to control actions. Genetic Algorithm-based optimization is then applied to derive building control rules to be stored in a knowledge base that a facility manager can choose from, e.g. to strive for energy savings targets. The approach is validated using three months of simulation and two months of experiments for a care home in the Netherlands where heating supply, window opening, the degree of shading, and light levels are controllable. Weather-normalized energy savings amount to approximately 25%.

Reinforcement Learning

Using Reinforcement Learning (RL) to optimize the economic aspects of operating electric water heaters, [94] demonstrates in simulations 24% savings for using day-head prices and 34% savings for the imbalance prices (stemming from forecasting errors) compared to the default strategy. A 40-day lab experiment achieves 15% cost savings. When excluding the algorithm's exploration phase, savings reach up to 28% confirming the simulation results. Features reflected are the day of the week, the index of the quarter of the day, as well as 50 temperature sensors. An auto-encoder compresses the features to five dimensions.

Using an auto-encoder to reduce state vector dimensionality, [127] demonstrates by simulation of winter and summer seasons to be able to save 4%-11% energy of a heat pump with a set-back strategy in two different buildings. As no thermal or physical modeling is involved, the approach is transferable to other buildings and other climatic zones without requiring extensive effort.

[128] uses an ensemble of 40 NN to assist batch RL in creating an efficient HVAC DR controller able to control on-off decisions. A simulation of 40 days with different temperature regimes validates the approach. After collecting 16 days' data, the inferred control

policies are stable within 90% of the mathematical optimum. A shorter experiment in a living lab validates the findings qualitatively.

For a Swiss low exergy residential building [129] controls the mass flow parameter through a photovoltaic-thermal array to improve power output. Over the course of three simulated years, 5-11% power improvement is achieved when compared to a rule-based controller configured by domain experts.

Focused on lighting and blinds operation, [130] presents an intuitive human machine interface via which users can provide feedback on their individually perceived light level comfort to a q-learning based controller. That aims to minimize lighting and HVAC energy consumption while avoiding violations of users' minimum/maximum light level constraints. The usability is validated by a trial with ten students and two office workers lasting five months. Energy savings of up to 10% are derived by simulating cloudy and sunny conditions with different user preferences when comparing the reinforcement learning based controller with conventional automated lighting control.

Regression Trees

Motivated to maximize participation in DR programs, [95] relies on regression tree ensembles to predict the building electricity baseline from environmental parameters and system state variables. By rearranging the regression trees into two stages where non-control parameters are represented at the top of the tree and control variables towards its bottom, a region of desired control variables can be inferred to derive DR strategy actions dynamically. The inference is executed every five minutes by a linear program. For a large reference building, assuming 20 DR events over summer, $45,600 in revenue for participating in DR (37.9% of the campus' energy bill) could be expected. The authors report a 17% higher curtailment than a rule-based DR strategy while maintaining thermal comfort.

3.5 Hybrid

[131] combines a linear resistance-capacitance model with a NN. The work shows by simulation and experiment at the check-in hall of Adelaide airport's terminal T-1 that this hybrid approach successfully combines the non-linear approximation ability of NN with the capability to extrapolate to new situations. The approach learns optimal start-stop pre-cooling strategies for HVAC operation. Pre-cooling saved 13% electricity cost at the expense of 5.6% increased energy consumption, while the start-stop strategy during hours of occupation achieves up to 41% energy savings.

[132] uses a simplified model-based controller with non-linear filters for indoor climate control. The study experiments in a mock-up office and meeting room environment in winter and summer seasons in Sweden. By closely taking into account IAQ, the controller reduces room ventilation rates by 12% - 19%.

3.6 Mixed

[133] applies Parametrized Cognitive Adaptive Optimization (PCAO) to optimize a ten-office building in Greece. The work studies two variants: (simulation-)*model-based* and *model-free*. Before deploying a PCAO-derived controller to the real building, its performance is assessed by a thermal building simulation. The model-free approach directly applies a control mechanism to the building after estimating a so-called *performance index*. In simulations, compared to two baseline rule-based controllers, model-based PCAO reaches energy savings of 45% and 25.6% respectively. At the same time, comfort is enhanced by 7.0%-8.7% and 30.7%-33.5%, respectively. In these simulations, model-free PCAO achieves energy savings 41.2%-44.6% and 20.5%-25.3%, respectively. Simultaneously, comfort improves by 3.5%-7.8% and 28.1%-32.9%. However, in real-life experiments on different days in 2012 and 2013, model-free PCAO achieves energy savings of 19%, outperforming the model-based approach due to modeling inaccuracies.

Abbreviation	Explanation
C	Comfort
Cl	Clustering
DBN	Deep Belief Network
DD	Category of data-driven approaches
HW	Hot Water
E	Energy
EnvCo	Environmental context, e.g ambient air temperature, solar irradiation, wind speed
FC	Forecast information about features, e.g. weather forecast
GH	Grass Heating
H	Heating
HDD(E)	Heating Degree Day Normalized Energy
HuCo	Human Context, e.g. occupation
HVAC	Heating, Ventilation & Air-Conditioning
Hy	Category of hybrid approaches
L	Lighting
Lecture	University/teaching environment
Med	Medical building, Hospital, Care center
Mix	Mixed studies
MPC	Model Predictive Control
NN	Neural Network
Office	Office Building
OpCo	Operational Context, e.g. other Systems' Operational Data
P	Power
PV/T	Photovoltaic-Thermal System
Res	Residential Building
RL	Reinforcement Learning
RT	Regression Tree(s)
S	Shading
Stadium	Sports Stadium
SysOp	Controlled System's Operational Data
t	Time
Test	Test Facility
Th	Category of theoretical approaches
UPR	Under Performance Ratio
UPT	Under Performance Time
VE	Validation by Experiment
VS	Validation by Simulation
W	Window
X	Exergy
Z	Target Zone parameters, e.g. IAQ

Table 1: Abbreviations for Table 2.

Ref.	Building Type	Systems optimized	BMS integr.	Validation Method & Period	Features	Time res. Interval	Category	Conflict handling	KPI	Effect size
[39]	Lecture	HVAC		VS:1D	EnvCo, HuCo, Z	1h	Th		X	-4% X, -12% E
[81]	Residential	HVAC		VS:1D	Cost, HuCo, Z	1h	Th		Cost, C	[-56,-42]% Cost
[118]		HVAC		VS:1D	EnvCo, HuCo, SysOp, Z	30m	Th		E, C	within 2% optimality, -17% pre-cooling E
[119]	Office	HVAC		VS:1W	EnvCo, FC, HuCo, SysOp, Z	15-30m	Th		E,C	
[120]	Res	HVAC		VS:1D	EnvCo, SysOp, Z Price, FC	1h	Th		C	Max. Comfort
[121]	Res	HEMS		VS:1D	EnvCo, HuCo, SysOp, Price, FC	1m	Th		Cost	[-19,-16]% Cost
[122]	Res	HEMS		VS:1D	EnvCo, HuCo, SysOp, Price, FC	30m	Th		Cost	-18% Cost
[123]	Office	HVAC		VS:5D	C, Cost, EnvCo, HuCo	30m	Th		Cost, C	[-60,-20]% Cost
[72]	Test	HVAC		VS:2W	EnvCo, SysOp, Z	60m	DD:NN		E, C	[-17,-12]% E
[75]	Test	HVAC		VS:1D	EnvCo, SysOp, Z	30m	DD:NN		E, C	[-17,-2]% E
[82]	Stadium	GH	✓	VE:3M	EnvCo, FC, OpCo, SysCo, Z	10m	DD:NN	✓	E,C	-56% norm. E
[125]	Lecture	HVAC	✓	VE:2W	EnvCo, FC	5m	DD:NN		E, C	-50% Cost expected
[126]	Med	H,L,S,W	✓	VS:3M,VE:2M	EnvCo, HuCo, SysOp, Z	15m	DD:NN		E, C	-25% norm. E
[94]	Test	HW		VE: 40D	FC, Price, SysOp, t	?	DD:RL		Cost	[-34,-15]% Cost
[127]	Res	HP		VS:1 su.,1 wi.	EnvCo, FC, SysOp, t	15m	DD:RL		E	[-11,-4]% E
[128]	Test	HVAC		VS:40D,VE:40D	EnvCo, FC, Price, SysOp, t, Z	5m	DD:RL		Cost, C	within 90% of optimum
[129]	Res	PV/T		VS:3Y	EnvCo, SysOp	30m	DD:RL		E	[6,11]% P output
[130]	Office	L, HVAC		VS:2D	E, EnvCo, Lux	?	DD:RL		E, C	-10% E
[95]	various	various		VS:4M	EnvCo, FC, HuCo, SysOp, t, Z	5m	DD:RT		E	+17% curtailment
[131]	Airport	HVAC	✓	VS:1D,VE:4D	EnvCo, FC, HuCo, Price, Z	10m	Hy		E, C, Cost	Start-Stop -41% E; Pre-cooling -13% Cost
[132]	Test	HVAC		VE:2D	EnvCo, HuCo, SysOp, Z	?	Hy		Flow	[-19,-12]% Flow
[133]	Office	HVAC	✓	VS:2W,VE:2W	EnvCo, HuCo, SysOp, Z	10m	Mix		E, C	VE:-19% E VS: [-25.3,-20.5]% E, [3.5,7.8]% C

Table 2: Categorization of studies using data-driven predictive control for improving building energy efficiency. Table 1 explains the abbreviations.

4 Open Research Questions

In light of the reviewed research studies documented in Section 3, this section identifies seven open research questions.

4.1 Buildings as CPS - Methodology

The simulations and experiments described in Section 3 demonstrate the positive effects of applying predictive control strategies to buildings. That promotes the widespread adoption of predictive control in buildings, to meet global greenhouse gas emission targets. However, the field lacks a concise methodology to develop and deploy highly effective strategies to specific existing buildings. None of the works in Table 2 describes a general methodology for turning existing buildings into a closed-loop CPS supporting the deployment of predictive control strategies.

The methodology to be developed could e.g. be based on the established general Model-Based Design Methodology for CPS [134] but adapted to the specifics of the building community to increase usability. For example, the methodology needs to account for the specifics of existing buildings, e.g. to integrate already pre-existing automation infrastructure and building instrumentation. Further, especially in bigger commercial buildings, the methodology also needs to address the possibly complex stakeholder landscape. The potential is enormous: of all commercial buildings in the U.S., 42% are equipped with automation systems [1].

RQ 1: What is a suitable methodology to evolve existing buildings into a CPS for higher levels of operational efficiency?

4.2 Feature Selection

Selecting meaningful features is a cornerstone to creating well-performing predictive models. In the SCADA of a common medium or large-scale building, a considerable number of variables is available for study. For example, in [82] the soccer stadium's BMS provides access to approximately 13,000 variables. The binary question whether or not to include a feature in combination with other variables yields 2^N possible combinations. The number of possible combinations increases even more, when

- studying the effects of varying the amount of history information for each of the variables considered;
- applying different linear and non-linear techniques to transform or normalize the variables;
- applying different linear and non-linear modeling techniques;
- tuning the techniques' hyper-parameters (e.g. number of hidden layers and neurons in a NN).

Discretizing the space of possible combinations to explore (often referred to as *grid search*) reduces that number, but this heuristic has large effects on the optimality of the final result and the efficiency of building the predictive model.

Unfortunately, the works in Table 2 do not describe the rationale how relevant features (variables as well as their history lengths) are selected. While the field of feature selection is a prominent research area, additional expert knowledge can guide the feature selection process to reduce the overwhelming complexity of an exhaustive feature space search. As BIM is becoming prevalent in the building domain, its use to effectively select features in an algorithmic way should be investigated. While the notion of semantic feature selection itself is not novel, it has never been used for predictive building control applications. [126] identifies relevant environment parameters and set-points from an ontological building description to derive control rules; however, the feature definition, as well as the relevant system or building operational context, are not studied. More generally, semantic feature extraction has been applied successfully in the areas of mining text [135] and image data [136, 137]. Also, graph-based feature selection has been used successfully in DNA sequencing [138] (available e.g. in R library FGSG [139]). Further, a recent publication in the industry automation domain describes how a manufacturing process ontology can be processed to select meaningful features from a SCADA system on which then machine learning methods can be applied [140], but does not describe how appropriate history lengths for each feature can be deduced.

To conclude, the concept of semantic feature selection should be extended to also take BIM information into account when considering the relevant history lengths for the different variables considered. For example, the thermal interdependencies between building zones could be derived from a wall's thermal admittance [141] and its materials. These parameters determine a wall's decrement delay (time lag between the timing of the temperature peaks at either of the wall's sides) and its decrement factor (dampening the temperature peak of one side of the wall to the other) [142]. That information should lead to the appropriate history lengths and inter-feature lags.

Beyond studying smart feature selection based on BIM, it is evident that additional sources of information that describe the human context (e.g. occupation schedules) and the environmental context (e.g. weather forecast) need to be taken into account. In this line of thought, the BIM or another linked ontological information source could evolve to indicate connectivity to these information sources such as calendars or scheduling information.

RQ 2: How to perform semantic feature selection for predictive building control?

4.3 Inter-building Transfer

The large number of buildings built anywhere on the planet renders savings by predictive control strategies impossible if they cannot be rolled out and adapted to new buildings efficiently. Commercial M2M platforms facilitate deployment of predictive control applications to new buildings by abstracting from lower layer communication details [49]. Still, the transfer of a predictive control application to another building remains time-consuming, error-prone, and costly, because

- an adaptation of the variable names is typically necessary, i.e. input and actuator data point names need to be mapped, and
- the new building has different characteristics, i.e. the predictive models may have poor performance and may require re-training with different features.

It is necessary to study effective approaches to address this. Conceptually we see the following fields as promising:

1. The transfer of a predictive control application to a new building can be seen as an abrupt and drastic form of *concept drift*.
2. *Transfer learning* focuses on solving new but similar problems by utilizing previously acquired knowledge. Typically, the feature spaces of source and target domain are assumed to be equal [143, 144].

These fields may be complemented by approaches such [145, 146] that analyze the meta-information in a BMS, e.g. the data point names as well as the data, by data mining techniques to identify and map variables of interest correctly with minimal human intervention. Further, e.g. [147] could be used in combination with e.g. transfer learning as it recommends the most appropriate Building energy model to use for a particular building - to which then transfer learning principles could be applied to map to the new building.

RQ 3: How to transfer a particular building's predictive control strategies to another building?

4.4 Control Conflicts

Several human-centric examples of control conflicts stemming from users' preferences and activities are documented in the literature on domotics and smart homes. For example, [148, 149] introduce an ontology-based reasoning to automatically detect and resolve conflicts stemming from different users' requirements. Upon identifying conflicts on environment variables and activities, the works propose to use constraint programming to settle the conflict situation. The works use ontological reasoning to maximize user comfort and minimize energy consumption, but only provide qualitative, not quantitative statements on energy savings. [150] uses agents to communicate in a smart building to reflect a user's personal preferences regarding Fanger's PMV to reflect this user's personal comfort appropriately. If multiple users are present, compromise preferences are looked for (and users might be suggested to change their clothes). [89] detects conflicts as changes of the environment state resulting in an undesired context of the application or user expressed by a constraint satisfaction problem. Conflicts are reasoned about in an attempt to find a compromise solution. [151] introduces an ontology based multi-agent home automation system and resolves conflicts identified during the concept covering phase by a utility based negotiation scheme. The agents negotiate based their individually configured utility definitions that they keep secret. A central home automation mediator strives to optimize global utility.

While these solutions address conflicting control decisions originated from human preferences and activities, other sources for conflicting control decisions are e.g.

- resource scarcity, e.g. due to coincidence factor based boiler capacity planning: the coincidence factor captures the amount of peak demand overlap; if all thermal building systems have their peak at the same time (i.e. coincidence factor was chosen wrong or control strategies have changed), the boiler capacity will be insufficient. However, current works in buildings typically do not resolve shares/demands/capacity constraints in case of resource conflicts [89]: for example, [152] uses priority-based queuing of user requests for resources and exclusively grants access to these.

- inter-dependent zones are heated and cooled at the same time, causing a potential waste of energy may result in a negative feedback loop of successively stronger control actions of the involved systems' control agents.

According to Table 2, the literature focuses on controlling a single building system serving one or more building zones. It seems feasible to encapsulate the individual system control approaches in a multi-agent system. However, only a single study reflects the impact of its control scheme onto other building systems and possible conflicts. It does so in a reactive manner by monitoring the controlled system's operational context. Predicting situations of conflict and scarcity is for further study.

For situations of conflict in multi-agent systems, literature often assumes cooperation among agents towards a common goal. For settings of *cooperative* agents where task planning is admissible, [153] describes in the context of an Ambient Assisted Living application a coordinated multi-agent action scheduling subject to resource constraints that supports conflict resolution.

However, the data-driven predictive building control domain may also face scenarios of competitive agents. For example, complex multi-tenant structures within a multi-story office building may lead to dedicated agents per tenant. Capacity constrained resources, e.g. a limited boiler capacity, a shared PV installation providing cheap electricity, or participation in Demand Response (DR) events may plausibly be argued to cause competition among different control agents. When extending the control scenario to multiple buildings, the problem space becomes even more complicated: will multi-tenant houses cooperate to compete against other houses for larger shares of a neighborhood-level electrical storage, but compete for PV usage? The insight that tenants inside a building may rent multiple zones adds further complexities: assuming each zone is controlled by an agent, the tenant's agents should intuitively be willing to cooperate, while they might be in competition with other tenants' agents. As tenant structures may change over time, as well as tenants' attitudes and policies towards each other, coalitions of cooperative agents of different tenants may emerge and disappear over time. The insights of [154, 155] may help address this setting. However, agents need to be aware of their own and the other agents' association. A possible way to realize this is enhancing agents with self-descriptiveness as introduced in [156, 157].

In *competitive* settings, possibly issues of trust and data access need to be resolved or negotiated. Either, agents directly get access to the variables relevant for their operational decisions, or, if e.g. access on another agents' variables is an issue, appropriate communication schemes and the identification of the correct responsible agent are also issues. However, some variables of the operational context may be less controversial to share among agents of different tenants: for example, the room temperatures of workers' offices may be more contentious to share with another tenant's agent than the supply temperatures and the working status of the ventilation. In certain competitive situations, a dedicated agent representing the shared resource as in [118, 151] might mediate or negotiate between conflicting interests. Note that this assignment of a dedicated agent may be a source of contention in scenarios where multiple stakeholders are involved and compete.

For handling scarce resources, the fields of Mechanism Design and, more generally, Game Theory apply. Notably, recent work [158] documents a robust mechanism that allows the mechanism designer to incorporate imprecise estimates of the distribution over bidder (agents) valuations (cost functions) providing strong guarantees that the mechanism will perform at least as well as "ex-post" mechanisms, while in many cases performing better. Exploiting this trait for predictive control in buildings with multiple agents appears as promising and should be investigated.

RQ 4: Depending on the involved agents' assertiveness and willingness to cooperate, how can conflicts of control due to systemic interdependencies or resource scarcities be appropriately mitigated in multi-agent building control systems?

RQ 5: Do agents learning to predict situations of conflict increase building energy efficiency?

4.5 Energy Disaggregation

To apply predictive control, the works listed in Table 2 require system level or appliance level sensing and metering. While sensing devices become cheaper, professional metering installations are still expensive - especially when the effort to install is complex, e.g. for heating distribution pipes that require welding, emptying of the pipes, and changes in the thermal insulation. The costs of installing and commissioning sub-metering can threaten the economics of projects aiming to implement any of the methods surveyed. Considering that existing buildings' BMS typically have access to main meters, several important sub-meters, and operational data, it is appealing to consider inferring appliance or system energy consumption from BMS data, i.e. from building system operation.

Many recent approaches to energy disaggregation (or non-intrusive load monitoring, NILM) focus on household appliance disaggregation, not large facilities. For example, [159] proposes a two-stage method that generalizes to previously unseen households after having trained the appliances' probabilistic Hidden Markov Models. Similarly, [160] combines Hidden Markov Models with time warping techniques to disaggregate household appliance data. These works have in common that they rely on a supervised training phase that could be challenged: Considering the availability of BMS operational data, possibly no calibration would be needed for predictive control purposes as long as the building system (or appliance) energy can be disaggregated with sufficient accuracy.

Unfortunately, the problem of disaggregating energy consumption of any commercial building into individual appliances poses several technical challenges.

- Most disaggregation research focuses on households and their appliances.
- A typical commercial facility has a large number of appliances which often run simultaneously. As a consequence of this, multiple energy signatures overlap complicating the task of identifying individual appliances' signatures from the aggregate consumption.
- Many approaches base on the assumption that only one appliance switches its operating state at a time. This may hold for buildings with low numbers of appliances and high-frequency data, but this assumption does not hold in the case of commercial buildings with larger numbers of appliances and systems.

Furthermore, the disaggregation works in the literature focus almost exclusively on learning electricity consumption models of the different appliances typically encountered in households based on a training dataset. The models are then applied to new homes. This approach stems from the absence of historical data in a typical household. While not harmful, this transferability is not required in buildings with existing instrumentation as data is typically logged for some time. Thermal systems such as hydronic space heating are by definition slower than electric systems and, to the best of our knowledge, not covered at all in recent energy disaggregation literature. Only [161] addresses gas consumption disaggregation by introducing an additional sensor to analyze the acoustic response of houses' gas regulators. Given that building management systems already provides rich data about building system operations, it should be investigated if disaggregation can also do without additional equipment installations. Recent works attempt to disaggregate based on low-frequency data [159, 162]. They rely on multi-second to multi-minute data, as opposed to the sub-second or even kHz data sampling rates commonly encountered in literature. Further investigation of the applicability to controlling a larger number of appliances and systems is required though.

RQ 6: Are recent disaggregation approaches sufficient to enable predictive control of large buildings with existing BMS installations?

RQ 7: Can the disaggregation approaches be extended beyond electricity or are different methods required?

5 Conclusion

The survey review in Sections 2 and 3 leads to the following insights:

- The majority of studies focuses on optimizing operational energy cost or consumption. Most take into account thermal comfort, often by formulating a multi-objective optimization, e.g. by calculating the Pareto front. Little attention is given to exergy or alternative KPIs such as system performance (UPR), green factor, or CO_2 savings. Suffice to say, studies performing optimization of energy costs may result in higher building energy usage.

- Where PMV and PPD are used for thermal comfort assessment, works do not discuss whether they use the static or adaptive definitions of the comfort KPI.

- A minority of studies addresses the aspect of BMS integration.

- Systemic interdependencies or conflicting control commands are rarely studied.

- Most works perform validation in the form of simulation. Fewer studies validate the control in experiments - and of those that do, the majority uses relatively short experimental periods.

- Few works account for weather conditions when assessing energy performance. That may be appropriate for simulations as conditions are reproducible. However, real world experiments' results may be influenced by changing weather conditions. Even fewer works apply statistical methods to draw robust conclusions by quantifying the confidence intervals of the savings they achieve.

- Most works do not explain how the features taken into account are derived or why they are used.

- Nature-inspired optimization heuristics such as the Genetic Algorithm or Particle Swarm Optimization are frequently encountered. Robust optimization techniques are not prominent in the field of data-driven predictive building control.

- Data-driven predictive control studies reach similar effect sizes as simulation-driven MPC studies. Neural Networks, and to a lesser extent Reinforcement Learning, are commonly used in the literature.

- Although the field of predictive building control is clearly related to the CPS concept, none of the works explicitly applies the general CPS research findings. In particular, a methodology for evolving buildings into energy efficient predictive CPS is lacking.

With these insights in mind, future research is guided by the following questions derived in Section 4. Studies should investigate each of the following research questions:

RQ 1: What is a suitable methodology to evolve existing buildings into a CPS for higher levels of operational efficiency?

RQ 2: How to perform semantic feature selection for predictive building control?

RQ 3: How to transfer a particular building's predictive control strategies to another building?

RQ 4: Depending on the involved agents' assertiveness and willingness to cooperate, how can conflicts of control due to systemic interdependencies or resource scarcities be appropriately mitigated in multi-agent building control systems?

RQ 5: Do agents learning to predict situations of conflict increase building energy efficiency?

RQ 6: Are recent disaggregation approaches sufficient to enable predictive control of large buildings with existing BMS installations?

RQ 7: Can the existing disaggregation approaches be extended beyond electricity or are different methods required?

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Paper G

Optimizing Legacy Building Operation: The Evolution Into Data-Driven Predictive Cyber-Physical Systems

Authors:
Mischa Schmidt, M. Victoria Moreno, Anett Schülke, Karel Macek, Karel Mařík, Alfonso Gordaliza Pastor

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Optimizing Legacy Building Operation: The Evolution Into Data-Driven Predictive Cyber-Physical Systems

Mischa Schmidt, M. Victoria Moreno, Anett Schülke, Karel Macek, Karel Mařík,
Alfonso Gordaliza Pastor

Abstract

Fossil fuels serve a substantial fraction of global energy demand, and one major energy consumer is the global building stock. In this work, we propose a framework to guide practitioners intending to develop advanced predictive building control strategies. The framework provides the means to enhance legacy and modernized buildings regarding energy efficiency by integrating their available instrumentation into a data-driven predictive Cyber-Physical System. For this, the framework fuses two highly relevant approaches and embeds these into the building context: the generic *Model-Based Design Methodology for Cyber-Physical Systems* and the *CRoss-Industry Standard Process for Data Mining*. A Spanish school's heating system serves to validate the approach. Two different data-driven approaches to prediction and optimization are used to demonstrate the methodological flexibility: (i) a combination of Bayesian Regularized Neural Networks with Genetic Algorithm based optimization, and (ii) a Reinforcement Learning based control logic using Fitted Q-Iteration are both successfully applied. Experiments lasting a total of 43 school days in winter 2015/2016 achieved positive effects on weather-normalized energy consumption and thermal comfort in day-to-day operation. A first experiment targeting comfort levels comparable to the reference period lowered consumption by one-third. Two additional experiments raised average indoor temperatures by 2K. The better of these two experiments only consumed 5% more energy than the reference period. The prolonged experimentation period demonstrates the Cyber-Physical System-based approach's suitability for improving building stock energy efficiency by developing and deploying predictive control strategies within routine operation of typical legacy buildings.

1 Introduction

1.1 Motivation

On a global scale, buildings are major consumers of energy that produce significant amounts of greenhouse gas emissions. For example, US building stock (residential and commercial) accounted for 41% of the US' primary energy use in 2010 [1], of which fossil fuels served 75%. In Europe, the ODYSEE and MURE databases indicate that buildings accounted for 40% of the EU-28 final energy use in 2012, with residential buildings being responsible for two-thirds of the total building consumption [2]. These figures stress that improving the energy efficiency of building stock is paramount to address resource scarcity and realize international climate preservation goals. Different studies of buildings over their life-cycle phases show that for typical buildings, irrespective of the type of construction, the operational phase accounts for up to 90% of lifetime energy use [3]. For low energy buildings, the operation phase's proportion still reaches 50%. Buildings use 60% of their consumption for thermal end uses: space heating, space cooling, and water heating [1]. Thus, one promising direction for improving the energy efficiency of buildings is to focus on improving the operational strategies of their thermal systems by predictive analytics - an approach complementary to refurbishment measures.

1.2 State of the Art

Current research on predictive building control strategies achieves high increases of performance by relying on predictive models learned from sensor data:

- [4] optimizes the operation of a multi-zone Heating, Ventilation and Air Conditioning (HVAC) system using neural networks for room temperature and energy consumption, taking relative humidity and room temperature as the input. The system controls the supply air's static pressure set-points to minimize energy subject to comfort conditions. The study's approach to validation is computational, based on data of a single day. Energy savings range between 2% (most strict comfort constraints) and 17% (most relaxed constraints).

- Related to [4], [5] extends the energy optimization to consider also indoor CO_2 levels. Compared to seven other regression models, a neural network ensemble performed best. A modified Particle Swarm Optimization algorithm solves for Pareto-optimal solutions of indoor air quality, comfort, and energy consumption. Different weightings of these objectives create different Pareto-optimal trade-offs. Regression models created from a recorded two week period indicate average estimated electricity savings of 12-17%.

- [6] uses neural networks and multi-objective optimization for HVAC operation to minimize economic cost while ensuring user comfort. The study takes into account indoor temperatures, schedule information, cost, and weather variables. Energy consumption is documented for three out of a total of six experiments conducted in winter and summer seasons at University of Algarve, Portugal. The experiment lengths are relatively short with a maximum of two days. The results suggest financial savings while spending more energy to ensure minimized comfort violation: "savings in the order of 50% are to be expected".

- Starting from a thermal building simulation, [7] proposes - after a pre-processing stage of sensitivity analysis and Principal Component Analysis (PCA) - to use neural networks to learn building behavior regarding energy and comfort subject to control actions. The Genetic Algorithm [8] is then applied to derive building control rules. A knowledge base stores these, enabling facility managers e.g. to strive for energy savings targets. The approach is verified using three months of simulation and two months of experiments for a care home in the Netherlands where heating supply, window opening, the degree of shading, and light levels can be controlled. Weather-normalized energy savings reach approximately 25%.

- [9] applies Reinforcement Learning to optimize heat pump operation. The study demonstrates energy savings of 4-11% for two different buildings by simulation of winter and summer seasons.

- [10] applies Reinforcement Learning to control the operation of blinds and lights in an office, taking into account also user feedback on the comfort achieved. Experiments show that 92% of the users reported high satisfaction, while the control also showed energy savings potential of up to 10% when considering lighting in combination with cooling load.

- [11] uses an ensemble of neural networks to assist batch Reinforcement Learning in creating an effective HVAC demand response controller able to control on-off decisions. A simulation of 40 days with different temperature regimes validates the approach. After collecting 16 data of days, the inferred control policies are stable within 90% of the mathematical optimum. A shorter experiment in a living lab verifies the findings qualitatively.

- For a Swiss low exergy residential building, [12] controls the mass flow parameter through a photovoltaic-thermal array to improve power output. Validation is performed by simulation: over the course of three simulated years, a 5-11% power improvement is achieved compared to a rule-based controller configured by domain experts.

- [13] applies Reinforcement Learning to data-driven predictive HVAC control. For reasons of scalability, the work uses weighted learning in a distributed multi-agent setting. A toy example optimizing the heating of two different zones validates the approach's concept.

In larger facilities, it is common to encounter automation systems of varying complexity and sophistication. Commonly these are controlled by Building Management Systems (BMS) intended to help facility staff to conveniently and efficiently operate building systems. Most often, these systems provide basic means of configuration, e.g. simple supervisory control rules and schedules. In building automation, hierarchical system structures are very common. According to [14], these are typically designed in a three-layered architecture as illustrated in Figure 1:

1. The lowest layer, the so-called *Field Level*, consists of sensors and actuation devices.

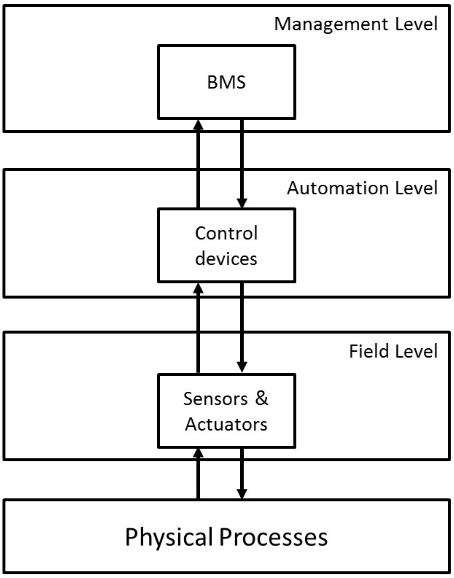

Figure 1: The common three layer BMS structure described in [14]. Own illustration.

2. The middle layer (*Automation Level*) consists of controllers implementing control loops to meet configured set-points.

3. The top layer, the *Management Level*, usually consists of the computer hosting the BMS offering a user interface that allows configuring set-points as well as rules and schedules to change these. Examples of such simple rules are linear heating set-point curves based on current outdoor temperatures as well as scheduled operation such as nightly heating set-back lowering operating temperatures.

1.3 Contribution

The referenced efforts demonstrate the effectiveness of applying different methods of regression and optimization to implement data-driven predictive control strategies in buildings. They focus extensively on the development and execution of control strategies as well as the required information to assess performance, but they do not reference or propose a general methodology that applies to buildings equipped with BMS - regardless of the individual methods chosen for modeling and optimization. For example, the methodology proposed in [7] focuses purely on the setting studied: a thermal building simulation generates data for multiple hypothetical control variable scenarios to train neural networks. The Genetic Algorithm [8] relies on these to optimize the energy consumption while ensuring comfortable indoor conditions. However, the fact that large buildings typically have pre-existing automation infrastructure demands that this infrastructure shall be leveraged as much as possible when deploying predictive control strategies. To the best of our knowledge the literature currently lacks guiding researchers or practitioners on how to plan, develop, and deploy a system that enhances building operation efficiency levels using data-driven predictive control strategies and at the same time leverages pre-existing automation infrastructure.

This work addresses the identified methodological gap and proposes a systematic approach to develop and deploy data-driven predictive control strategies in buildings. It guides researchers as well as practitioners without prescribing or limiting the specific choice of methods. The proposed step-wise approach interprets buildings already equipped with BMS as Cyber-Physical Systems (CPS). In the context of buildings, the CPS approach means that "computers and networks monitor and control the [buildings'] physical processes, usually with feedback loops where physical processes affect computations and vice versa" [15]. The framework extends the building CPS concept with predictive capabilities and integrates two highly relevant approaches: the generic Model-Based Design Methodology for CPS [16] and the CRoss-Industry Standard Process for Data Mining [17].

Beyond the methodological contribution, this work provides reliable results for establishing confidence in using data-driven predictive control strategies in the routine operation of real deployments. On the one hand, this robustness stems from a prolonged experimentation period (43 experiment days). On the other hand, the Heating Degree Days concept [18] accounts for weather influences on energy consumption statistics. Statistical inference methods further improve the results' robustness. This combined robustness achieved by weather normalization, inferential methods, and prolonged experimentation is not commonly found in the literature. None of the referenced works applies statistical inference on collected data; all but [7] avoid accounting for weather-induced effects, and all but [7] use only a short period of experimental validation in a real building (if any).

Reference [7] is closest to our work. It mentions BMS integration, it performs prolonged experimentation, and it normalizes for weather conditions. Nevertheless, there are distinct differences between this work and [7], which are summarized as follows:

- [7] is not purely data-driven: it trains the predictive models using a thermal building simulation. This simulation allows a rich data-sampling to train the predictive models in various hypothetical scenarios. However, it requires the existence of digital building information for creating the simulation, e.g. CAD models. Unfortunately, these are not readily available to be used in simulations for a large fraction of the legacy building stock. For example, during the BaaS project [19] the Sierra Elvira School presented in Section 4 could not be modeled with sufficient accuracy for use in thermal building simulation tools - which effectively prevents using the approach of [7]. The present work focuses on general applicability to legacy buildings by not relying on thermal simulations - although these may be incorporated.

- The use of statistical inference methods on top of weather-normalized energy data.
- The framework proposed in Section 2 is of a more general nature than that of [7]: it describes the process of integrating building and system knowledge, identifying the control targets and operational constraints, and the BMS integration itself. Further, it allows for a variety of modeling and optimization techniques to be used.

This work validates the proposed approach by applying it to a public school building, the Sierra Elvira School, Granada, Spain. The school's architecture, its heating system components, as well as its mode of operation, can be considered as typical for the construction year (1975). Therefore, this work's replication potential is considerable. The case study serves to demonstrate the proposed approach regarding:

- *Flexibility.* This is shown by applying two different methods to model and optimize the building operation: (i) an explicit combination of multiple regression techniques optimized by the Genetic Algorithm and (ii) Reinforcement Learning, an integrated approach to modeling and optimization. While the methods applied are not novel, they demonstrate the approach's versatility. Using other methods of choice within the framework is straightforward.
- *Effectiveness.* This is shown by three different experiments executed in the day-to-day heating system operation for 43 school days. This prolonged experimentation phase exceeds most building control experiments documented in the literature. To achieve robust results weather is accounted for by appropriate normalization. Methods of statistical inference provide robust estimates of effect sizes and quantification of the associated uncertainties.
- *The capability to fully integrate pre-existing infrastructure.* The school's BMS is integrated into the predictive CPS by relying on standard protocols. That leverages the existing lower level control loops and sensors of the building automation infrastructure, making it an economically attractive reuse of capital expenditure.

1.4 Notation and Terms

Table 1 summarizes the different variables used in this paper. The table also provides an indication if there is a corresponding BMS variable accessible. Table 2 gives an explanation of terms.

Table 1: Variables used.

Param.	Description	BMS	Unit
a^i	Reinforcement Learning: control action to be taken at i		
adj. R^2	Coefficient of determination [20] adjusted for variables included in model		[0,1]
b^i	Biomass storage level	✓	kg
Cj	Heating Circuit j serving Zone j		
dow	Day of week		$\{1, .. 7\}$
$HDD18$	HDD for base temperature of 18°C		DD
hr^i	Relative humidity of outside air	✓	%
hr^i_{FC}	Relative humidity forecast for i		%
i	Quarter-hourly time-step i, i.e. quantized time		$\{0, .. 95\}$
j	Zone and Heating Circuit index		$\in \mathbb{Z}$
Max	Maximum of data		
Med	Median of data,		
M	Arithmetic mean of data		
Min	Minimum of data		
occ^i_r	Scheduled occupation of room r		$\{0, 1\}$
Q_{Cj}	Daily energy use of C_j	✓	kWh
r	Classroom r, assigned to building Zone Zj		
RMSE	Root Mean Squared Error [20]		
SD	Standard Deviation [20]		
SE	Standard Error [20]		
$t_{op,Cj}$	Daily Circuit j operation time	✓	h
T^t_{air}	Outside air temperature at t	✓	°C
T^i_{air}	Air temperature at time-step i	✓	°C
$T^i_{air,FC}$	Forecast of air temperature for time-step i		°C
$\overline{T_{air}}$	Daily mean air temperature	✓	°C
T^i_r	Classroom r temperature at i	✓	°C
T^i_{Zj}	Zone j mean temperature of occupied rooms at i	✓	°C
$\overline{T_{Zj}}$	School day average Zone j occupancy weighted mean temperature	✓	°C
T^i_{Cj}	Circuit j supply temperature	✓	°C
$\overline{T_{Cj}}$	Circuit j's daily mean supply temperature during operation	✓	°C
$T^i_{set,Cj}$	Set-point: Circuit j supply temperature at i	✓	°C
T_{target}	Indoor target temperature		°C
tol	Tolerance to target indoor temperature deviations		K
t	Continuous time		
ws^i	Outside wind speed	✓	m/s
ws^i_{FC}	Outside wind speed forecast		m/s
x^i	Reinforcement Learning building state at i		
Zj	Building Zone j, a collection of rooms r, served by Cj		

Table 2: Glossary.

Expression	Explanation
Building Information Model (BIM)	Digital representation of physical and functional characteristics of buildings.
Building Management System (BMS)	System controlling and monitoring a building's mechanical and electrical equipment.
Cyber-Physical System (CPS)	System composed of computers monitoring and influencing a physical process.
Energy Service Company (ESCo)	Company concerned with maintenance, operation, and monitoring of buildings, focusing on energy efficiency aspects.
Grid Search (GS)	Process of searching hyper-parameters for regression models: each parameter's range is discretized. If multiple parameters are to be searched, their discrete values span a multi-dimensional grid of parameter combinations to try.
Heating Circuit	A building's piping to distribute thermal energy (typically a heated fluid) in a building zone. It resembles a loop: starting from a thermal energy source the heated fluid is passed through the piping within a zone and returns cooled back to the heat source.
Heating Degree Day (HDD)	A measure of deviation of daily air temperature from a base temperature used for weather normalization [18]. See Equation 2.
Hyper-Parameter	Parameter defining regression model characteristics, e.g. number of neurons of a neural network.
Industry Foundation Classes (IFC)	A specific BIM standard: [21].
Pareto Front	The set of set-point choices according to multiple criteria (e.g. comfort and energy consumption) so that these cannot be changed to improve on all criteria simultaneously.
Percentile	Indicating the value below which a given percentage of observations in a group of observations fall. For example, the Median is the 50^{th} percentile.
Principal Components Analysis (PCA)	Statistical procedure that linearly transforms possibly correlated data into uncorrelated data.
Return Temperature	The temperature of a heating circuit's fluid returning to a heat source.
Set-point	A target value for a control loop to reach by control actions (e.g. drawing energy from a heat source a heating circuit's supply temperature can be increased to meet its set-point).
Standardization	Transforming data features to have similar center and spread, helping regression model accuracy.
Statistical Inference	Process to infer properties about a data population assumed to be larger than the observed dataset, taking into account the stochasticity of sampling.
Supply Temperature	The temperature of a heating circuit's fluid when it enters the circuit.
Weather Normalization	Accounting for weather influences on energy consumption statistics to allow comparisons across different years.
Zone	A specified area within a building. Often a collection of closely located rooms, e.g. a floor.

1.5 Structure

The remainder of this document is structured as follows: Section 2 proposes a framework to evolve legacy buildings into cyber-physical systems. Section 3 describes candidate techniques and methods to be used in each of the framework's steps. Section 4 introduces a case study together with data defining the reference period and a description of how the selected techniques are applied. Section 5 describes the heating control experiments that validate the overall approach. Section 6 discusses the framework proposed in Section 2 and provides a detailed analysis of the experimental results. Finally, Section 7 concludes the work and provides an outlook on future work. A provides the interested reader with more details on the integrated methodologies' steps and how the proposed framework's steps relate to these. B provides supplementary tables on the predictive accuracies of different regression techniques applied to the building studied as Section 3 focuses on the best performing models only.

2 How to Evolve Buildings into Predictive Cyber-Physical Systems

With the goal to steer building operation towards higher levels of efficiency, this section proposes a general framework to turn legacy buildings into predictive CPS. Typical medium/large-scale buildings are already equipped with automation infrastructure to a certain extent. Hence, the proposed concept leverages any pre-existing building automation infrastructure and deploys additional sensing equipment only when needed. The information provided by the building automation infrastructure, deployed sensors, and possibly other sources (e.g. internet services) is used to derive computational (or *cyber*) representations of the building and the associated physical processes. These representations enable the predictive optimization of building system parameters, e.g. a heating system's temperatures and operation schedules. The predictive CPS issues appropriate control commands to the building automation infrastructure to enact these. Thus, the CPS commands can also be denoted as supervisory. Figure 2 illustrates the overall concept.

For this purpose, the *Model-Based Design Methodology for CPS* (MBD-CPS) [16] lends itself to adaptation. Given a problem statement, it designs a complex multidisciplinary CPS from scratch by applying ten steps. In the context of buildings several of the MBD-CPS steps are already pre-determined. For example, the largest part of the hardware is already given, if the building is pre-equipped with automation infrastructure. Furthermore, many building processes - thermal processes in particular - have low requirements on delay, and jitter. Typically, their inertia is in the range of tens of minutes. This section selects MBD-CPS steps and adapts them to the context of predictive supervisory building control.

With access to BMS data, it is possible to use data-driven techniques to address the model identification step of MBD-CPS Step 2, see A. Conceptually this can be approached as a data mining project. Following that notion, it is prudent to apply the

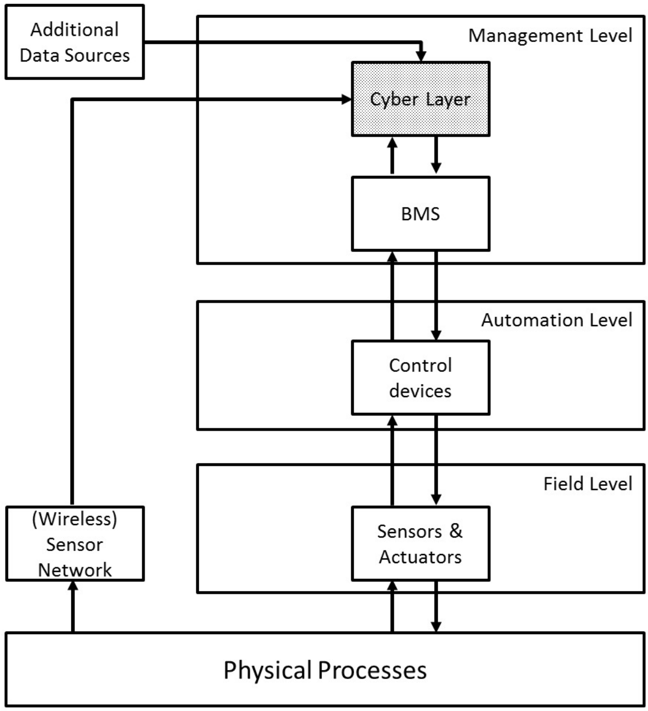

Figure 2: Integration of a predictive cyber layer (shaded) with the common three layer BMS structure described in [14] shown in Figure 1. Arrows indicate flows of information and interaction.

standard data mining methodology *CRoss-Industry Standard Process for Data Mining* (CRISP-DM). Consisting of six phases, the CRISP-DM reference model [17] applies to data mining projects in general. Inspired by both MBD-CPS and CRISP-DM, the following steps are proposed to build a closed-loop CPS reusing the already installed building infrastructure. The individual steps map to CRISP-DM and MBD-CPS as indicated in brackets. Not necessarily all steps are executed in sequence, and some may be repeated. Figure 3 provides a high-level illustration of the framework and A provides more details both MBD-CPS and CRISP-DM and their relation to the different steps.

1. Offline phase:

   (a) Business target, data, and system understanding (CRISP-DM 1, 2; MBD-CPS 1, 3)

   Before any in-depth analytical work, it is necessary to investigate the available data sources and to understand the business target. Also, the possible ways of interacting with the building infrastructure need to be understood. This

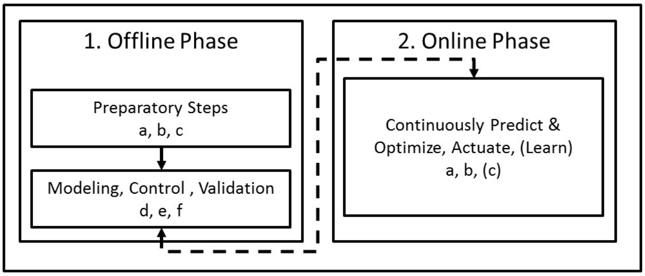

Figure 3: The offline phase consists of a preparatory phase (steps 1a-1c) and a phase of data-driven modeling, control and validation (steps 1d-1f). Once control is validated, online phase 2 continuously executes steps 2a, 2b, and optionally 2c. The dashed arrow indicates that step 1f may use phase 2 already and that step 2c may re-execute steps 1d and 1e.

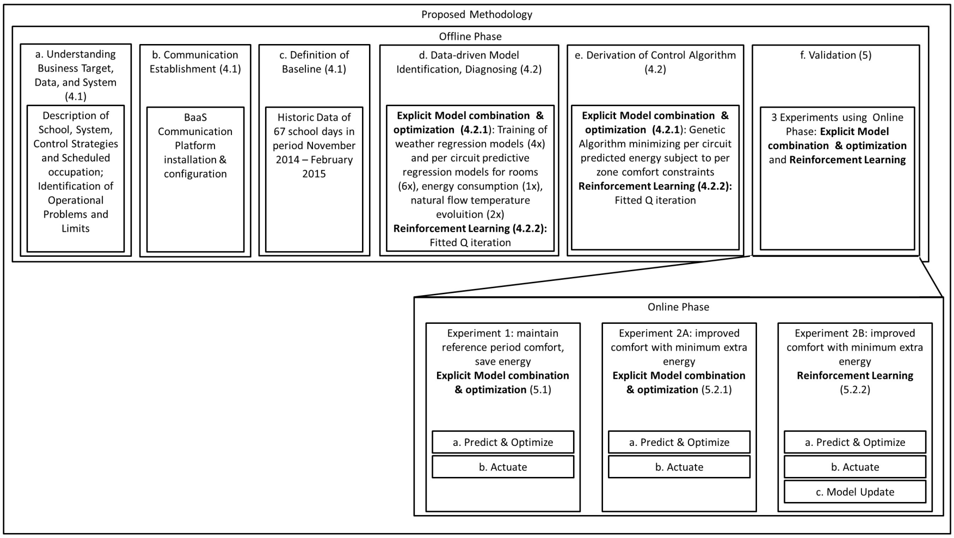

Figure 4: Methodology applied to the Sierra Elvira School case study. Section 4 covers the majority of the offline phase, the experimental validation is documented in Section 5. Numbers in brackets indicate the subsections documenting the particular steps.

assessment reveals if additional sensor, meter, or actuator installations are required, or if additional data sources such as internet services need to be taken into account. The assessment also defines the space of possible solutions and methods to apply. In the worst case, the building situation is such that the goal of energy efficiency with the help of a predictive CPS control is technically or economically infeasible. This outcome requires abandoning the project.

(b) Establishment of communication, possibly with additional installations as needed (CRISP-DM 3, MBD-CPS 6)

If the preceding assessment concludes that the overall goal may be reached, establishing a bi-directional communication with the building infrastructure, e.g. with the BMS, allows extraction of relevant operational data and instruction with actuation commands.

(c) Definition of a reference baseline for performance assessment (CRISP-DM NA, MBD-CPS NA)

Defining a performance baseline enables quantifying the effectiveness of the predictive control. Both historical information or data collected by the communication platform during a monitoring phase can serve to set the baseline.

(d) Data-driven model identification including diagnosing (CRISP-DM 4, 5; MBD-CPS 2, 3)

Relevant control variables are identified from system specifications and in discussions with operational experts. In light of these variables, based on a suitable amount of data, predictive models of the building's thermal and energetic behavior are derived. This *Model Identification* step [22] may benefit from commonly used data preparation techniques such as data standardization. Sensitivity analysis techniques can assess the identified models' robustness to changing input data.

Information from building experts gives valuable insights for developing the models. However, the selection of an appropriate modeling technique depends on the individual building, its systems, and the intended use case. Further, it also depends on the information sources' characteristics and the technical skills available to the project. The building's system configuration may also require a combination of multiple models: for example, large HVAC system installations may require a hierarchy of models (possibly of different types) to accurately reflect their various components. If available, digital information on the building and its facilities stored in a *Building Information Model* (BIM), e.g. compliant to the *Industry Foundation Classes* (IFC) standard [21], can be incorporated in the model identification. For example, [23] suggests two alternative approaches to deriving thermal building simulation models from BIM data as received from architectural CAD tools - which then allows pursuing the approach of [7]. Another possible use is the Building Energy Model Recommendation System proposed in [24] to guide the model type selection.

(e) Derivation of control algorithm subject to targets and specified constraints (CRISP-DM 4, 5; MBD-CPS 3, 4, 5)

In this step, it is necessary to form an understanding of the different systems under study with their individual operation needs and constraints. Typically, meetings with technical staff and the study of corresponding documentation provide the required information. Further, an analysis of the baseline data used in Step 1c may also provide deep insights into the status-quo operation as shown e.g. in our earlier work in a German soccer stadium [25]. Also the project goals influence the choice of constraints, e.g. concerning thermal comfort. The modeling language proposed in [26] could be one way to express application-specific as well as system-specific constraints. Depending on the building and the system to be optimized, the required complexity of the control may vary. For example, large HVAC system installations may require a hierarchy of decisions to reflect different distribution elements and branches accurately.

(f) Simulation / validation (CRISP-DM 5; MBD-CPS 7, 10)

Using thermal building simulation tools for validating the predictive models' accuracies and the control algorithm's performance allows gaining confidence in the approach before deploying it in the real building. Alternatively, it is also possible to use experimental validation with close supervision by staff. In the latter case, this step blurs the demarcation line to the subsequent online phase.

2. Online (productive) phase - loop over: (CRISP-DM 6; MBD-CPS 8, 9, 10)

(a) Predict & Optimize

With the model(s) developed in steps 1e and 1e it is possible to anticipate effects of different control decisions within a problem specific prediction horizon. These predictions are key to identifying the optimal decisions as described e.g. in Sections 3 and 4.

(b) Actuate

The predictive CPS control decisions are then communicated in the form of adjusted set-points to the BMS at appropriate times. The BMS enforces these via lower level control loops in the building's automation infrastructure. This approach of reusing the BMS as building actuation gateway prevents situations where predictive control commands conflict with the lower layer automation infrastructure. Special attention is required in cases where the BMS has its own pre-programmed logic of set-point manipulation, or when a human operator has the possibility to modify set-points manually. In these cases, appropriate measures need to be taken to avoid confusion or conflict. Possible means are communication with staff about the presence of predictive CPS control, as well as the possibility to switch the BMS between enacting (i) its internal logic and (ii) supervisory control commands received from the CPS.

(c) Optional: continuous adaptation of the predictive models based on prediction errors

As the predictive CPS controls the building systems and collects more data, it is sensible to continue fine-tuning the predictive models to increase their predictive accuracies and also account e.g. for any systemic changes such as deteriorating equipment.

To implement the methodology fully and efficiently a variety of factors needs to be accounted for. The next sections focus on the approach's core aspects to realize end-to-end scenarios. Several related aspects, such as database design or user experience are not addressed in detail for brevity. Figure 4 depicts the correspondence of methods, steps, and subsections of this study.

3 Methods to Apply and Evaluate the CPS Methodology

3.1 Method of Communication with the Building Instrumentation

A cornerstone of the proposed concept is bi-directional communication with the deployed BMS. A variety of standard protocols exist in the building automation domain, and thus, depending on the specific building, it is necessary to implement different interfaces. To abstract from the various field level protocols encountered in buildings such as BACnet/IP and OPC, the BaaS project [19] developed a modular communication platform [27]. This platform provides higher layer analytics and optimization services with a uniform interface to the building instrumentation. The modular design allows extending the platform with functionalities (e.g. new automation protocols) as needed. The platform also allows integrating other relevant information such as weather forecasts [28].

3.2 Methods for Data-Driven Predictive Heating Optimization

This work uses two different data-driven approaches to model thermal building dynamics and to optimize control decisions, demonstrating the flexibility of the proposed step-wise procedure introduced in Section 2. This subsection outlines the general concepts of both approaches. As both are designed to operate on numeric features, it is necessary to map categorical features to numeric values.

Explicit Model Combination and Optimization

The first approach to model building dynamics is rooted in an explicit combination of room temperature regression models per building zone, and estimating the associated energy use of the respective heating circuit. Studying the effect of different supply temperature set-point choices as input to these regression models allows optimizing the heating operation.

Modeling: The following general process generates predictive models for the various parameters required to optimize the heating system operation. The steps denoted *GS* indicate a *Grid Search* (Table 2) in the space of possible parameter combinations.

1. Identification of influencing variables based on information provided by the building's operational staff, stored in BIM, and by exploratory data analysis.
2. Creation of input feature vectors from relevant data. (GS)
   (a) The data is partitioned into datasets for training and testing of the models.
   (b) Standardization of each input feature of the training dataset to be centered around the origin with a standard deviation of 1 by shifting each feature datum by the feature's mean and dividing by its standard deviation.
   (c) Test if the application of Principal Component Analysis (PCA) to the input features and retaining principal components accounting for a pre-defined level of variation increases model accuracy. In some cases this technique may improve regression model generalization performance as high-frequency noise is disregarded [29]. Typical choices of retained variation found in the literature are 90%, 95%, or 99%. This step reduces feature vector dimensionality.
3. Predictive model training with 10-fold cross validation and five repetitions. Selection of the combination of regression technique, its tuning parameters, and input feature vector definition resulting in the best predictive performance (GS). Each technique is evaluated regarding predictive performance with the Root Mean Squared Error (RMSE) metric [20]:
   - As training uses five repetitions of 10-fold cross-validation, this RMSE is an average constituted by the five individual repetitions' RMSEs.
   - Based on the standard deviation of the individual repetitions' RMSEs, the associated standard error (SE) is calculated to express the reliability of the RMSE estimate.
   - Using a separate test set the models are re-tested to confirm that the resulting test set RMSE is within the 95% confidence interval.

Concerning Step 3, this work studies four different non-linear regression techniques:

- Multi-Layer Perceptron (MLP). This neuro-computing inspired technique has been applied in a variety of settings and applications in the artificial intelligence literature. [30] successfully uses it to model residential HVAC systems. Also, [5–7] rely on this technique.
- Bayesian Regularized Artificial Neural Network (BRANN), a technique extending MLP with the aim to prevent overfitting by penalizing imbalances in neural network weights [31].
- Support Vector Machines (SVM) with Radial Basis Function (RBF) Kernel. SVM have been proposed and evaluated to predict both the total short-term electricity load and the short-term loads of individual building service systems (air conditioning, lighting, power, and other equipment) that have electricity sub-metering systems installed [32].

- Gaussian Process (GAUSS) with RBF Kernel. For example, [33] applies this regression technique to predict building indoor temperature evolution. In simulations, the approach outperformed benchmark models for occupied times, especially when faced with previously unseen ambient temperatures.

Optimization: Understanding the building's response to particular set-point choices allows quantifying the effects associated with specific decisions. It is necessary to formulate the target outcome to derive a schedule of set-point adjustments over a prediction horizon. Typically it is possible to:

1. optimize the indoor temperature during occupation, i.e. minimize the temperature deviations from a target temperature,

2. minimize energy consumption, or

3. optimize a weighted mixture of the criteria, a so-called multi-objective optimization.

Constraints on maximum acceptable deviation from target comfort levels, or from a predetermined energy budget can be taken into account to ensure required performance.

Based on the selected criteria to optimize, it is possible to formulate a so-called *cost function* to derive the effects of set-point adjustments from the predictive models.

When the identified models are not of closed form, meta-heuristics are a common approach to optimizing cost functions. These heuristics often are inspired by nature as evident in the following:

- A commonly used heuristic is the *Genetic Algorithm* introduced in [8]. Inspired by natural selection and genetic recombination this stochastic search technique operates on a *population* of different possible candidate solutions. The population members' *chromosomes* consist of multiple *genes* (specific choices for optimization variables - e.g. heating system set-points). Over multiple evolutionary iterations, the genes of the fittest population members (in terms of a problem specific cost function) are stochastically mutated and exchanged to improve the solution. For example, [34] demonstrates its use for scheduling HVAC operation decisions: validation by simulation indicates system operation cost savings of 56% and improvements in thermal comfort.

- Another popular optimization heuristic is the *Particle Swarm Optimization* (PSO) that relies on a population (denoted *swarm*) of candidate solutions (denoted *particles*). The heuristic is based on a gravitational metaphor to iteratively update the particles according to simple rules of attraction and each particle's inertia. Various variants and applications exist as illustrated in [35]. For example, [5] extends the standard PSO with the ability to address multiple objectives to calculate the Pareto front of HVAC operation defined by energy consumption and comfort related parameters. This Pareto front allows specifying a trade-off between saving energy and addressing comfort aspects.

- While multiple other nature-inspired meta-heuristics for optimization exist, [36] argues most of these only differ marginally from PSO. For example, the *Firefly Algorithm* [37] (inspired by the flashing behavior of fireflies aiming to attract other fireflies (configurations of decision variables)) is for specific parameterizations equivalent to PSO. [4] successfully applies the Firefly Algorithm to optimize multi-zone HVAC operation in a dedicated HVAC test facility, outperforming PSO. To improve the balance between the exploration and exploitation [38] modifies the Firefly Algorithm's attraction equation with Gaussian distributions to avoid premature convergence to local minima. The work validates the approach using building simulation and attempts to minimize the energy consumption of two multi-chiller HVACs by distributing the chillers' loads optimally. Compared to other meta-heuristics, the results show improvements on one dataset and competitive performance on the other.

- An additional nature-inspired meta-heuristic similar to PSO is *Cuckoo Search* [39]. That heuristic identifies problem solutions with bird nests and decision variable selections as eggs within the nests. The algorithm draws on cuckoos placing eggs at random in the nests and an evolutionary aspect in that the best nests (containing high-quality eggs) will carry over to the next generation. However, for bad nests, the host bird owning the nest may discover the cuckoo egg and throw it away or even abandon the nest only to build an entirely new nest with a configurable probability. This concept is extended by [40] with a differential approach that lends a mutation operation inspired by the Genetic Algorithm to avoid that local search gets stuck in local minima. [40] applies the concept to slightly different case studies than [38] but achieves qualitatively similar results.

- *Simulated Annealing* is another prominent optimization heuristic. Its main operation consists of a local search to minimize a problem specific cost function. As local search methods are prone to get trapped in local optima, Simulated Annealing attempts to avoid entrapment in local optima by sometimes proposing a move to candidate solution that increases (worsens) the value of the cost function. Based on a configurable acceptance probability this uphill move may or may not be accepted. Focused on single objective optimization [41] uses a Genetic Algorithm's solution as the initial parameter configuration of a simulated annealing algorithm modified to avoid uphill exploration. [41] applies the proposed hybrid optimization scheme to a facade optimization planning problem in different climates validated by a building simulation. The documented case studies show that the combination both optimization heuristics achieves robust optimization results and reduces computational complexity compared to a repetitive use of the Genetic Algorithm to verify the optimization outcome.

As the focus of this work is to demonstrate the proposed methodology's flexibility concerning the choice of specific modeling and optimization techniques, we adopt the Genetic Algorithm for the approach of *Explicit Model Combination and Optimization*. This choice is prudent as according to survey [42] it is the most widely used optimization technique in the buildings control field. It is straightforward to replace the Genetic Algorithm with any of the other heuristics discussed. For optimizing the building operation, a prediction horizon of one time-step is chosen.

Optimization with Implicit Modeling: Reinforcement Learning

Reinforcement Learning is a well-established approach to dynamic optimization, especially in robotics and other applications of artificial intelligence. In contrast to evolutionary methods such as the Genetic Algorithm, it is closely related to dynamic programming and therefore closer to the field of control theory. For example, [9–13] successfully applied this approach to different aspects of improving building operation efficiency levels. As this work adopts a data-driven approach to building optimization, it uses *Fitted Q-Iteration* [43] - a specific Reinforcement Learning algorithm that is suitable for situations where the underlying model is unknown. Typically, the approach requires three components:

- The action a, e.g. set-point adjustments.
- Information state x. It captures information relevant to the building operation, identified in modeling process step 1 presented in the previous section.
- A reward function f to express application specific rewards. If rewards are negative, f is a penalty or cost function. In either case, f can represent a single objective or a weighted combination of multiple objectives.

At each instant t, Fitted Q-Iteration aims to maximize anticipated rewards. To do so, it relies on a learned mapping of how choosing a specific action a^i in current state x^i will evolve the state to x^{i+1} and which reward f^{i+1} can be expected. In this anticipated state, a^{i+1} can be chosen that will result in state x^{i+2} and reward f^{i+2}. Repeating this for a planning horizon, actions can be scheduled to maximize the anticipated rewards.

3.3 Methods for Experiments Analysis

Zonal Aggregation of Indoor Temperature Levels

The indoor temperature is a key aspect defining the acceptability of heating system strategies to occupants. When a building zone comprising of multiple rooms is impacted by a shared heating infrastructure, aggregation of room temperatures is required. The way of aggregation has strong effects on control decisions and performance assessment. For example, aggregating multiple rooms based on minimum indoor temperature will result in higher set-point choices and higher energy consumption as the coldest room dominates the zone. The other extreme is an optimistic setting - multiple rooms are aggregated based on maximum indoor temperature, resulting in lowered set-points and consumption. Between both extremes exist many possible options, the choice of which is application dependent: the simple arithmetic mean where each room has equal weight, a weighted average e.g. based on floor area or the number of occupants.

This work assesses how predictive strategies affect indoor climate by the simple arithmetic mean of a zone's rooms. Further, as the heating system's objective is to provide comfort during scheduled class hours, the control performance is assessed by the *occupancy weighted mean zonal temperature* (denoted T^i_{Zj}). Equation 1 defines it as the arithmetic mean of all occupied rooms' temperatures within a zone at a specific point in time. The indicator is undefined for outside class hours. Averaging this performance indicator over the scheduled classes allows assessing an entire school day (denoted $\overline{T_{Zj}}$). Equation 1 is undefined for days without classes.

$$T^i_{Zj} = \frac{\sum_{r \in Zj} occ^i_r T^i_r}{\sum_{r \in Zj} occ^i_r} \tag{1}$$

Energy Data Normalization

The widely used Heating Degree Day normalization mechanism [18] makes it possible to account for changing weather conditions across different years. The mechanism leverages the insight that building energy consumption is linear with the outside air temperature (T_{air}). It normalizes energy use by dividing Q by a normalization factor HDD that captures the extent to which T_{air} is below a use case specific *base temperature* ($T_{HDD,base}$).

$$HDD = \int f(t)dt \tag{2}$$

where

$$f(t) = \begin{cases} T_{HDD,base} - T^t_{air} & T_{HDD,base} > T^t_{air} \\ 0 & T_{HDD,base} \leq T^t_{air} \end{cases} \tag{3}$$

T^t_{air} denotes the air temperature at time t within a day. In practice, due to finite time resolution and possibly unreliable weather data, different approximations and quantizations to equations 2 and 3 are used. Following [44], this work relies on daily mean air temperature ($\overline{T_{air}}$) for normalization:

$$HDD \approx \begin{cases} T_{HDD,base} - \overline{T_{air}} & T_{HDD,base} > \overline{T_{air}} \\ 0 & T_{HDD,base} \leq \overline{T_{air}} \end{cases} \tag{4}$$

For the experimental validation presented in the next sections, the experts managing the building's operation defined this work's HDD base temperature as 18°C (indicated in the subscript: $_{HDD18}$). This work uses daily energy consumption and daily HDD to build meaningful statistical samples for analysis as described in the following subsection.

Descriptive and Inferential Statistics

For analyzing the statistics of observed data, this work uses standard measures of *descriptive* statistics: Minimum (Min.), Maximum (Max.), Median (Med.), Mean (M) and Standard Deviation (SD). Descriptive statistics are focused on describing the properties of the observed data and does not assume that the observations are sampled from a

Figure 5: Main building of Sierra Elvira School, built in 1975.

larger population. However, a change to control strategies can also be interpreted as a change to population characteristics. Therefore, *inferential* statistics are applicable for analyzing the effects of changing heating strategies.

The process of statistical inference deduces properties of an underlying distribution by analysis of data. It allows inferring the strategies' statistics of interest (e.g. the mean of the observed daily $Q_{Cj,HDD18}$) and quantifying the associated uncertainty. Further, statistical inference also allows robustly estimating the pairwise differences between two datasets' statistics. That enables pairwise comparisons of the strategies' effects with an associated measure of uncertainty. As the experiments in this study lasted several school weeks, the data sample per experiment is small. Therefore, the Student's t-distribution is used to construct confidence intervals around the statistics of interest. In cases where the underlying assumptions of the t-distribution are not met (normality - tested with the Shapiro-Wilk test implemented in R [45] - and independence of observed data samples), we apply the common technique of bootstrapping to validate the results.

4 Case Study: Sierra Elvira School Building

This section follows the high-level steps described in Section 2 by applying the methods identified in Section 3 to a real building in daily operation. The correspondence of methods, steps, and subsections is visualized in Figure 4.

4.1 Building and System Description

This section addresses steps 1a, 1b, and 1c of the proposed framework. The Sierra Elvira School is an elementary school located in the city of Granada, Spain. Its hydronic

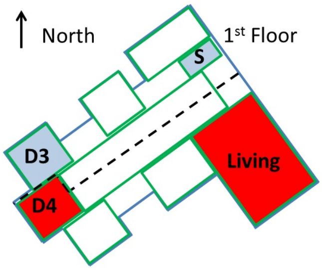

Figure 6: Distribution of the monitored rooms in the different floors of the Sierra Elvira School (Circuit 1 rooms red, Circuit 2 rooms light blue). Room indicator abbreviations: C=Computer, M=Music, S=Secretary, D3=Dinner (age 3), D4=Dinner (age 4)

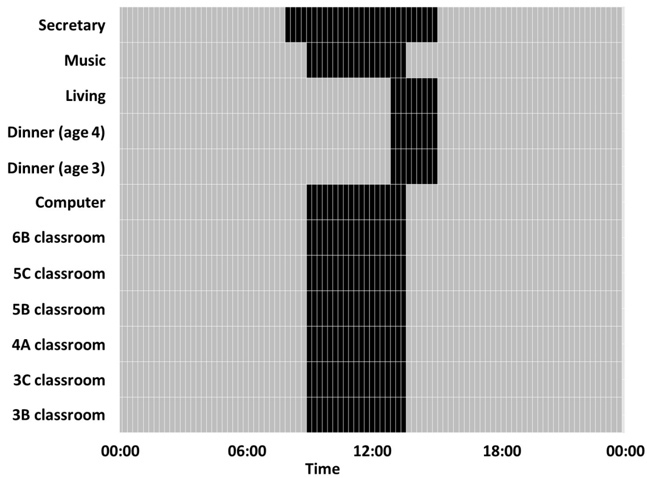

Figure 7: Scheduled room occupancy (black=occupied) in quarter-hourly intervals.

heating system consists of a single biomass boiler (energy price €0.068/kWh) serving three heating distribution circuits, each with a maximum allowed supply temperature of 70°C. The zones are composed of several rooms of varying sizes and usage patterns: regular classrooms, a music room, a computer room, multiple dining halls, and a library. According to each room's size, the number of radiators varies.

Two of the heating circuits serve the school's older three-story main building shown in Figure 5, i.e. $j \in \{1, 2\}$. It was built in 1975 with a low level of thermal insulation and with poor air-tightness. The building's indoor temperatures are known to be uncomfortably low in winter. The third circuit exclusively serves a newly constructed building

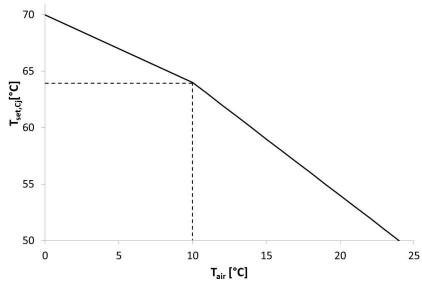

Figure 8: Current best practice operation: circuits' supply temperatures $T^t_{set,Cj}$ are chosen as a function of T^t_{air}. At T^t_{air} = $10°C$, the slope changes from -0.6 to -1.0.

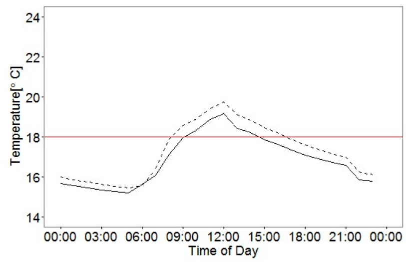

Figure 9: Hourly profile: average indoor temperatures per building zone (Zone 2: dashed line) on 67 school days with active heating in the reference period November 2014 - February 2015. Red line indicates the reference control temperature target of 18°C, derived from Table 3.

containing the library. That building has an improved level of insulation and adequate indoor temperature levels. The remainder of this work focuses on managing the school's main building to improve its indoor conditions under energetic considerations.

In 2014, as a result of the first step of the proposed methodology (assessment of data available), temperature sensors were installed in 12 rooms of the main building and integrated with the BMS. Consequently, the BMS monitors six rooms per building zone. The monitored rooms are located in different corners of the building as well as on different floors (Figure 6). The BMS provides data from a local weather station measuring air temperature, wind speed, wind direction, and relative humidity; the heating circuits' supply and return temperatures; the circuits' energy meters; the circuits' supply temperature set-points; and the biomass storage level. The BaaS middleware platform [27] retrieves these 25 variables from the school's BMS via a standard BACnet/IP protocol interface in quarter-hourly time-steps (indexed with i). The same interface allows setting the circuits' supply temperature set-points. Figure 7 illustrates the daily scheduled occupation of the monitored rooms: for classrooms between 09:00 - 13:30, for the secretary 08:00 - 15:00 and for dining and living rooms 13:00 - 15:00.

The status quo heating strategy is static: during scheduled operating hours, each circuit's supply temperature is defined by equation 5 (illustrated in Figure 8) as a function of the outdoor temperature. During winter, the school's heating system operates on Mondays 06:00 - 17:00 and on the other school days 06:00 - 13:30. Otherwise, the heating system is inactive for periods without occupation: nights, weekends, and holidays. Compared to the scheduled occupation, the reference period operation strategy already exploits the school building's thermal inertia to some extent during Tuesday to Friday: heating system operation ends before the last scheduled occupation of the secretary's room, the living room, and the dining rooms.

Table 3: Descriptive statistics of 67 school days in reference winter 2014/2015.

	$\overline{T_{Z1}}$ [°C]	$\overline{T_{Z2}}$ [°C]	$Q_{C1,HDD18}$ [kWh/DD]	$Q_{C2,HDD18}$ [kWh/DD]
Min.	12.9	13.8	8.9	9.3
Med.	18.0	18.4	33.0	33.7
M±SD	18.0±2.2	18.6±2.3	33.7±11.6	34.8±11.6
Max.	21.9	23.2	71.6	78.1

$$T^t_{set,Cj} = \begin{cases} 70 - \max(0, T^t_{air}) \times 0.6, & \text{if } T^t_{air} \leq 10°\text{C}. \\ 64 - (T^t_{air} - 10) \times 1.0, & \text{otherwise.} \end{cases} \tag{5}$$

Table 3 presents the descriptive statistics for the reference period 2014/11/02-2015/02/28 based on data recorded by the operational staff. The table provides the daily average occupancy weighted mean zonal temperatures and the heating circuits' daily weather-normalized energy consumptions. The statistics exclude weekends, holidays, and the first day following the winter holidays from the analysis as the associated indoor temperature levels were extremely low. Further excluded are days in the period February 23$^{\text{rd}}$ - 28$^{\text{th}}$ due to a data recording gap. Hence, the statistics in Table 3 cover 67 representative winter school days considered as the reference baseline. From both zones' median and mean temperatures a reference period target indoor temperature of approximately 18°C can be inferred. Figure 9 depicts the hourly averages of zonal indoor temperatures of the considered school days (note that this figure does not take into account occupation weighted averaging as Equation 1 is undefined outside school hours). It shows that on average, both zones reach 18°C until 09:00, and that Zone 2 reaches higher temperatures than Zone 1. The latter is surprising as Zone 1 is facing south. However, an exploratory analysis reveals that the living room's temperature levels are considerably lower when unoccupied than the other rooms due to low levels of insulation and low air-tightness - which in turn reduces the average temperature of Zone 1.

4.2 Data-Driven Modeling and Predictive Control of the Heating Operation

Mapping to the methodology steps 1d and 1e, this section documents the application of two different data-driven modeling approaches to the Sierra Elvira School as introduced in Section 3.2. The first explicitly combines several regression models describing various building dynamics of interest for heating system operation. The second approach treats the different building components as a single black box and focuses on learning and optimizing a combined cost function using Reinforcement Learning.

Explicit Model Combination and Optimization

This section summarizes the results of applying the modeling process presented in Section 3.2 to data of the reference period November 2014 - February 2015. The overall concept of this approach is to predict the temperature evolution of each of the 12 monitored rooms one time-step into the future. Zonal aggregation per Equation 1 allows deciding on supply temperatures resulting in acceptable indoor comfort levels. To do so, this approach needs to take weather parameters, the relevant circuit's supply temperatures, and the individual room's prior temperatures into account. Understanding the circuits' energy consumption patterns is key to also optimize heating decisions from an energy perspective.

In line with the BMS polling interval, time is discretized into quarter-hourly time-steps. The categorical feature of scheduled room *occupation* maps to a binary representation (0/1, denoted occ_r^i). This feature influences the calculation of Equation 1 which in turn influences the Genetic Algorithm's assessment of zonal temperature constraints. Further, occupation impacts classroom temperature predictions due to the occupants' body heat. The second categorical feature to consider is the day of the week (dow). It is mapped to integer values $dow \in \{1, \dots 7\}$. After this mapping, all features are numeric and subject to standardization as described in Section 3.2. Table 4 summarizes the models performing best, i.e. the models and hyper-parameters exhibiting lowest RMSE, based on the reference period data along with the input features used. Refer to B for more extensive details on model performances.

Model 1 - Room Indoor Temperatures: Studying the 12 monitored rooms' indoor temperature data, [46] identified that training for each classroom an individual regression model promised to capture their individual characteristics best. When comparing the different regression techniques' performances, BRANN consistently outperformed the others. Pre-processing input vectors with PCA retaining 95% of variation helps model performance. A zonal aggregation of the rooms allows deciding supply temperature set-points with consideration of the impact on zonal indoor temperatures.

For each of the rooms, the following input feature vector definition derived from a parameter grid search performed best, resulting in feature vectors $\in \mathbb{R}^{21}$:

- the four last measurements of each of the parameters T_{air}, hr, ws, and respective heating circuit's T_{Cj},
- the three last measurements of the respective room's *indoor temperature* T_r,
- the scheduled occupation occ_r, and
- the weekday - dow.

Table 4: Best performing regression models for Sierra Elvira School when executed at time-step t^i. See also B.

Model	Technique	RMSE	SE	Input features, normalized
Model 1 - Zone 1 indoor temperature prediction models, all with PCA retaining 95% of variation.				
3B classroom	BRANN, 30n	0.16 K	0.009 K	$T_{air}^{\{i-3,..i\}}$, $T_{C1}^{\{i-3,..i\}}$, $T_{hr}^{\{i-3,..i\}}$, $T_{ws}^{\{i-3,..i\}}$, $T_{3B}^{\{i-2,..i\}}$, occ_{3B}^{i}, dow
3C classroom	BRANN, 10n	0.25 K	0.011 K	$T_{air}^{\{i-3,..i\}}$, $T_{C1}^{\{i-3,..i\}}$, $T_{hr}^{\{i-3,..i\}}$, $T_{ws}^{\{i-3,..i\}}$, $T_{3C}^{\{i-2,..i\}}$, occ_{3C}^{i}, dow
4A classroom	BRANN, 20n	0.23 K	0.013 K	$T_{air}^{\{i-3,..i\}}$, $T_{C1}^{\{i-3,..i\}}$, $T_{hr}^{\{i-3,..i\}}$, $T_{ws}^{\{i-3,..i\}}$, $T_{4A}^{\{i-2,..i\}}$, occ_{4A}^{i}, dow
6B classroom	BRANN, 50n	0.16 K	0.012 K	$T_{air}^{\{i-3,..i\}}$, $T_{C1}^{\{i-3,..i\}}$, $T_{hr}^{\{i-3,..i\}}$, $T_{ws}^{\{i-3,..i\}}$, $T_{6B}^{\{i-2,..i\}}$, occ_{6B}^{i}, dow
Dinner (age 4)	BRANN, 20n	0.17 K	0.009 K	$T_{air}^{\{i-3,..i\}}$, $T_{C1}^{\{i-3,..i\}}$, $T_{hr}^{\{i-3,..i\}}$, $T_{ws}^{\{i-3,..i\}}$, $T_{D4}^{\{i-2,..i\}}$, occ_{D4}^{i}, dow
Living	BRANN, 10n	0.18 K	0.012 K	$T_{air}^{\{i-3,..i\}}$, $T_{C1}^{\{i-3,..i\}}$, $T_{hr}^{\{i-3,..i\}}$, $T_{ws}^{\{i-3,..i\}}$, $T_{L}^{\{i-2,..i\}}$, occ_{L}^{i}, dow
Model 1 - Zone 2 indoor temperature prediction models, all with PCA retaining 95% of variation.				
5B classroom	BRANN, 10n	0.18 K	0.015 K	$T_{air}^{\{i-3,..i\}}$, $T_{C2}^{\{i-3,..i\}}$, $T_{hr}^{\{i-3,..i\}}$, $T_{ws}^{\{i-3,..i\}}$, $T_{5B}^{\{i-2,..i\}}$, occ_{5B}^{i}, dow
5C classroom	BRANN, 50n	0.32 K	0.018 K	$T_{air}^{\{i-3,..i\}}$, $T_{C2}^{\{i-3,..i\}}$, $T_{hr}^{\{i-3,..i\}}$, $T_{ws}^{\{i-3,..i\}}$, $T_{5C}^{\{i-2,..i\}}$, occ_{5C}^{i}, dow
Computer	BRANN, 20n	0.09 K	0.005 K	$T_{air}^{\{i-3,..i\}}$, $T_{C2}^{\{i-3,..i\}}$, $T_{hr}^{\{i-3,..i\}}$, $T_{ws}^{\{i-3,..i\}}$, $T_{Co}^{\{i-2,..i\}}$, occ_{Co}^{i}, dow
Dinner (age 3)	BRANN, 20n	0.26 K	0.019 K	$T_{air}^{\{i-3,..i\}}$, $T_{C2}^{\{i-3,..i\}}$, $T_{hr}^{\{i-3,..i\}}$, $T_{ws}^{\{i-3,..i\}}$, $T_{D3}^{\{i-2,..i\}}$, occ_{D3}^{i}, dow
Music	BRANN, 10n	0.24 K	0.020 K	$T_{air}^{\{i-3,..i\}}$, $T_{C2}^{\{i-3,..i\}}$, $T_{hr}^{\{i-3,..i\}}$, $T_{ws}^{\{i-3,..i\}}$, $T_{M}^{\{i-2,..i\}}$, occ_{M}^{i}, dow
Secretary	BRANN, 20n	0.28 K	0.018 K	$T_{air}^{\{i-3,..i\}}$, $T_{C2}^{\{i-3,..i\}}$, $T_{hr}^{\{i-3,..i\}}$, $T_{ws}^{\{i-3,..i\}}$, $T_{S}^{\{i-2,..i\}}$, occ_{S}^{i}, dow
Model 2 - Heating circuit energy consumption models.				
Q_{C1}	BRANN, 15n	43.76 kWh	7.31 kWh	$t_{op,C1}$, $\overline{T_{air}}$, $\overline{T_{C1}}$
Q_{C2}	BRANN, 3n	25.17 kWh	4.74 kWh	$t_{op,C2}$, $\overline{T_{air}}$, $\overline{T_{C2}}$
Model 3 - Micro-climatic models				
T_{air}	BRANN, 5n	1.47 K	0.14 K	$T_{air}^{\{i-3,..i\}}$, $T_{air,FC}^{i+1}$
hr	BRANN, 20n	4.20 %	1.98 %	$T_{hr}^{\{i-3,..i\}}$, $T_{hr,FC}^{i+1}$
ws	BRANN, 2n	1.72 m/s	1.97 m/s	$T_{ws}^{\{i-3,..i\}}$, $T_{ws,FC}^{i+1}$
Model 4 - Day start heating circuit supply temperature models				
T_{C1}	BRANN, 5n	0.58 K	0.22 K	$T_{air}^{\{i-3,..i\}}$, $T_{hr}^{\{i-3,..i\}}$, $T_{ws}^{\{i-3,..i\}}$, $T_{C1}^{\{i-2,..i\}}$, dow
T_{C2}	BRANN, 5n	0.51 K	0.20 K	$T_{air}^{\{i-3,..i\}}$, $T_{hr}^{\{i-3,..i\}}$, $T_{ws}^{\{i-3,..i\}}$, $T_{C2}^{\{i-2,..i\}}$, dow
Model 5 - Day end heating circuit supply temperature models				
T_{C1}	BRANN, 3n	2.19 K	0.66 K	$T_{air}^{\{i-3,..i\}}$, $T_{hr}^{\{i-3,..i\}}$, $T_{ws}^{\{i-3,..i\}}$, $T_{C1}^{\{i-2,..i\}}$, dow
T_{C2}	BRANN, 5n	2.09 K	0.63 K	$T_{air}^{\{i-3,..i\}}$, $T_{hr}^{\{i-3,..i\}}$, $T_{ws}^{\{i-3,..i\}}$, $T_{C2}^{\{i-2,..i\}}$, dow

Model 2 - Daily Heating Energy Consumption: The quarter-hourly data received from the school's BMS contains the heating circuits' energy meters. This information allows understanding the energetic impact of the heating control decisions. In theory, the heating system's consumption for each circuit is related to the duration of operation, the temperature of the hot water flowing through the radiators controlled by the respective supply temperature set-point, and the heat loss from the rooms' radiators. In this school, the latter is strongly influenced by the outdoor temperature due to low thermal insulation.

Modeling the energy consumption with high temporal resolution is desirable as this would simplify the optimization strategy formulation. Unfortunately, the meters' relationships to the parameters mentioned above are unacceptably weak on quarter-hourly and hourly timescales, caused by the meters' measurement sensitivities. These undercut even the R-squared threshold of 0.75, which is "often considered a reasonable indicator of a good causal relationship amongst the energy and independent variables" [20]. However, coarsening the timescale for each circuit to daily calculations results in satisfactorily strong relationships. The analysis indicates that the length of the daily period of operation, the mean circuit supply temperature and the mean outdoor temperature are the parameters most strongly correlated with the daily energy consumption. Thus, the feature vector definition $\in \mathbb{R}^3$:

- Daily heating system runtime $t_{op,Cj}$
- $\overline{T_{Cj}}$
- $\overline{T_{air}}$

Model 3 - Hourly Outdoor Conditions: The environmental parameters air temperature, humidity, and wind speed influence the classroom temperatures as well as the heating system energy consumption. Therefore, taking weather forecast information into account helps in optimizing set-point scheduling decisions for the upcoming day. This model captures the micro-climatic conditions in Granada as well as systematic measurement differences between the school's weather station and the weather forecast provided by [28].

For each weather parameter best results are achieved using the weather forecast prediction for i and the weather station's last four parameter measurements, resulting in feature vectors $\in \mathbb{R}^5$.

Model 4 - Circuit Flow Temperature Trend At Day Start: This model predicts the "natural" supply temperature evolution of an inactive heating circuit, i.e. predicting each heating circuit's flow temperature with inactive heating. That helps in predicting the associated room temperature levels more accurately for times when the heating system is not active yet. Also, it can be used to minimize heating operation as much as possible: delaying heating start in the morning is therefore of interest. If the estimated "natural" circuit flow temperature T^i_{Cj} is higher than the first set-points $T^i_{set,Cj}$ returned by the optimization strategy, the heating system activation for the respective circuit is not necessary yet. If T^i_{Cj} lower, the heating system must be activated. Both circuits' models use feature vectors $\in \mathbb{R}^{16}$:

- the four last measurements of each of the parameters T_{air}, hr, and ws,
- the three last measurements of the circuit's T_{Cj}, and
- the *dow*.

Model 5 - Circuit Flow Temperature Trend At Day End: Inspired by the status-quo operation switching off the heating operation prior to school day end Tuesdays - Fridays, this model investigates if the heating system could be switched off before school day end. For each circuit, the flow temperature evolution is predicted assuming the system was to be switched off at this instant. Using this estimation as input to the room temperature models allows assessing if heating system deactivation will cause discomfort. Model 5 reuses the feature vector definition of Model 4.

Optimization Strategy: Section 3.2 identifies the Genetic Algorithm as appropriate to optimize heating system operation. Applying the Genetic Algorithm to the aforementioned predictive models derives optimized schedules per heating circuit set-points. After discussions with the operational staff, it was decided to focus on minimizing a single objective, the energy consumption, subject to zonal comfort constraint - see Equation 6.

$$min\ Q_{Cj} \tag{6}$$

subject to

$$|T^i_{Zj} - T_{target}| \leq tol\ \forall i \text{ where } \sum_{r \in Zj} occ^i_r > 0$$

The different classroom temperature models predict T^{i+1}_r from current i. As sensor readings are only available until the time optimization starts, iterative model execution is required to predict the upcoming school day and schedule the heating operation accordingly. Figure 10 illustrates this concept: the predictions made for T^i_r when the Genetic Algorithm operated on $i-1$.

The Genetic Algorithm invokes Model 2 with set-point information, heating circuit operation runtime, and mean outdoor temperatures to calculate the energy consumption Q_{Cj} in Equation 6. Setting population members resulting in violations of hard constraints of T^i_{Zj} (Equation 1) to infinite cost in the Genetic Algorithm's cost function implements problem specific hard comfort constraints. An appropriate choice of the chromosome space realizes operational constraints such as permissible circuit supply temperatures or the heating system's thermal inertia.

Intuitively, there are two different design choices to optimize a single heating circuit's set-point decisions in the school:

1. Interpret the T_{Cj} schedule of an entire day as a single chromosome.

   This approach will return with a complete schedule for the coming day that takes into account effects of set-point choices on the classrooms' temperature evolutions over time, naturally enabling appropriate pre-heating before scheduled class hours. Further, the set-point schedule calculated provides exact $t_{op,Cj}$ as well as $\overline{T_{set,Cj}}$

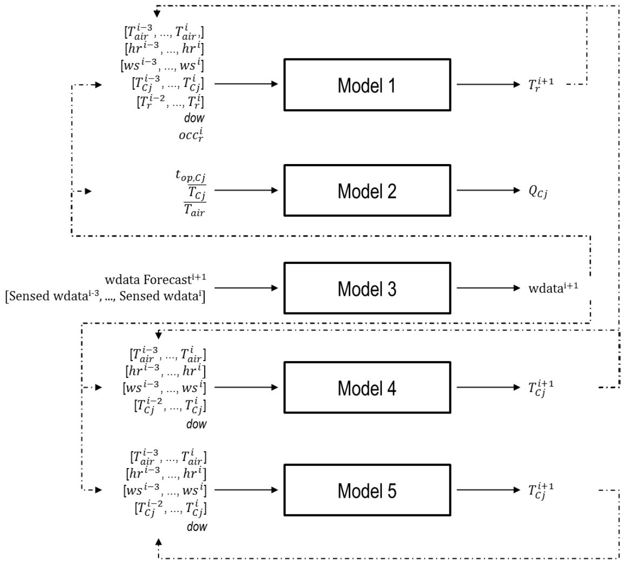

Figure 10: Data-driven models executed at time-step i: inputs, outputs and their relationships. For brevity, the weather models for the different parameters have been subsumed into one (Model 3, data is abbreviated wdata*). Dashed lines indicate the relation to the next iteration of model execution, i.e. when* $i \rightarrow i+1$

for the entire day as input to the energy calculations of Model 2. This approach exploits the Genetic Algorithm's operations of mutation and cross-over.

Unfortunately, modeling of operational constraints that imply a time dependency - for example, a maximally allowed change of a set-point in relation to an earlier set-point - are difficult to express in the mutation or cross-over operations. Also, a single circuit's full day set-point schedule is $\in \mathbb{R}^{96}$ making full-day optimization computationally expensive: empirical tests indicated several hours of computation time which would require a very early start of optimization. However, to minimize compounding errors due to iteratively executing models with input from preceding time-steps' model predictions, it is desirable to start heating schedule optimization as late as possible in the day - allowing to use as many real sensor readings (instead of model predictions) as possible. Thus, it is favorable to delay optimization start until shortly before school start, risking that optimization is not finished by the time school starts.

2. Interpret each T_{Cj}^{i} as a chromosome.

   On the one hand, this approach will not easily cover classroom temperature evolution through time, i.e. it only accounts for pre-heating classrooms for a single time-step. Further, it also avoids making use of the Genetic Algorithm's cross-over operation among generations (as the chromosome is $\in \mathbb{R}^1$), but gene mutation still applies. Also, to assess a chromosome's fitness, the per circuit energy calculations require approximations of $t_{op,Cj}$ as well as $\overline{T_{set,Cj}}$. While scheduled set-points of previous time-steps are known, the period remaining until the end of the scheduled occupation can only be estimated, e.g. by replicating the current chromosome for all remaining time-steps until the end of the school day. However, towards day-end, the estimates of $t_{op,Cj}$, as well as $\overline{T_{set,Cj}}$, should become more accurate as more and more set-points have been scheduled.

On the other hand, this approach allows establishing a dependency on prior iterations' set-point choices by appropriately limiting permissible parameter ranges. This flexibility to limit chromosome ranges in the different iterations makes it straightforward to take operational constraints into account. Additionally, each time-step optimization is relatively inexpensive (empirical tests indicated several minutes computation time) so that scheduling set-points iteratively is possible (as opposed to the first option, where at the end of optimization all set-point decisions are only retrieved simultaneously).

Considering both options, we favor the second approach leading to Algorithm 1. The algorithm relies on the models summarized in Table 4 and R's Genetic Algorithm implementation provided by the *genalg* package [47]. The main part of the algorithm iteratively schedules optimized set-points for each time-step (loop in line 15 of Algorithm 1). The single time-step chromosome definition described above is unable to pre-heat longer than a single time-step, which is a significant drawback at school day start. Historical data suggested that one full hour heating (four time-steps) prior to the earliest scheduled room (the Secretary room) suffices to meet indoor comfort targets. Thus, line 13 in Algorithm 1 introduces a dedicated day-start optimization chromosome $\in \mathbb{R}^4$. Algorithm 2 evaluates the candidate heating set-points concerning energy consumption and comfort constraints. If at any time-step during school day no $T^i_{set,Cj}$ can be found satisfying thermal comfort, the maximum permissible set-point of $T^i_{set,Cj} = 70°C$ is scheduled.

Repeated optimization runs executed on reference period data show that starting computation at 5 AM each school day ensures that optimization finishes the latest at noon, i.e. more than 3 hours before last scheduled occupation of any day. For each quarter-hourly time-step of the upcoming school day the following steps for are executed both heating circuits in parallel:

- Use weather forecasts and Model 3 to derive the anticipated local conditions at the Sierra Elvira School.

- Build the input feature vectors from previous time-steps. The Genetic Algorithm evaluates the effects of different candidate heating circuit set-point values. Only on day-start: use Model 4 to predict the circuits' supply temperatures before the heating system starts operation instead of using heating circuit set-points.

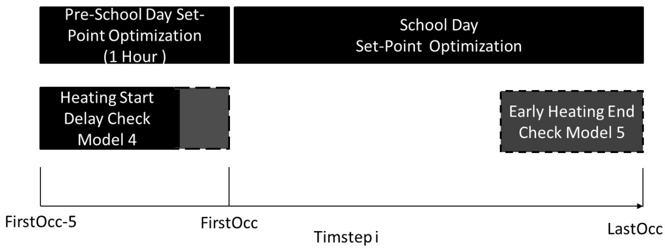

Figure 11: Per heating circuit relation of optimization, day-start checks for heating delay and early heating stops.

- Use the Genetic Algorithm to evaluate the developed models for the population. Identify set-point minimizing circuit energy consumption (when extrapolated to the entire day) while satisfying the zonal room temperature targets, taking into account the scheduled occupancy levels.

- Schedule the desired set-points.

To further minimize heating system energy consumption, the possibilities to delay the heating system start and to advance the heating system stop times are investigated as follows (see also Figure 11):

- After Algorithm 1 scheduled the first set-points for both circuits at day-start, Model 4 is used to predict the "natural" circuit flow temperature evolution iteratively (i.e. without active heating). If the predicted flow temperature at time-step i is above the corresponding scheduled set-point, the scheduled set-point is discarded. On the other hand, if the predicted flow temperature is below the scheduled set-point, the checks for delaying heating start are aborted and the scheduled set-point is kept.

- Similarly, Model 5 is applied iteratively from 2 pm onwards to assess the possibility of an early heating system deactivation as inspired by the status-quo heating strategy. Once the predicted flow temperature cool-down is maximally 2K lower than the scheduled set-points until school-end, these set-points are discarded, and the heating system is stopped.

Implicit Modeling and Optimization: Reinforcement Learning

Over the course of a school day, the reinforcement learning algorithm seeks to minimize expected total cost (defined in Section 5). Actions a^i are defined as the heating circuits' flow temperature set-points. The information state x^i at time-step i is defined by all the current measured classroom temperatures, the circuits' temperatures, the time of day i, and the weather forecast from i until the end of the school day. As the dimension of the information state depends on the time of day (longer in the morning, shorter in the afternoon), multiple Q functions for specific daily times are trained. As opposed to the

Algorithm 1: Explicit Model Combination and Optimization with Genetic Algorithm

output: Full Day Cj Heating Schedule
input : j: index of circuit to optimize
$T_{Cj,min}$: Minimum set-point permissible
$T_{Cj,max}$: Maximum set-point permissible
Data: $T[r \in Zj][0 \dots 20]$: Zone j measurements
$T_{Cj}[0 \dots 20]$: Circuit j measurements
$ws[0 \dots 20]$: Local ws measurements
$wsFC[0 \dots 95]$: Internet ws forecasts
$hr[0 \dots 20]$: Local hr measurements
$hrFC[0 \dots 95]$: Internet hr forecasts
$T_{air}[0 \dots 20]$: Local T_{air} measurements
$T_{air}FC[0 \dots 95]$: Internet T_{air} forecasts
dow: Current day of week
$occ[r \in Zj][0 \dots 95]$: Rooms' occupations
$FirstOcc$: The very first scheduled occupation of any room in Zone j
$LastOcc$: The very latest scheduled occupation of any room in Zone j

begin
  for $i \in \{20 \dots LastOcc - 2\}$ **do**
    $T_{air}[i+1] :=$ model3$_{T_{air}}$ $(T_{air}[i-3 \dots i], T_{air}InternetFC[i+1])$
    $hr[i+1] :=$ model3$_{hr}$ $(hr[i-3 \dots i], hrInternetFC[i+1])$
    $ws[i+1]:=$ model3$_{ws}$ $(ws[i-3 \dots i], wsInternetFC[i+1])$
  end
  for $i \in \{20 \dots FirstOcc - 5\}$ **do**
    $T_{Cj}[i+1] :=$ model4$_{Cj}$ $(T_{air}[i-3 \dots i], hr[i-3 \dots i], ws[i-3 \dots i], T_{Cj}[i-2 \dots i], dow)$
    for $r \in Z_j$ **do**
      $T[r][i+1] :=$ model1$_r$ $(T_{air}[i-3 \dots i], T_{Cj}[i-3 \dots i], hr[i-3 \dots i], ws[i-3 \dots i], T[r][i-2 \dots i], occ_r[i], dow)$
    end
  end
  $T_{Cj}[FirstOcc - 4 \dots FirstOcc] :=$ genalg::rgba(stringMin=rep($T_{Cj,min}$, 4), stringMax=rep($T_{Cj,max}$, 4), popSize=200, iters=100, mutationChance=$\frac{1}{popSize+1}$, elitism=0.2, evalFunc=$Algorithm2$)
  $Schedule(T_{Cj}[FirstOcc - 4 \dots FirstOcc])$
  for $i \in \{FirstOcc + 1 \dots LastOcc\}$ **do**
    $T_{Cj}[i] :=$ genalg::rgba(stringMin=$T_{Cj,min}$, stringMax=$T_{Cj,max}$, $popSize = T_{Cj,max} - T_{Cj,min}$, iters=100, mutationChance=$\frac{1}{popSize+1}$, elitism=0.2, evalFunc=$Algorithm2$)
    if $T_{Cj}[i] == NA$ **then**
      $T_{Cj}[i] := T_{Cj,max}$
    end
    $Schedule(T_{Cj}[i])$
  end
end

Algorithm 2: Heating Cost Evaluation

output: Cost associated to one or more T^{ti}_{Cj}

input : $T_{class,min}$: Minimum permissible T_r

$\widehat{T_{Cj}}[]$: Array of candidate heating set-points

i: Time-step related to first $\widehat{T_{Cj}}$ entry

data : Access to Data in Algorithm 1

$T_{work,Cj}[4 + length(\widehat{T_{Cj}}[])]$: working storage of heating temperatures

$T_{work}[r][3 + length(\widehat{T_{Cj}}[])]$: working storage of room temperatures

Q_{Cj}: Energy

begin
- $T_{work,Cj}[0 \ldots 3] := T_{Cj}[i-3 \ldots i]$
- $T_{work,Cj}[4 \ldots 3 + length(\widehat{T_{Cj}}[])] := \widehat{T_{Cj}}[]$
- **for** $r \in Z_j$ **do**
  - $T_{work}[r][0 \ldots 2] := T[r][i-2 \ldots i]$
- **end**
- **for** $l \in \{0 \ldots (length(\widehat{T_{Cj}}[]))\}$ **do**
  - **for** $r \in Z_j$ **do**
    - $T_{work}[r][3+l] :=$ model1$_r$ $(T_{air}[i+l-3 \ldots i+l], T_{work,Cj}[l \ldots 3+l], hr[l \ldots 3+l], ws[l \ldots 3+l], T_{work}[r][l \ldots l+2], occ_r[i+l], dow)$
    - **if** $T_{work}[r][3+l] < T_{class,min}$ **then**
      - $Q_{Cj} := \infty$
      - $return(Q_{Cj})$
    - **end**
  - **end**
- **end**
- $stepsTillEnd := LastOcc - i;$
- $\overline{T^{exp}_{Cj}} := mean(T_{Cj}[0..i], rep(mean(\widehat{T_{Cj}}[]), stepsTillEnd))$
- $\overline{T_{air}} := mean(T_{air}[])$
- $t_{op,Cj} := \frac{LastOcc-(FirstOcc-5)}{4}$
- $Q_{Cj} := model2(t_{op,Cj}, \overline{T_{air}}, \overline{T^{exp}_{Cj}})$
- $return(Q_{Cj});$

end

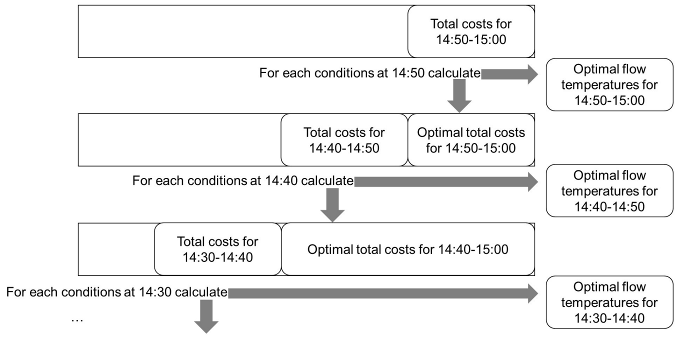

Figure 12: Per heating circuit relation of optimization, multiple cost estimations per day.

approach of explicit model combination and optimization, it is intended to be able to react to sensor data during the day at these specific times. Hence, the execution during the day is time sensitive. To reduce the optimization space, the range of permissible circuit flow temperature actions is discretized to three settings per circuit: $a \in \{60, 65, 70\}^2$. For fitting the Q functions, the TreeBagger [48] implementation of Matlab is used with a single tree. With a total of 9 possible set-point combinations, it is sufficiently fast to evaluate the Q functions for all combinations to select the optimum. To implement exploration of the set-point space, a small amount of noise $\mathcal{N}(0, 1)$°C is added to the optimal circuit set-points. Figure 12 illustrates the concept of executing multiple optimizations the during the school-day.

5 Experimental Validation

This section documents experiments addressing methodology step 1f to validate the developed predictive control strategies. As this work's validation is *in situ*, the CPS methodology's online phase, i.e. step 2, is demonstrated at the same time. To avoid possible situations of conflict between local and supervisory control eluded to in Section 2, close communication with operational staff is an important part of the experimental procedure. Also, a boolean flag programmed into the BMS allows switching between BMS internal logic and the CPS supervisory control commands, ensuring that staff is always able to interrupt experiments in case of unsatisfactory performance or emergencies.

5.1 Experiment 1: Minimizing Energy Consumption, Maintaining Comfort

Description

This first experiment demonstrates the feasibility of the proposed method to data-driven heating schedule optimization in real life operation. It focuses on minimizing the energy

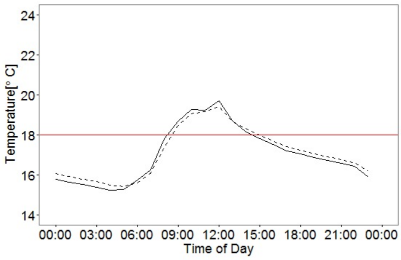

Figure 13: Hourly profile: average indoor temperatures per building zone (Zone 2: dashed line) during Experiment 1. Red line indicates the reference control temperature target of 18° C.

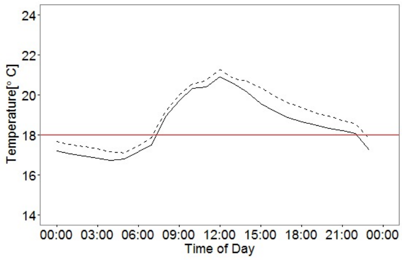

Figure 14: Hourly profile: average indoor temperatures per building zone (Zone 2: dashed line) during Experiment 2A. Red line indicates the reference control temperature target of 18° C.

Table 5: Descriptive statistics of data collected during Experiment 1 for school hours.

	$\overline{T_{Z1}}$ [°C]	$\overline{T_{Z2}}$ [°C]	$Q_{C1,HDD18}$ [kWh/DD]	$Q_{C2,HDD18}$ [kWh/DD]
Min.	17.8	17.6	18.7	20.9
Med.	18.2	18.2	24.1	24.8
M±SD	18.3±0.4	18.1±0.4	24.3±3.7	24.2±2.9
Max.	19.0	18.6	28.0	27.4

consumption of the school's heating circuits 1 and 2 while maintaining indoor temperatures at the level observed during the reference period. That is realized by the single objective constrained optimization problem in Equation 6. During hours of heating operation, the Genetic Algorithm decides $T^i_{set,Cj} \in [30, \dots, 70]$°C for each time-step i. The reference period's heating system operation statistics in Table 3 define the Experiment 1 optimization constraints: from the median and the mean of $\overline{T_{Z1}}$ and $\overline{T_{Z2}}$ follows a target temperature of 18°C. The statistics further indicate an acceptable indoor temperature tolerance threshold of 2K. Operational staff confirmed these values.

Observed Data

The experiment was executed on the 14 school days of 2015/11/11 - 2015/11/30. Table 5 documents the descriptive statistics of the data collected during this period. Figure 13 depicts the hourly average zonal temperatures observed. These reach 18°C during the first hour of classes, i.e. between 09:00 and 10:00.

Operational Feedback

An analysis of the supply temperature set-point schedules and the associated operational data identified the produced schedules as overly aggressive: in certain situations, due to

Table 6: Descriptive statistics of data collected during Experiment 2A for school hours.

	$\overline{T_{Z1}}$ [°C]	$\overline{T_{Z2}}$ [°C]	$Q_{C1,HDD18}$ [kWh/DD]	$Q_{C2,HDD18}$ [kWh/DD]
Min.	17.6	18.2	26.6	27.3
Med.	20.0	20.3	42.5	39.6
M±SD	19.7±1.2	20.0±1.0	40.6±9.0	37.3±8.4
Max.	21.3	21.5	53.7	49.8

the low circuit thermal demand at times of low supply temperatures T_{Cj}, boiler temperatures could rise to too high levels. As a consequence, the allowed minimum T_{Cj} should be raised.

Furthermore, the schedules did not correctly reflect the boiler's inertia. Consequently, the chromosome evolution requires adaptation to accommodate the inertia appropriately.

5.2 Experiment 2: Improving Comfort

After successfully demonstrating the feasibility of the overall concept in the first experiment, the second experiment aims at raising the room temperatures. In cooperation with the operational staff, its temperature target is defined as 20±2°C for $\overline{T_{Z1}}$ and $\overline{T_{Z2}}$.

To ensure satisfactory levels of comfort during classes, an additional watchdog mechanism monitors classroom temperature levels. When a configurable minimum temperature is violated the watchdog increases the respective circuit's temperature set-point to 70°C, irrespective of scheduled set-points, until the temperature violation is rectified. This watchdog serves as a real-time safeguard against inaccuracies of temperature predictions, e.g. due to compounding model errors, stochastic effects (doors and windows opening and closing), or inaccurate weather forecasts.

Experiment 2A: Explicit Approach

Description: The operational feedback received in response to Experiment 1 is accounted for by constraining the Genetic Algorithm's populations per iteration to suitable supply temperature ranges. One implication of these adaptations is that the checks serving to reduce heating circuit runtime are disabled. Each zone's watchdog is configured to trigger when any classroom temperature violates a minimum threshold of 17°C during classes. In this experiment, the Genetic Algorithm decides $T^{i}_{set,Cj} \in [max(T^{i-1}_{set,Cj} - 5, 45), \ldots, 70]$°C for each time-step. That is implemented by changing the *stringMin* argument in line 16 of Algorithm 1 accordingly.

Observed Data: The set-point schedules derived from the optimization strategy were executed on 14 school days in the period of 2016/02/10 - 2016/03/21. Table 6 documents the descriptive statistics of the data collected during this period. Figure 14 depicts the average hourly zonal temperatures, which reach 18°C before the first hour of classes and 20°C at approximately 11:00.

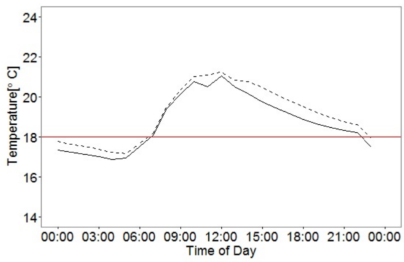

Figure 15: Hourly profile: average indoor temperatures per building zone (Zone 2: dashed line) during Experiment 2B. Red line indicates the reference control temperature target of 18° C.

Table 7: Descriptive statistics of data collected during Experiment 2B for school hours.

	$\overline{T_{Z1}}$ [°C]	$\overline{T_{Z2}}$ [°C]	$Q_{C1,HDD18}$ [kWh/DD]	$Q_{C2,HDD18}$ [kWh/DD]
Min.	18.3	18.6	24.5	25.0
Med.	20.1	20.3	33.9	36.1
M±SD	19.9±0.8	20.1±0.8	35.0±6.7	36.2±6.0
Max.	20.9	21.0	49.6	46.6

Experiment 2B: Reinforcement Learning

Description: To be able to capture indoor temperature levels and energetic considerations simultaneously, the cost function f combines a penalty for energy consumption with a discomfort penalty. Energy consumption is penalized by the biomass price of €0.068/kWh. The discomfort penalty is set to 100 EUR per classroom per interval of temperature below 16°C. This discomfort penalty decreases linearly to 0 at 19°C. The rationale of choosing this high discomfort cost is that for low temperatures, it might be necessary to suspend classes and to pay a supervisor with an average hourly wage. As all rooms contribute equally to the penalty function, and since energy cost is much lower than the discomfort penalty, the total cost function is dominated by cooler rooms. Due to the classroom temperature spread observed in each zone most rooms should tend to exceed 19°C - in line with the experiment targets. As explained in Section 3.2 the reinforcement learning chooses $T^i_{set,Cj} \in \{60, 65, 70\}$°C with additive noise at each time-step during heating operation hours.

For ensuring a minimal level of comfort, each zone's watchdog is configured to trigger when any classroom temperature violates a minimum threshold of 16°C during classes.

Observed Data: This experiment was executed on 15 school days between 2016/01/20-2016/02/09. Table 7 summarizes the statistics of the data collected. Figure 15 depicts the average hourly zonal temperatures: they reach 18°C before 09:00 (first hour of classes) and 20°C at approximately 11:00.

6 Discussion

6.1 Framework

The experiments executed at Sierra Elvira School in daily operation demonstrate the practicality of the proposed framework. It is feasible to evolve a legacy building with its pre-existing instrumentation and additional sensor installations into a data-driven predictive cyber-physical system. The framework allows using different modeling and optimization approaches, depending on the data available, the building's characteristics, and the technical staff's skill set. Further, the experiments show that it is possible to flexibly decide optimization targets depending on the operational needs.

6.2 Data-Driven Approaches to Heating Optimization

The experiments show that the overall approach to a data-driven optimization is feasible and produces consistent results in routine operation. The following provides more detailed insights into both concepts outlined in Section 4.2.

- Explicit Model Combination and Optimization:
  - For all parameter prediction tasks, the BRANN technique outperforms the other techniques on the test dataset. This can be attributed to its robustness to overfitting [31].
  - PCA accommodating 95% of the input feature variation improves all indoor temperature models' RMSEs. The other models do not benefit from PCA. This is an indication that PCA suppresses noise in the data, e.g. due to stochasticity of human behavior in the rooms, and thus helps to avoid overfitting.
  - The grid search returns for all temperature related models (room temperature models, circuit flow temperature models at day start and day end) equivalent input feature definitions: roughly speaking one hour of history for the different involved parameters. Potentially, this is a characteristic of the building's intrinsic characteristics (e.g. the insulation level). However, a deeper investigation is needed.
  - The considerable variation in the number of neurons of the different best performing BRANN room temperature models requires further investigation.
- Reinforcement Learning:
  - The high discomfort penalty in relation to biomass price favors satisfactory classroom temperature levels.
  - The choice of Fitted Q-Iteration proves to be appropriate because the level of pre-installed building automation is low and indoor temperatures are affected by many non-modelable disturbances.

- Executing optimization several times over the day (instead of once) improves responsiveness to disturbances or prediction errors. However, the chosen approach requires training multiple Q functions and a discretization of the action space to ensure sufficiently fast optimization.

6.3 Predictive Control Experiments, Thermal and Energetic Effects

Descriptive Statistics

For Experiment 1, compared to the reference period's descriptive statistics (Table 3), Table 5 shows that the experiment successfully maintains the zonal average room temperature conditions per school day: for Zone 1 the median and mean increase by 0.2K and 0.3K. For Zone 2 the median and mean room temperatures decrease by 0.2K and 0.5K but remain above the temperature target of 18°C. The normalized daily energy consumption of Heating Circuit 1 reduces by 8.9 kWh/DD (median) or 9.4 kWh/DD (mean). For Heating Circuit 2 it is reduced by the experiment by 8.9 kWh/DD (median) or 10.6 kWh/DD (mean). Comparing figures 9 and 13, the experiment exerts tighter control of the indoor temperatures than the reference strategy: the zones' temperature profiles are much closer aligned.

For Experiment 2A, the descriptive statistics in tables 3 and 6 show increasing zonal average room temperatures per school day. For Zone 1 the median increases by 2K and the mean increases by 1.7K. For Zone 2 the median and mean room temperatures increase by 1.9K and 1.4K respectively. The higher indoor temperatures come at a cost: the normalized daily energy consumption of Heating Circuit 1 increases by 9.5 kWh/DD (median) or 6.9 kWh/DD (mean). For Heating Circuit 2 the energy consumption increases by 5.9 kWh/DD (median) or 2.5 kWh/DD (mean).

According to tables 3 and 7, also Experiment 2B succeeds in improving the indoor comfort conditions: for Zone 1 the median increases by 1.9K and the mean increases by 1.6K. For Zone 2 the median and mean room temperatures increase by 2.1K and 2.0K respectively. Again, the increased indoor temperatures come at a cost: the normalized daily energy consumption of Heating Circuit 1 increases by 0.9 kWh/DD (median) or 1.3 kWh/DD (mean). For Heating Circuit 2 consumption increases in the experiment by 2.4 kWh/DD (median) or 1.4 kWh/DD (mean). Compared to Experiment 2A, the temperature data to be less spread and energy consumption is lower.

Statistical Inference of a Single Mean

The Shapiro-Wilk test confirms the normality of the sampled data for all experiments: for the reference period and the experiments all p-values for $\overline{T_{Z1}}$, $\overline{T_{Z2}}$, $Q_{C1,HDD18}$, and $Q_{C2,HDD18}$ substantially exceed 0.05. It is thus permissible to deduce the experiments' impacts concerning a possible change to the underlying data distribution when compared to the reference heating strategy by statistical inference using the t-distribution.

Inference for a *single* mean illustrates the individual experimental results. Figure 16 and Table 8 provide the 95% confidence intervals for the mean daily average room temperatures per zone for the reference period and the experimental phases during school hours. Figure 16 shows:

- for Zone 1 (denoted by *Z1* prefix), Experiment 1 (*E1* suffix) slightly increases daily average temperature levels compared to the reference period (*ref* suffix), Zone 2 (*Z2* prefix) slightly decreases.

- the Experiment 2A (*E2A* suffix) significantly increases temperature levels for both zones but shows a notable width of the zonal temperature levels' confidence intervals.

- Experiment 2B (*E2B* suffix) is at similar levels of indoor comfort as Experiment 2A, i.e. their confidence intervals overlap, but with a much smaller temperature spread.

In analogy, Figure 17 and Table 9 show the confidence intervals of each heating circuit's mean daily normalized energy consumption. Figure 17 shows:

- for Circuits 1 (*C1* prefix) and 2 (*C2*), Experiment 1 decreases average daily weather-normalized energy consumption compared to the reference period.

- Experiment 2A appears to have increased energy consumption for both circuits but the confidence intervals of experiments and reference period overlap. Statistical inference of two sample means is required to estimate the actual differences, see Section 6.3.

- Experiment 2B exhibits confidence intervals for both circuits that appear lower and narrower than those of Experiment 2A. Energetically, Experiment 2B appears to be comparable with the reference period (that was associated with much lower zonal comfort levels). However, there is significant overlap of Experiment 2B's confidence intervals with those of Experiment 2A and those of the reference period. Section 6.3 investigates that further.

Statistical Inference for Two Means

This subsection relies on the method of statistical inference for *two* sample means to calculate the experiments' savings in normalized energy per heating circuit. With 95% confidence, the normalized daily energy consumption and the daily mean occupancy weighted zonal temperature are impacted by the control strategy experiments as explained in the following.

- Experiment 1 compared to the reference period:

Table 8: Intervals of mean daily zonal average temperature [°C] with 95% confidence.

	Min.	Mean	Max.
$\overline{T_{Z1}}$, ref. period	17.4	18.0	18.6
$\overline{T_{Z1}}$, exp. 1	17.7	18.3	18.8
$\overline{T_{Z1}}$, exp. 2A	18.8	19.7	20.6
$\overline{T_{Z1}}$, exp. 2B	19.4	19.7	20.3
$\overline{T_{Z2}}$, ref. period	17.9	18.6	19.2
$\overline{T_{Z2}}$, exp. 1	17.6	18.1	18.6
$\overline{T_{Z2}}$, exp. 2A	19.2	20.0	20.8
$\overline{T_{Z2}}$, exp. 2B	19.7	20.1	20.6

  - Consumption changes by [-10.1, -8.6] kWh/DD, and [-11.4, -9.9] kWh/DD for heating circuits 1 and 2, respectively. Compared to the reference period's confidence interval bounds for mean daily consumption, this constitutes energy savings of 23.5-32.8% and 26.3-35.6%.
  - A total of 57.2 HDD aggregated on the school days during the experiment. Therefore, the total savings during this period amount to [1.1, 1.2] MWh.
  - The difference in zonal temperatures is [0.3, 0.6] K, and [-0.4, -0.1] K, respectively.

- Experiment 2A compared to the reference period:
  - Consumption changes by [6.0, 7.8] kWh/DD, and [1.6, 3.3] kWh/DD, respectively. That is an increase of consumption of 16.4-25.3%, and 4.2-10.3%, respectively. The strong increase of consumption for Circuit 1 stems from the school's coldest and biggest room being attributed to Zone 1: the living room of the second floor.
  - A total of 82.5 HDD aggregated on the days of Experiment 2A. Therefore, the additional consumption during this period amounts to [0.6, 0.9] MWh.
  - Zonal temperatures increase during school hours by [1.7, 2.0] K, and [1.5, 1.8] K, respectively.

- Experiment 2B compared to the reference period:
  - Consumption changes by [0.4, 2.1] kWh/DD, and [0.5, 2.1] kWh/DD, respectively. This constitutes an increased consumption of 1.1-6.8%, and 1.3-6.6%, respectively.
  - A total of 144.7 HDD aggregated during the experiment. Therefore, the additional consumption during this period amounts to [0.1, 0.6] MWh.
  - The zonal temperatures change during school hours by [1.9, 2.2] K, and [1.6, 1.9] K, respectively.

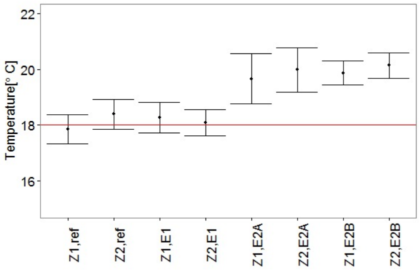

Figure 16: Confidence intervals for mean daily average room temperatures during school hours per zone for reference period and experiments. Red line indicates reference control target temperature. See also Table 8.

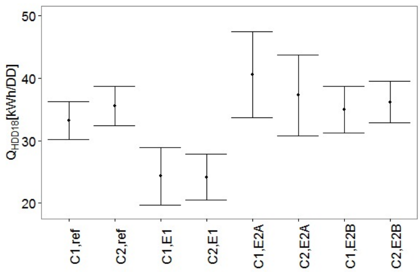

Figure 17: Intervals of 95% confidence for mean daily HDD normalized circuit energy consumption: reference period and experiments. See also Table 9.

Considering the high comfort experiments, the strategy of Experiment 2B is preferable over that of Experiment 2A:

- Experiment 2B created more uniform temperature levels at lower normalized energy use while achieving comparable indoor temperature levels.
- Statistical inference shows with 95% confidence that Experiment 2B's zonal temperatures are [0.1, 0.3] K and [0.1, 0.2] K higher than those of Experiment 2A.
- At the same time, the circuits' consumptions are [5.0, 6.3] kWh/DD and [0.5, 1.7] kWh/DD lower.

Experiment 2B's higher performance comes from the strategy's ability to react to human behavior and possible inaccuracies in predictions during the day. More specifically, Experiment 2A exhibited on several days a high level of watchdog activity for zone 1. The activity was caused by strongly stochastic occupant behavior. These random effects rendered predictions made at day-start inaccurate and resulted in too optimistic set-point schedules. That required rectification by the energetically inefficient watchdog-driven heating. Still, the watchdog made it possible also for Zone 1 to reach the targeted range of indoor temperatures during Experiment 2A as seen in the collected statistics in Table 8 and illustrated in Figure 16.

Extrapolation to the Average Winter Season

Based on the prior inference, this subsection extrapolates the experiments' energetic results to the average heating season conditions. As the school's historical weather data does not cover seasons before the reference period, [49] is relied on to characterize average winter conditions for the city of Granada, Spain. The HDD18 5-year-average (2010 to 2014) in the period of November - February is 1,467. Hence, in an average winter,

Table 9: Intervals of mean daily normalized energy consumption [kWh/DD] with 95% confidence.

	Min.	Mean	Max.
$Q_{C1,HDD18}$, ref. period	30.8	33.7	36.6
$Q_{C1,HDD18}$, exp. 1	19.7	24.3	29.0
$Q_{C1,HDD18}$, exp. 2A	33.7	40.6	47.5
$Q_{C1,HDD18}$, exp. 2B	31.2	35.0	38.7
$Q_{C2,HDD18}$, ref. period	32.0	34.8	37.7
$Q_{C2,HDD18}$, exp. 1	20.5	24.2	27.8
$Q_{C2,HDD18}$, exp. 2A	30.8	37.3	43.7
$Q_{C2,HDD18}$, exp. 2B	32.9	36.2	39.5

- the reference operation strategy is expected to consume on average [92.1, 109.0] MWh;
- based on inference of the difference of two means, the anticipated savings of Experiment 1 compared to the reference strategy would amount to [27.1, 31.5] MWh - a reduction by 24.9-34.2%;
- for Experiment 2A, the improved comfort is expected to come at an increased consumption of [11.1, 16.3] MWh compared to the reference strategy - an increase of 10.2-17.7%;
- Experiment 2B is expected to raise consumption by [1.3, 6.2] MWh compared to the reference strategy (1.2-6.7%).

6.4 Stakeholder Feedback

This section summarizes the feedback of the involved stakeholders after the experiments. Interviewed were the operational staff of the Energy Service Company (ESCo) that manages school operation; Granada Municipality as the owner of the building; the personnel of the school represented by the head and teachers; and the students represented by their parents or tutors.

- From the ESCo's operations manager experience, the different measures implemented in the school had a direct effect on its performance, increasing the regulation and control points as well as the possibilities to follow-up and supervise the operation. The operations manager also highlighted that all the experiments carried out increased the performance and improved the operation of the biomass-fired boiler. Moreover, the energy consumption was reduced while improving the comfort conditions during the heating season. The energy consumption was a key constraint of the client (i.e. Granada Municipality) while the comfort improvement was an urgent requirement for the school personnel and the students.
- From the ESCo's operational and technical staff point of view, the operation of the facility was significantly improved due to the different measures accomplished

during BaaS project. However, the lack of access to the supervisory control system was perceived negatively.

- Granada Municipality was very satisfied with the results of the project because this pilot solution improved the operation and performance of one of their facilities without additional cost. The initial experiment had low indoor temperatures, but no complaints were received from the teachers nor the children (or their parents) for experiments 2A and 2B. The developed system is a very attractive solution to be deployed in other schools owned by the municipality as it allowed providing significantly improved thermal comfort while keeping energy costs stable.

- Sierra Elvira School's personnel expressed positive feedback about the heating system performance. Working conditions improved compared to before in terms of thermal sensation.

- Parents and children valued the final heating control very positively. The comfort level in the different classrooms and areas of the school has been significantly increased compared to the original situation. However, the first experiment that targeted standard indoor temperature levels created an initial uncertainty and mistrust regarding the different experiments to come.

In summary, the all stakeholders expressed a positive perception of the equipment installed and the strategies developed within the project as they improved the heating system's performance. The experiments focused on improved comfort were perceived very positively. However, the initial test phase and the first experiment received negative responses and created an initial dissatisfaction. This was addressed in Experiment 2A and 2B by deliberate communication as well as a dedicated watchdog mechanism. The operational staff's mentioned lack of access to the supervisory control can be addressed in future work by an appropriate user interface to provide local access to the control parameters and diagnostic information.

6.5 Limitations

Figures 9, 13, 14, and 15 indicate a heating memory effect despite the low building insulation: zonal indoor temperatures at day start are higher for the high comfort experiments than for the reference period and for Experiment 1. This potential memory effect casts doubt on the prerequisite of independence of the collected daily data as a basis for statistical inference methods. To address this, the results were verified by applying bootstrapping on each of the inference statements. Further, we applied the comparative methodology [50] to the collected data. Both re-examinations yielded results comparable to the inference analysis (omitted for brevity). As also the descriptive statistics confirm the results of the statistical inference, the presented evaluation is robust.

The extrapolation of savings to average winter conditions relies on weather data from [28] for the city of Granada, not the school's weather station. However, the error introduced by this difference is considered as negligible for the overall evaluation and the general trends.

This work is in line with current practice in that it treats maintaining indoor air temperature at target levels (see e.g. [51]) as a proxy to meeting thermal comfort goals. However, also other metrics are available for the thermal discomfort. One of the most popular metrics is the Predictive Mean Vote (PMV) [52] that estimates the average thermal sensation assuming a large group of people by combining six parameters: air temperature, mean radiant temperature, relative humidity, air speed, an individual's metabolic rate, and level of clothing. As it has been adopted by international standards such as [53], it would be desirable to rely on PMV instead of only the indoor temperature for predictive control. In the case of Sierra Elvira School, reasonable guesses for metabolic rate and clothing level could be argued for, but the classrooms' mean radiant temperature, relative humidity, and air speed are not measured for reasons of cost and integration complexity.

7 Conclusion and Future Work

With the target to improve operational efficiency by predictive supervisory control strategies, this work introduces a framework to evolve legacy buildings into predictive Cyber-Physical Systems. That framework combines two well established generic CPS and data-mining methodologies [16, 17] and adapts these for the building environment.

Focusing on the lion's share of building energy use, the approach is validated in experiments controlling the heating system of a public school building constructed in 1975 with a low level of thermal insulation. A modular communication infrastructure establishes bi-directional communication with the school's building management system for data extraction and actuation. This work successfully applies two different data-driven approaches on top of this communication platform to create cyber-representations of the building dynamics, illustrating the proposed framework's methodological flexibility. Three experiments lasting in total 43 school days demonstrate the approach's suitability for developing and deploying real-world predictive control strategies in legacy buildings. On the one hand, an experiment maintaining comfort levels at baseline levels lowers energy consumption by 30%. In an average winter season, these savings would amount to 30 MWh (€ 2,040). On the other hand, two experiments also address a known operational problem of this school by achieving higher indoor temperatures. The best of the comfort-focused experiments increases indoor temperatures by 2 K while increasing consumption by only about 5%.

As the Sierra Elvira School is a typical Spanish school building, the proposed framework, as well as the chosen predictive control approaches, have a considerable potential for replication. This work's prolonged experimental period integrated into the routine building use exceeds the typical experiment durations in the related work, demonstrating the maturity of predictive control concepts as well as the methodology's suitability for daily operation. Through the combination of weather normalization with methods of statistical inference, the conclusions drawn are highly robust. Finally, the collected stakeholder feedback is very positive and constructively indicates points for future improvement.

For future work, it remains to improve the operational staff's level of interaction with, and control of the predictive heating strategies. Also, an investigation of the significant variation of neurons for the indoor room temperature models could provide further insights into the building dynamics. Additional sensor installations for comfort assessment and occupancy detection could further enhance the predictive strategies.

8 Acknowledgments

The authors would like to thank the Sierra Elvira School's administration and Veolia's operational staff for supporting this research. This work has been partially sponsored by European Commission through the FP7-BaaS-288409 Project and the Science and Technology Séneca-Agency Foundation of the Region of Murcia (Spain) by means of the "Talento Investigador y su Empleabilidad" Program, Postdoctoral Category (Consejería de Educación y Universidades) (grant 19782/PD/15).

A Methodology

The proposed framework in Section 2 is inspired by MBD-CPS [16] and CRISP-DM [17]. This appendix summarizes both methodologies' steps. Figure 18 illustrates their relationships to the steps proposed in Section 2.

In summary, the 10 MBD-CPS steps, not necessarily executed in sequence and possibly repeated, are:

1. *State the Problem*: a common language definition of the problem to be solved.
2. *Model Physical Processes*: derivation of a model representation of the physical system to be controlled.
3. *Characterize the Problem*: identification of the fixed, adjustable and controllable parameters and how the physical process may interact with the computation and vice versa.
4. *Derive a Control Algorithm*: determination of conditions under which the physical process can be controlled. Possible requirements on the computation (e.g. runtime, jitter, delays) can be derived from the previous steps.
5. *Select Models of Computation*: definition of allowable set of instructions and rules on the control flow of computational components. If derived, an explicit representation of the computation models allows for formal analysis.
6. *Specify Hardware*: based on the problem's environment, its characteristics, and the computation models described, the hardware necessary to meet the requirements must be selected.

7. *Simulate*: using suitable simulation tools of the various components designed and interacting, it can be assessed if the problem can be solved with the selected models, computation, and hardware. If not, refinement of the earlier steps is needed.

8. *Construct*: building the CPS as designed, and depending on the situation possibly a re-iteration of earlier steps is needed.

9. *Synthesize Software*: code synthesizers may be used to derive software from the simulation environments, otherwise the software has to be implemented with standard tools and skills according to the defined computation models.

10. *Verify, and Validate, and Test*: testing the CPS and its individual components in simple test environments provides diagnosing of the CPS. Possibly refinements of the earlier steps are needed based on the test results. Formal verification and validation can provide insight into runtime behavior.

The CRISP-DM steps summarized from [17] are:

1. *Business understanding*: the data mining problem definition based on the project objectives and requirements from a business perspective.

2. *Data understanding*: the initial data collection to identify data quality issues and forming hypotheses. This step should also include the identification of where available data is lacking with respect to the business understanding.

3. *Data preparation*: performing all activities needed to construct the dataset that is actually fed into the models.

4. *Modeling*: various modeling techniques are applied and their parameters are tuned. An alternation between the data preparation phase and this phase may be needed, depending on the specific techniques.

5. *Evaluation*: objective assessment if the business objectives can be met by the model(s) created.

6. *Deployment*: Actual use of the model(s) created in business environment, if the evaluation was positive.

B Regression Model Accuracy Tables

This appendix lists the different techniques' prediction performances (RMSE and SE) achieved with 5 repetitions of 10-fold cross-validation for models 1 (indoor room temperatures), 2 (circuits' daily energy consumption) and 3 (weather parameters). The best hyper-parameter setting of each combination ¡technique, PCA¿ is given as found by grid search. The analysis for best performing feature combinations per model was skipped for brevity. The best performing features are provided in Section 3.2, Table 4.

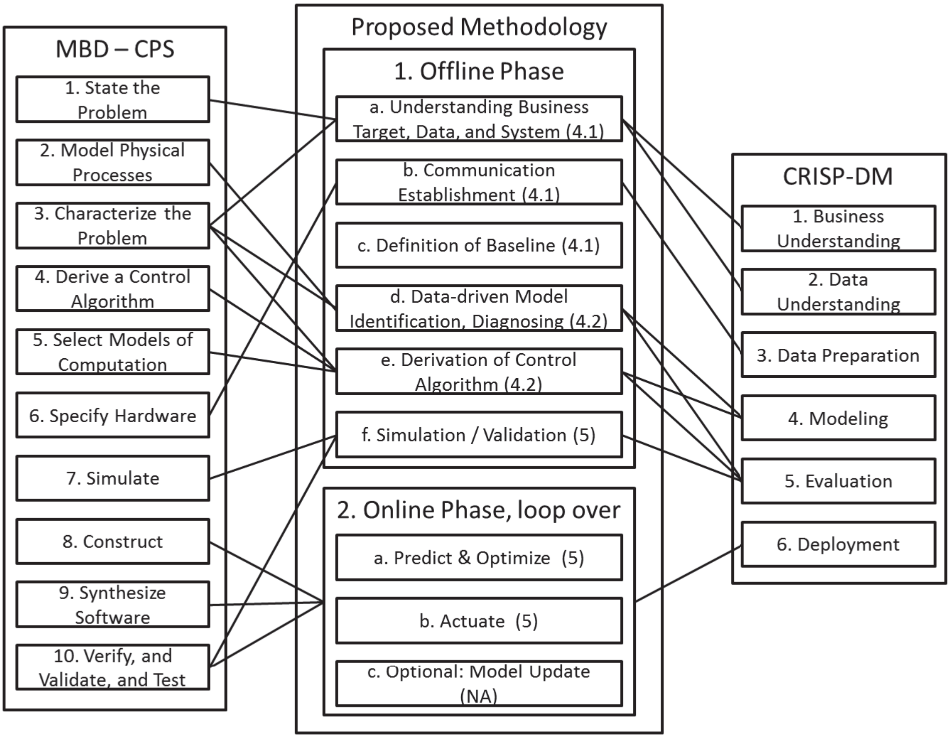

Figure 18: Methodological steps to develop data-driven predictive building control in legacy buildings mapped to those of MBD-CPS and CRISP-DM. Numbers in brackets indicate the sections in which the respective steps are applied to the Sierra Elvira School.

All models have been trained on periods of data for which exploratory analysis showed no data gaps, no abnormal sensor or meter readings and no extraordinary events during the reference period. Concretely data of the periods 2014/12/01-2014/12/07 and 2015/01/19-2015/01/31 was of sufficient quality for usage. A sliding window mechanism created training and test sets for the different models. The models were trained with a training set of size 1,437. To estimate the RMSE and its associated standard error values listed in tables 10-21, training with 10-fold cross-validation and 5 repetitions was used. For each model, an additional test (skipped for brevity) with a separate test set of size 480 validated that the resulting test-set error was within the 95% confidence interval $RMSE \pm 2.78 \times SE$[1].

In summary, the following tables show:

[1]The critical value of 2.78 follows from the desired confidence level, the number of repetitions in cross-validation, and the t-distribution.

Table 10: Model 1 - Zone 1 indoor temperature prediction performances for different techniques for Classroom 3B temperature models. With and without PCA.

Technique	Parameters	RMSE	SE
GAUSS	$\sigma = 1.8$; PCA=NA	0.82K	0.069K
GAUSS	$\sigma = 0.1$; PCA=95%	0.27K	0.028K
GAUSS	$\sigma = 0.5$; PCA=90%	0.30K	0.037K
MLP	$n = 60$; PCA=NA	0.89K	0.066K
MLP	$n = 10$; PCA=95%	0.21K	0.021K
MLP	$n = 20$; PCA=90%	0.27K	0.032K
SVM	$c = 25$; PCA=NA	0.84K	0.092K
SVM	$c = 15$; PCA=95%	0.25K	0.016K
SVM	$c = 25$; PCA=90%	0.29K	0.019K
BRANN	$n = 20$; PCA=NA	0.85K	0.069K
BRANN	$n = 30$; PCA=95%	0.16K	0.009K
BRANN	$n = 30$; PCA=90%	0.22K	0.026K

Table 11: Model 1 - Zone 1 indoor temperature prediction performances for different techniques for Classroom 3C.

Technique	Parameters	RMSE	SE
GAUSS	$\sigma = 1.8$; PCA=NA	1.18K	0.104K
GAUSS	$\sigma = 0.1$; PCA=95%	0.41K	0.044K
GAUSS	$\sigma = 0.5$; PCA=90%	0.44K	0.042K
MLP	$n = 50$; PCA=NA	1.27K	0.109K
MLP	$n = 10$; PCA=95%	0.29K	0.025K
MLP	$n = 20$; PCA=90%	0.31K	0.040K
SVM	$c = 20$; PCA=NA	1.23K	0.141K
SVM	$c = 15$; PCA=95%	0.47K	0.045K
SVM	$c = 25$; PCA=90%	0.34K	0.045K
BRANN	$n = 30$; PCA=NA	1.20K	0.099K
BRANN	$n = 10$; PCA=95%	0.25K	0.011K
BRANN	$n = 20$; PCA=90%	0.35K	0.041K

- As seen in tables 10-21 for almost all indoor room temperature predictions PCA accounting for 95% of input feature variation achieves lowest RMSE. It is presumed that this PCA suppressing high frequency noise in the data as argued in [29] has avoids that the models overfit stochastic indoor room temperature fluctuations.
- No positive effects of PCA were recorded on models 2 and 3 (tables 22-26).
- BRANN outperformed for almost all settings and models in tables 10-26.

Table 12: Model 1 - Zone 1 indoor temperature prediction performances for different techniques for Classroom 4A.

Technique	Parameters	RMSE	SE
GAUSS	$\sigma = 1.5$; PCA=NA	0.82K	0.067K
GAUSS	$\sigma = 0.1$; PCA=95%	0.31K	0.034K
GAUSS	$\sigma = 0.5$; PCA=90%	0.31K	0.040K
MLP	$n = 60$; PCA=NA	0.84K	0.075K
MLP	$n = 10$; PCA=95%	0.24K	0.017K
MLP	$n = 50$; PCA=90%	0.32K	0.034K
SVM	$c = 25$; PCA=NA	0.77K	0.087K
SVM	$c = 15$; PCA=95%	0.30K	0.038K
SVM	$c = 25$; PCA=90%	0.29K	0.034K
BRANN	$n = 30$; PCA=NA	0.77K	0.083K
BRANN	$n = 20$; PCA=95%	0.23K	0.013K
BRANN	$n = 40$; PCA=90%	0.35K	0.038K

Table 13: Model 1 - Zone 1 indoor temperature prediction performances for different techniques for Classroom 6B.

Technique	Parameters	RMSE	SE
GAUSS	$\sigma = 1.8$; PCA=NA	0.90K	0.100K
GAUSS	$\sigma = 0.1$; PCA=95%	0.32K	0.030K
GAUSS	$\sigma = 0.5$; PCA=90%	0.34K	0.038K
MLP	$n = 60$; PCA=NA	0.96K	0.090K
MLP	$n = 10$; PCA=95%	0.19K	0.010K
MLP	$n = 30$; PCA=90%	0.35K	0.039K
SVM	$c = 22$; PCA=NA	0.95K	0.145K
SVM	$c = 25$; PCA=95%	0.27K	0.020K
SVM	$c = 25$; PCA=90%	0.27K	0.026K
BRANN	$n = 20$; PCA=NA	0.90K	0.099K
BRANN	$n = 50$; PCA=95%	0.16K	0.012K
BRANN	$n = 40$; PCA=90%	0.24K	0.033K

Table 14: Model 1 - Zone 1 indoor temperature prediction performances for different techniques for Dinner (age 4).

Technique	Parameters	RMSE	SE
GAUSS	$\sigma = 1.8$; PCA=NA	0.98K	0.080K
GAUSS	$\sigma = 0.1$; PCA=95%	0.33K	0.039K
GAUSS	$\sigma = 0.1$; PCA=90%	0.32K	0.041K
MLP	$n = 60$; PCA=NA	1.03K	0.100K
MLP	$n = 10$; PCA=95%	0.24K	0.020K
MLP	$n = 10$; PCA=90%	0.26K	0.044K
SVM	$c = 15$; PCA=NA	1.01K	0.108K
SVM	$c = 15$; PCA=95%	0.22K	0.022K
SVM	$c = 18$; PCA=90%	0.21K	0.029K
BRANN	$n = 30$; PCA=NA	0.99K	0.087K
BRANN	$n = 20$; PCA=95%	0.17K	0.009K
BRANN	$n = 30$; PCA=90%	0.24K	0.012K

Table 15: Model 1 - Zone 1 indoor temperature prediction performances for different techniques for Living room.

Technique	Parameters	RMSE	SE
GAUSS	$\sigma = 1.8$; PCA=NA	0.89K	0.087K
GAUSS	$\sigma = 0.1$; PCA=95%	0.21K	0.038K
GAUSS	$\sigma = 0.1$; PCA=90%	0.27K	0.039K
MLP	$n = 50$; PCA=NA	0.91K	0.096K
MLP	$n = 10$; PCA=95%	0.18K	0.025K
MLP	$n = 20$; PCA=90%	0.26K	0.032K
SVM	$c = 20$; PCA=NA	0.94K	0.123K
SVM	$c = 15$; PCA=95%	0.18K	0.032K
SVM	$c = 15$; PCA=90%	0.25K	0.032K
BRANN	$n = 20$; PCA=NA	0.90K	0.091K
BRANN	$n = 10$; PCA=95%	0.18K	0.012K
BRANN	$n = 20$; PCA=90%	0.18K	0.022K

Table 16: Model 1 - Zone 2 indoor temperature prediction performances for different techniques for Classroom 5B.

Technique	Parameters	RMSE	SE
GAUSS	$\sigma = 1.8$; PCA=NA	1.03K	0.093K
GAUSS	$\sigma = 0.1$; PCA=95%	0.17K	0.034K
GAUSS	$\sigma = 0.5$; PCA=90%	0.21K	0.045K
MLP	$n = 60$; PCA=NA	1.11K	0.088K
MLP	$n = 20$; PCA=95%	0.17K	0.031K
MLP	$n = 30$; PCA=90%	0.20K	0.043K
SVM	$c = 25$; PCA=NA	1.11K	0.146K
SVM	$c = 15$; PCA=95%	0.18K	0.031K
SVM	$c = 22$; PCA=90%	0.20K	0.035K
BRANN	$n = 20$; PCA=NA	1.03K	0.103K
BRANN	$n = 10$; PCA=95%	0.18K	0.015K
BRANN	$n = 30$; PCA=90%	0.18K	0.012K

Table 17: Model 1 - Zone 2 indoor temperature prediction performances for different techniques for Classroom 5C.

Technique	Parameters	RMSE	SE
GAUSS	$\sigma = 1.8$; PCA=NA	0.88K	0.094K
GAUSS	$\sigma = 0.1$; PCA=95%	0.34K	0.030K
GAUSS	$\sigma = 0.5$; PCA=90%	0.36K	0.026K
MLP	$n = 60$; PCA=NA	0.92K	0.084K
MLP	$n = 10$; PCA=95%	0.33K	0.032K
MLP	$n = 40$; PCA=90%	0.37K	0.023K
SVM	$c = 20$; PCA=NA	0.91K	0.119K
SVM	$c = 22$; PCA=95%	0.31K	0.033K
SVM	$c = 25$; PCA=90%	0.34K	0.037K
BRANN	$n = 30$; PCA=NA	0.93K	0.094K
BRANN	$n = 50$; PCA=95%	0.32K	0.018K
BRANN	$n = 20$; PCA=90%	0.33K	0.027K

Table 18: Model 1 - Zone 2 indoor temperature prediction performances for different techniques for Computer room.

Technique	Parameters	RMSE	SE
GAUSS	$\sigma = 1.8$; PCA=NA	0.95K	0.105K
GAUSS	$\sigma = 0.1$; PCA=95%	0.09K	0.005K
GAUSS	$\sigma = 0.5$; PCA=90%	0.16K	0.010K
MLP	$n = 60$; PCA=NA	0.99K	0.112K
MLP	$n = 10$; PCA=95%	0.10K	0.007K
MLP	$n = 30$; PCA=90%	0.15K	0.012K
SVM	$c = 18$; PCA=NA	1.02K	0.159K
SVM	$c = 20$; PCA=95%	0.10K	0.004K
SVM	$c = 15$; PCA=90%	0.14K	0.009K
BRANN	$n = 20$; PCA=NA	0.98K	0.113K
BRANN	$n = 20$; PCA=95%	0.09K	0.005K
BRANN	$n = 40$; PCA=90%	0.09K	0.008K

Table 19: Model 1 - Zone 2 indoor temperature prediction performances for different techniques for Dinner (age 3).

Technique	Parameters	RMSE	SE
GAUSS	$\sigma = 1.8$; PCA=NA	1.08K	0.111K
GAUSS	$\sigma = 0.1$; PCA=95%	0.26K	0.030K
GAUSS	$\sigma = 0.5$; PCA=90%	0.27K	0.036K
MLP	$n = 60$; PCA=NA	1.13K	0.098K
MLP	$n = 10$; PCA=95%	0.26K	0.031K
MLP	$n = 20$; PCA=90%	0.29K	0.044K
SVM	$c = 25$; PCA=NA	1.15K	0.149K
SVM	$c = 25$; PCA=95%	0.27K	0.019K
SVM	$c = 25$; PCA=90%	0.26K	0.021K
BRANN	$n = 20$; PCA=NA	1.05K	0.117K
BRANN	$n = 20$; PCA=95%	0.26K	0.019K
BRANN	$n = 40$; PCA=90%	0.26K	0.017K

Table 20: Model 1 - Zone 2 indoor temperature prediction performances for different techniques for Music room.

Technique	Parameters	RMSE	SE
GAUSS	$\sigma = 1.8$; PCA=NA	1.03K	0.079K
GAUSS	$\sigma = 0.1$; PCA=95%	0.34K	0.032K
GAUSS	$\sigma = 0.1$; PCA=90%	0.32K	0.029K
MLP	$n = 60$; PCA=NA	1.09K	0.100K
MLP	$n = 20$; PCA=95%	0.28K	0.028K
MLP	$n = 20$; PCA=90%	0.27K	0.017K
SVM	$c = 22$; PCA=NA	1.10K	0.123K
SVM	$c = 20$; PCA=95%	0.27K	0.041K
SVM	$c = 20$; PCA=90%	0.28K	0.022K
BRANN	$n = 20$; PCA=NA	1.03K	0.083K
BRANN	$n = 10$; PCA=95%	0.24K	0.020K
BRANN	$n = 30$; PCA=90%	0.25K	0.018K

Table 21: Model 1 - Zone 2 indoor temperature prediction performances for different techniques for Secretary.

Technique	Parameters	RMSE	SE
GAUSS	$\sigma = 1.8$; PCA=NA	0.93K	0.086K
GAUSS	$\sigma = 0.1$; PCA=95%	0.33K	0.027K
GAUSS	$\sigma = 0.5$; PCA=90%	0.36K	0.019K
MLP	$n = 50$; PCA=NA	0.96K	0.085K
MLP	$n = 20$; PCA=95%	0.30K	0.018K
MLP	$n = 40$; PCA=90%	0.33K	0.010K
SVM	$c = 22$; PCA=NA	0.85K	0.136K
SVM	$c = 25$; PCA=95%	0.30K	0.021K
SVM	$c = 25$; PCA=90%	0.32K	0.025K
BRANN	$n = 30$; PCA=NA	0.85K	0.094K
BRANN	$n = 10$; PCA=95%	0.28K	0.018K
BRANN	$n = 30$; PCA=90%	0.29K	0.022K

Table 22: Model 2 - Circuit 1 energy consumption models. As T_{air} drives heating operation and supply temperatures mostly linearly, PCA had little effect.

Technique	Parameters	RMSE [kWh]	SE [kWh]
GAUSS	$\sigma = 0.1$	47.61	23.11
MLP	$n = 60$	54.13	12.46
SVM	$c = 1$	59.94	32.86
BRANN	$n = 15$	43.76	7.31

Table 23: Model 2 - Circuit 2 energy consumption models. As T_{air} drives heating operation and supply temperatures mostly linearly, PCA had little effect.

Technique	Parameters	RMSE [kWh]	SE [kWh]
GAUSS	$\sigma = 0.1$	36.57	20.37
MLP	$n = 60$	38.74	8.79
SVM	$c = 15$	60.85	29.29
BRANN	$n = 3$	25.17	4.74

Table 24: Model 3 - Microclimatic Models, outdoor temperature T^i_{air}. PCA had no positive effect on test errors.

Technique	Parameters	RMSE [K]	SE [K]
GAUSS	$\sigma = 0.5$	1.74	0.52
MLP	$n = 60$	1.67	0.47
SVM	$c = 15$	1.92	0.68
BRANN	$n = 5$	1.47	0.14

Table 25: Model 3 - Microclimatic Models, relative humidity hr^i. PCA had no positive effect on test errors.

Technique	Parameters	RMSE [%]	SE [%]
GAUSS	$\sigma = 0.5$	4.06	2.01
MLP	$n = 40$	4.00	1.97
SVM	$c = 18$	4.47	1.95
BRANN	$n = 2$	4.20	1.98

Table 26: Model 3 - Microclimatic Models, wind speed ws^i. PCA had no positive effect on test errors.

Technique	Parameters	RMSE [m/s]	SE [m/s]
GAUSS	$\sigma = 0.1$	1.78	1.96
MLP	$n = 40$	1.75	1.96
SVM	$c = 18$	2.02	1.94
BRANN	$n = 2$	1.72	1.97

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