POLITECNICO DI TORINO

ICT IN BUILDING DESIGN

PROJECT REPORT - GROUP 4

Optimization and prediction of the energy consumption of a school building in Turin

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Abstract

The rapid growth of information and communication technology has led to a significant rise in the number of Smart Cities and Internet of Things (IoT) devices in recent years, resulting in substantial transformations across several industries. ICT has a crucial role in optimizing, predicting, and visualizing energy usage in building design. The conversion of traditional buildings into smart buildings employing advanced technology has gained increasing popularity. The primary goals of smart energy technology are to decrease consumption of energy and promote environmental sustainability. This study aims to enhance the energy efficiency of a school building in Turin by using appropriate python libraries. Additionally, it seeks to forecast future energy usage and temperatures by employing a fine-tuned neural network model. Specifically, our model was developed using the DesignBuilder software, and the optimization and energy simulation components were carried out using BESOS, Energyplus, and eppy. A collection of sensors was simulated to extract data from the smart building. The data was saved in an InfluxDB database and shown using a user-friendly interface called Grafana. After obtaining the simulated data, we conducted the energy signature analysis and made predictions for future heating and cooling usage as well as temperature values. In order to achieve this objective, we used a well-calibrated neural network equipped with LSTM neurons.

Keyword:Design Builder, EnergyPlus, Surrogate model, Optimization, Energy Signature

1 Introduction

In an era marked by rapid urbanization and increasing environmental awareness, the integration of Information and Communication Technology (ICT) in building design has become pivotal. Our project is at the intersection of these global trends, aiming to redefine the energy landscape of educational infrastructure within the smart city framework. The focus is set on a school building in Turin, chosen for its representational value and operational dynamics, embodying the challenges and opportunities of integrating smart technologies in educational environments.

This study engages with the core aspects of Smart Cities, which strive not just for technological advancement but for a holistic enhancement of urban life. Smart Cities optimize resource management and improve the socio-economic landscape, making urban spaces more efficient and responsive to the needs of their residents [1]. In this context, our school building serves as a microcosm of broader Smart City objectives, such as reducing environmental impacts and fostering sustainable communities.

The primary goal of our research is to optimize and predict the energy consumption of this school building. We aim to explore and refine various building parameters such as insulation levels, window glazing types, and HVAC system efficiency to enhance energy performance. Employing advanced simulation tools, IoT integration, and predictive analytics, we will meticulously model energy usage patterns and forecast future consumption. This approach not only aids in achieving immediate energy efficiency but also sets a precedent for future educational infrastructure planning.

Through this project, we contribute to the global efforts epitomized by the European Green Deal, aiming to transform energy usage in public buildings and reduce their ecological footprints. By systematically analyzing energy flow and optimizing operational parameters, this study will provide actionable insights that could be replicated in similar educational settings, aligning with our ultimate vision of sustainable and smart educational environments.

2 State of the Art

The domain of building energy consumption has seen significant advances, particularly in the prediction and optimization of energy usage through the application of innovative technologies and methodologies [2]. The growing importance of accurate and robust energy consumption forecasting is underscored by its critical role in resource planning and building operations management. Recent studies have increasingly focused on the development and implementation of sophisticated predictive models to enhance the efficiency and sustainability of buildings [3].

Long Short-Term Memory (LSTM) models have become a cornerstone in forecasting energy consumption in buildings due to their ability to handle time series data effectively without prior knowledge of the data's statistical properties. Namini et al. have demonstrated that LSTM models consistently outperform traditional ARIMA models, enhancing prediction accuracy by approximately 85% in energy-related applications. This superiority is crucial in our context, where accurate energy forecasting can significantly impact the operational strategies of educational buildings [4].

Moreover, the selection of LSTM over other potential models, such as Kalman Filters, is supported by research conducted by the University of Southern Denmark, which highlights the efficacy of black-box models (like LSTM) in predicting thermal behavior with greater precision compared to gray- or white-box models [5]. This distinction is critical as it directly influences our approach to modeling energy dynamics within a school environment, where factors such as occupancy and usage patterns vary considerably.

In addition to LSTM, other machine learning techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest (RF) classifiers have also been widely used for predicting thermal comfort and energy management in buildings. These models offer a robust framework for handling complex datasets and non-linear relationships inherent in building energy systems [6].

The use of data-driven techniques for building thermal modeling and energy performance prediction is further exemplified by the AutoRegressive eXogenous (ARX) model, noted for its quick implementation and accuracy. However, challenges remain, particularly in adapting these models to account for dynamic changes in building use, equipment configurations, and external environmental factors.

Recent research by Xu et al. [7] has explored the effectiveness of deep learning algorithms, particularly LSTM, in improving prediction performance for indoor temperature in public buildings. The results highlight the superior performance of LSTM in terms of lower Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), which are critical metrics for our project's aims [8].

The broader context of this research includes advancements in artificial intelligence (AI) and big data analytics in building energy management, as reviewed by Cao et al.[9], They discuss the current global status of building energy consumption and the latest technological strategies for achieving energy-efficient and zero-energy buildings. These strategies encompass a range of solutions from passive design and building-integrated photovoltaics to energy storage systems and advanced control systems.

This research aligns with our project's objective to optimize and predict energy consumption in a school building in Turin, employing a combination of advanced simulation tools, IoT technologies, and AI-driven predictive analytics to model energy use patterns and forecast future consumption effectively. By integrating these state-of-the-art technologies, we aim to contribute to the transformation of educational facilities into more sustainable and energy-efficient environments [10].

3 Methodology

Our research uses a thorough, data-driven methodology to forecast and optimize the amount of energy used in a school. Firstly, we use DesignBuilder [11] to construct a building model, which allows us to produce an Input Data File (IDF) that includes essential architectural and operational parameters. In EnergyPlus [12] simulations, the data is utilized in conjunction with weather data to evaluate baseline energy performance.

Physical aspects in the ".idf", such insulation thickness, window properties, Heating and Ventilation, are adjusted throughout the optimization process under the direction of a surrogate model. This model facilitates the identification of the most favorable configurations that result in the most energy efficiency. Concurrently, data on energy use is gathered by a virtual network of sensors, sent using the MQTT protocol [13], and saved in an InfluxDB [14] database. This live data enables ongoing monitoring and is integrated into a Grafana dashboard for display.

The last stage of the project makes use of an LSTM model to forecast future energy use using both newly simulated and historical data. Predictive modeling facilitates efficient energy management, enabling informed decision-making about operational methods to minimize consumption of energy while ensuring interior comfort. By using a more simplified approach, we can combine advanced modeling methods with practical energy management strategies, laying the foundation for continuous improvements in building energy efficiency.

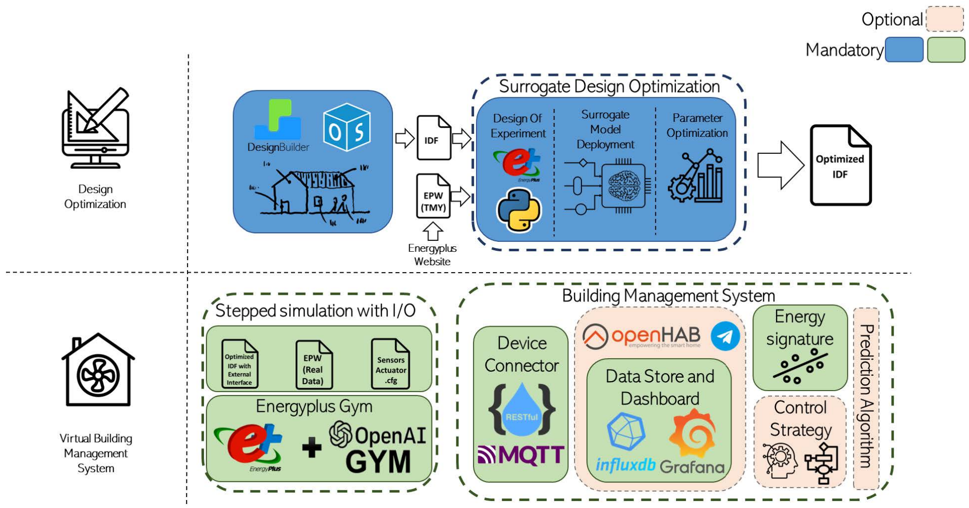


Figure 1: Workflow pipeline.

3.1 DesignBuilder

DesignBuilder serves as the foundational tool for generating the building model of the school in Turin, which is essential for subsequent simulations and optimizations. This sophisticated software allows for detailed modeling of various building characteristics and operational dynamics tailored to the specific architectural and climatic conditions of Turin.

Furthermore, DesignBuilder's capabilities extend to integrating advanced features such as solar shading, which is controlled based on solar irradiation and outdoor air temperature, enhancing the building's energy efficiency. The software's robust simulation engine, powered by EnergyPlus, allows for detailed energy performance analysis under various scenarios, providing critical data that informs the optimization process.

3.2 Parameters optimization in building energy simulation

In our pursuit to optimize the energy efficiency of a school building in Turin, we employed a rigorous simulation process using BESOS [15] and EnergyPlus. Our approach centered on a single ".idf" file configured with double-glazing windows to align with the climatic needs and architectural standards of the region. This file served as the baseline for our simulations, aiming to minimize the total energy consumption per area, denoted as Q [kWh/m^2].

3.3 Energy simulation

While an EnergyPlus Weather (.epw) file was available for Turin for the year 2005, data for subsequent years were scattered and incomplete. To address this, we sourced climate data from the Climate One Buildings website [17]—an online resource that aggregates EnergyPlus Weather files tailored for building simulations. From this resource, we extracted and compiled a comprehensive .epw file specifically for the year 2012. This file integrates historical weather data, ensuring that our energy simulations for the school building in Turin are based on accurate and relevant climatic conditions.

A comprehensive energy simulation of the Turin school building was performed using the ideally configured ".idf" file and ".epw" file for the year 2005. EnergyPlus, a sophisticated energy modeling tool from the U.S. Department of Energy, was used to model the building's energy performance in Turin's climate.

Using eppy [18], a Python package for editing and processing EnergyPlus input and output files, the simulation generated hourly data for the year. This simulation generated a ".csv" file with important data like indoor and outdoor temperatures, air ventilation rates, and electricity usage. These data were essential for evaluating our energy optimization techniques to reduce heating, cooling, and electrical use. The output data, structured in columns representing different energy metrics and rows delineated by hourly intervals, allowed us to perform granular analysis and visualization of the building's energy dynamics throughout the year.

3.4 Surrogate design optimization

The surrogate model is used in this study to discover the best school building reducing energy consumption design parameters. The full surrogate design optimization method is shown in Figure 2. The building ".idf" file and ".epw" file are loaded into EnergyPlus to generate a sample dataset for surrogate model building. The surrogate model will be trained with ANN and optimized with a genetic algorithm. A new optimized ".idf" file is generated after the surrogate model selects the optimal settings.

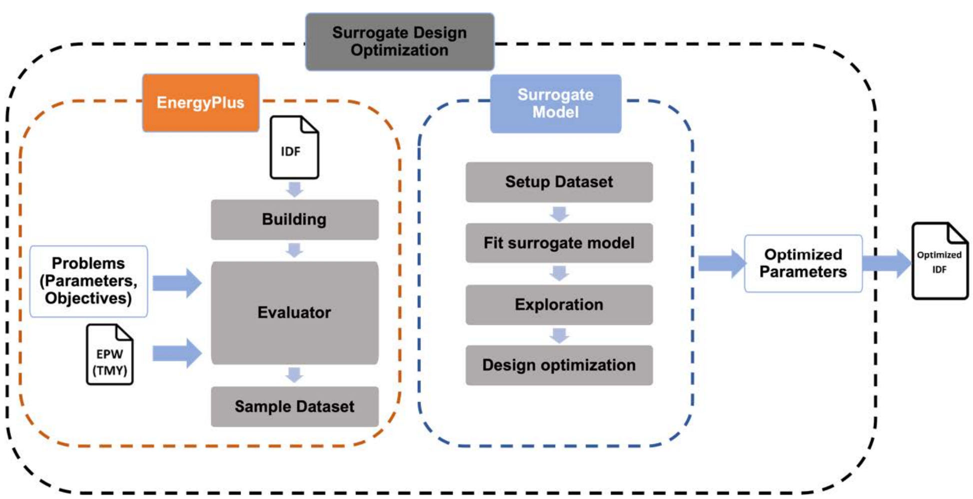


Figure 2: Surrogate design optimization workflow.

3.5 Stepped Simulation with I/O using EnergyPlus Gym

The stepped simulation with I/O facilitated by EnergyPlus Gym enables dynamic interaction and data exchange between EnergyPlus simulations and external systems. This capability is crucial for real-time monitoring and control of simulations, supporting the seamless integration of various building control strategies. The process typically involves:

- **Defining Simulation Parameters**: Setting up the simulation with necessary parameters such as the optimized ".idf" file for EnergyPlus input and the ".epw" file for weather data.
- **Configuring Control Inputs and Outputs**: Tailoring the inputs and outputs required for the simulation, including the setup of files needed.
- **Variable Selection**: Choosing essential variables like zone mean temperature to be monitored in each room, which are vital for assessing the building's performance. Additional variables could be temperature, humidity, and lighting.
- **Data Integration**: Adding these selected variables to the ".idf" file ensures comprehensive data capture during the simulation, which is crucial for subsequent analysis, optimization, and evaluation of the building's performance and its control strategies.

3.6 Integration of InfluxDB and Grafana for building energy data visualization

In our project, InfluxDB serves as a vital component for data storage and management. As a specialized time-series database, InfluxDB is optimized for handling sequences of data values tagged with time stamps, making it ideal for storing measurements from various sensors installed throughout the school building. This database architecture facilitates not only efficient data storage but also quick retrieval for analysis and visualization purposes.

To visualize and interpret this data, we employ Grafana [19], an open-source platform developed by Grafana Labs. Grafana integrates seamlessly with InfluxDB, allowing us to create dynamic dashboards that display the building's energy data in real-time. These dashboards are designed with capabilities to display a variety of charts and graphs that represent different energy usage metrics such as temperature variations, energy consumption rates, and HVAC efficiency.

The use of Grafana enhances our ability to monitor and analyze the building's performance over time. It provides intuitive visualizations that help in identifying trends, peak demand times, and potential inefficiencies within the building's energy systems.

Figure 3: InfluxDB environment.

3.7 Energy signature analysis

In our project, the energy signature serves as a key metric to understand the energy dynamics of the school building in Turin. It is calculated by analyzing the relationship between the difference in internal and external temperatures (ΔT) and the corresponding energy consumption over specific time intervals. This relationship is visualized by plotting ΔT against energy consumption, forming a distinctive pattern that illustrates how energy usage varies with changes in climatic conditions.

To enhance the precision of our analysis, we applied Ordinary Least Squares (OLS) regression to the data. This statistical method helps in quantifying the building's responsiveness to temperature fluctuations, thereby providing a clear indicator of its thermal characteristics and energy efficiency. Hourly, daily, weekly, and monthly energy consumption data were used to develop a comprehensive energy signature that aids in identifying potential areas for energy optimization and efficiency improvements.

3.8 Prediction model

In our study, we employed a Long Short-Term Memory (LSTM) model to forecast the thermal and energy consumption patterns of our building over a two-year period. This approach utilizes a black-box model, relying heavily on a robust dataset for validation without requiring explicit understanding of the internal workings of the model. LSTMs are particularly suited for this task due to their architecture, which includes memory blocks that help maintain information across time, making them ideal for time series data like energy consumption. These blocks contain three types of gates—Forget, Input, and Output—that manage the flow of information by selectively retaining or discarding data, thus enabling the model to learn from long-term dependencies in the dataset. This structure allows the LSTM to make informed predictions by adjusting its internal state through a learning process that optimizes gate behaviors based on historical data.

4 Building design optimization

4.1 Building design

The school building is comprehensively modeled to include 12 zones, divided into 4 classrooms, 2 office rooms, 3 toilets, storage room, a corridor, and a reception room. Each zone is accurately depicted to reflect real-life connections through doors and windows, ensuring that the simulation captures the true energy dynamics of the building. Furthermore, the whole surface area is 119.21 square meters.

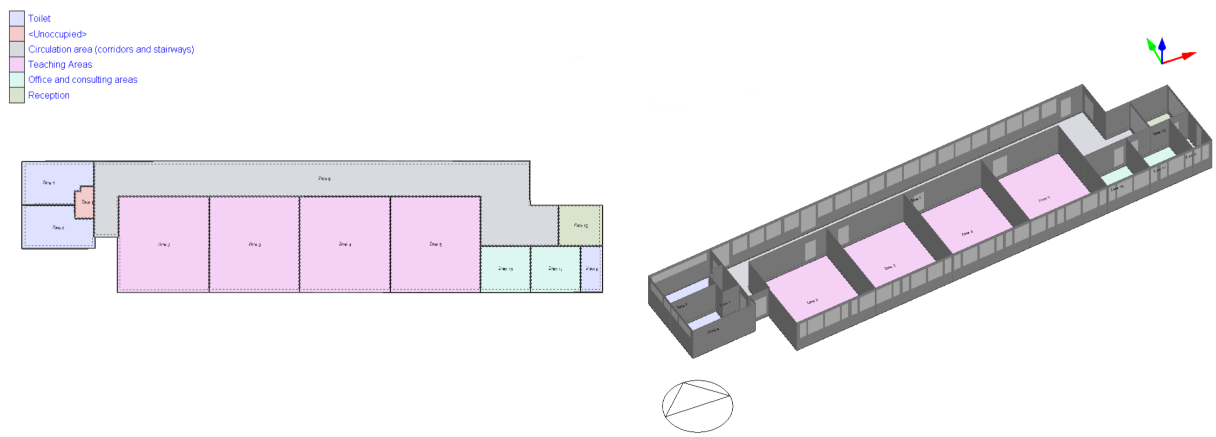


Figure 4: Case study – School building.

Key parameters such as window placement, wall insulation, and HVAC settings are meticulously configured. For insulation, we utilize materials like XPS Extruded Polystyrene, selected for its superior insulation efficiency and resilience, ensuring that the building's thermal performance is optimized.

Heating and cooling setpoints are strategically set based on typical occupancy patterns and local weather conditions, with heating set between 20°C and 16°C during cooler months, and cooling set between 26°C and 30°C in warmer months. These settings are vital for maintaining comfortable indoor temperatures while minimizing energy consumption.

- **Ventilation**: We adjusted the ACH, which represents the number of times the air within a space is replaced per hour. Recognizing the variance in room types and usage within the school, we set ACH values to range from 0 to 6, slightly below the typical residential range recommended by ASHRAE. This adjustment allowed us to tailor ventilation rates optimally for both energy savings and indoor air quality.

- **Shading**: The simulation also included dynamic control of window shading, activated by specific thresholds related to solar irradiation and external air temperature. This adaptive shading helps in mitigating heat gain during sunny conditions and reducing the cooling load, thus optimizing energy usage throughout the year.

- **U-Value of opaque surfaces**: The U-value of opaque surfaces, particularly external walls, was a critical focus. We chose XPS Extruded Polystyrene - CO2 Blowing_.0795 as our insulation material for its superior thermal resistance. The U-value is determined by the material's thermal resistance and the insulation thickness. By manipulating the thickness of the insulation, we aimed to achieve an optimal balance between thermal comfort and energy efficiency.

- **U-Value of windows**: For the windows, the U-value is crucial for determining heat transfer through glazing. The U-value for our double-glazed windows was set between 2.8-3.0 W/(m^2K). This value reflects the efficiency of the windows in preventing unwanted heat loss or gain, contributing significantly to the overall energy performance of the building.

Table 1: Ranges for the parameters optimization.

Parameter		***Range***
Ventilation	ACH [ACH]	[0-6]
Shading	Irradiation [W/m^2]	[80-300]
	External temperature [°C]	[18-28]
Opaque surfaces U-value	Insulation layer thickness [m]	[0.01-0.35]
Windows U-value	Glazing	Double

The outcomes of these simulations provide a quantitative basis for selecting the most effective energy-saving measures. By adjusting these parameters, we can significantly enhance the building's energy performance, ensuring it meets sustainability goals while providing a comfortable learning environment for students.

4.2 Sampling and Evaluation

We generated a set of 100 sample configurations using the Latin Hypercube Sampling (LHS) method to ensure a comprehensive exploration of potential solutions. Each configuration was evaluated using an EvaluatorEP object, which simulates the building's performance with each set of parameters. The results were stored and described, providing a detailed statistical summary of energy performance across all simulations.

Table 2: Minimum and maximum value for optimizing parameters.

Parameter	***minimum value***	***maximum value***
Insulation Thickness	0.01 [m]	0.35 [m]
ACH	0 [ACH]	6 [ACH]
Irradiation Setpoint	80 [W/m^2]	300 [W/m^2]
Temperature Setpoint	18 [°C]	28 [°C]

To enhance the efficiency of our building energy optimization, a surrogate model was developed using an artificial neural network (ANN). This model acts as a predictive tool, learning the complex relationships between various building design parameters and their impact on energy consumption.

4.3 Data Preparation and Normalization

Initially, the comprehensive dataset obtained from simulation outputs was divided into training and testing subsets with an 80/20 split. This separation ensures a robust training process while retaining a significant portion of data for model validation. To facilitate effective learning and prevent issues related to scale differences among features, all input values were normalized within a range of (0, 1).

4.4 Model Configuration and Hyperparameter Tuning

To mitigate the risk of overfitting and optimize the network's performance, critical hyperparameters were carefully selected before model training. These included the number of layers in the neural network and the regularization parameter (α). A systematic grid search approach was employed to explore various combinations of these hyperparameters, aiming to identify the configuration that yields the best predictive accuracy. Following the hyperparameter tuning, the ANN was trained on the normalized training data. This training involved adjusting the weights of the network through a backpropagation algorithm, ensuring that the model accurately captures the underlying patterns in the data. After training, the model's performance was evaluated on the test set to assess its generalization capability.

4.5 Performance Metrics

The effectiveness of the ANN surrogate model was quantified using the Mean Absolute Error (MAE) across the defined objectives, including aspects such as electricity usage, heating, and cooling demands. The resulting MAE values, detailed in Table 3, illustrate the model's accuracy in predicting building energy performance based on the input design parameters.

Table 3: MAE values for the problem objectives.

	Electricity:Facility	*DistrictHeating:Facility*	*DistrictCooling:Facility*
MAE	0.000059	1.264588	0.460608

The model was tested on previously produced samples using the evaluator. The 5 "best" samples, those with the lowest objective values, are reviewed in the table that follows.

Table 4: Best samples.

	Insulation Thickness	*Irradiation*	*Temperature*	*ACH*	*Electricity:Facility*	*DistrictHeating:Facility*	*DistrictCooling:Facility*
1	0.347654	109.778565	19.240609	5.796314	1.404415e+10	1.401558e+10	1.174911e+10
2	0.348906	89.935729	19.621443	5.921698	1.404422e+10	1.409949e+10	1.173193e+10
3	0.340498	144.095008	18.234892	5.615442	1.404404e+10	1.403278e+10	1.181675e+10
4	0.337780	150.939080	18.171073	5.642403	1.404401e+10	1.403177e+10	1.182900e+10
5	0.328016	114.694470	18.717458	5.984272	1.404413e+10	1.417823e+10	1.167381e+10

4.6 Optimization Strategy and Setup

We utilized a Non-Dominated Sorting Genetic Algorithm (NSGA-II) to generate a more diverse set of potential solutions. This approach is particularly effective in handling multi-objective optimization problems and helps in finding a set of Pareto-optimal solutions that reduce the objectives, which in our case are the various components of energy consumption. Below is Genetic Algorithm implementation:

- **Evaluator Setup**: We first defined an evaluation function that uses the surrogate model to predict the energy performance based on the given parameters. This function was integrated into a EvaluatorGeneric object, ensuring that each candidate solution could be assessed accurately.
- **Sample Generation and Initial Assessment**: Initially, we generated 100 samples using the Latin Hypercube Sampling (LHS) method to perform a sensitivity analysis. These samples were evaluated using our generic evaluator to determine their baseline performance.
- **Optimization Execution**: The NSGA-II algorithm was then deployed with a configuration of 5000 evaluations and a population size of 10000. This extensive search not only ensured thorough exploration of the design space but also improved the chances of finding optimal configurations.

The optimization process output a diverse set of potential solutions, each with associated energy performance metrics. We computed the total energy consumption per unit area (Q) for each solution using the formula:

$$Q = \frac{\text{Electricity:Facility} + \text{DistrictHeating:Facility} + \text{DistrictCooling:Facility}}{\text{HOUSE\_DIMENSION}}$$

where HOUSE_DIMENSION is taken as 120 square meters based on the specifications from Design Builder.

The plot below is a visual representation of a multi-objective optimization analysis for a building's energy performance, focusing specifically on cooling demand, heating demand, and electricity demand. This 3D scatter plot is instrumental in understanding the interplay and trade-offs between these different aspects of building energy use.

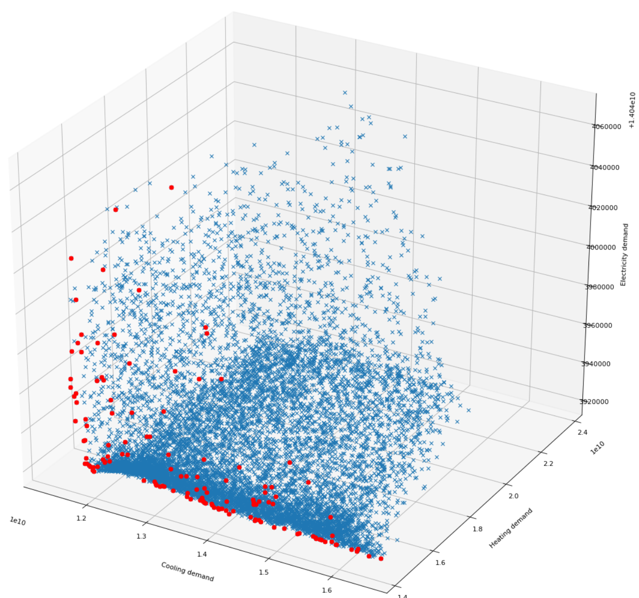


Figure 5: Pareto points.

- **Distribution of Points**: The bulk of the data points (blue crosses) exhibit a pattern where they spread out significantly along the cooling and heating demand axes while clustering more tightly along the electricity demand axis. This suggests that variations in building design or operational parameters might influence heating and cooling demands more dramatically than they affect overall electricity consumption.

- **Pareto Optimal Points**: The red dots, which represent Pareto optimal solutions, are scattered throughout the plot but tend to aggregate more towards the lower end of all three axes. This indicates that the most efficient configurations in terms of minimizing energy demands generally achieve lower values across cooling, heating, and electricity demands simultaneously.

- **Trends and Trade-offs**: There appears to be a broad, diffuse correlation where increases in cooling or heating demands correlate with increases in electricity demand, although this relationship is not strictly linear or uniform. This pattern suggests that efforts to reduce heating or cooling loads in the building could lead to proportionate reductions in electricity usage.

The graphs below illustrate the relationship between various building parameters—insulation thickness, irradiation, temperature, and air changes per hour (ACH)—and their respective impacts on electricity, heating, and cooling demands in a building, following the implementation of an optimization strategy.

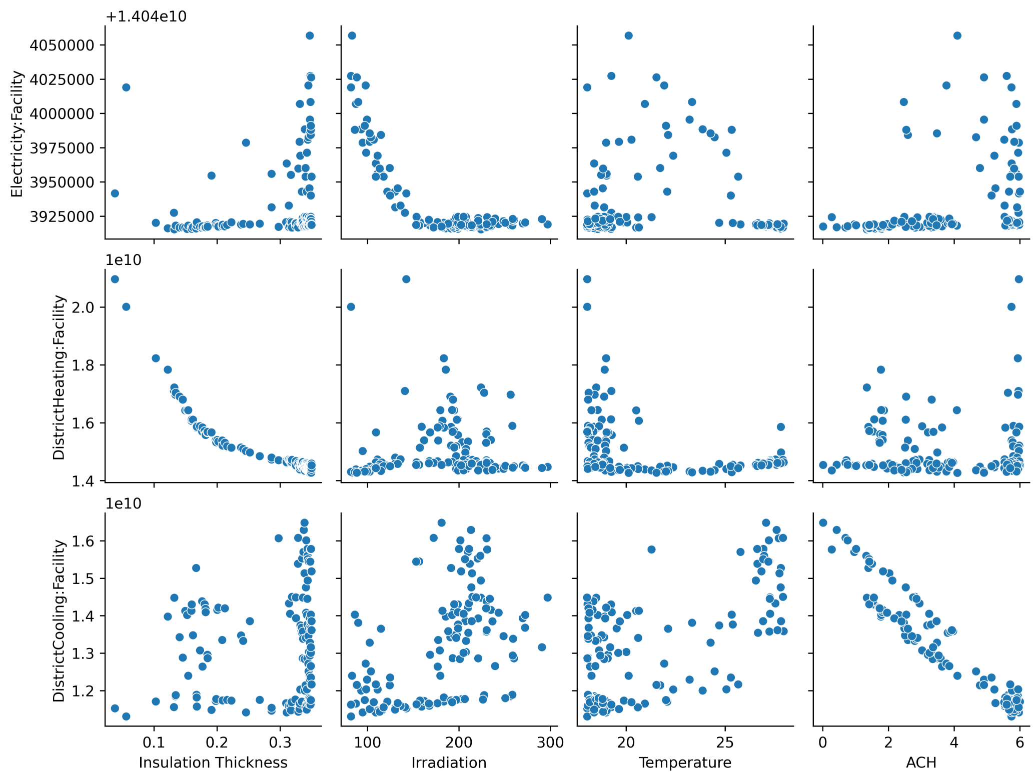


Figure 6: Graphs showing how input parameters change energy consumptions.

These plots demonstrate that the optimization has refined the sensitivity of energy demands to changes in building parameters:

- **Insulation Thickness** remains a critical factor, especially for heating demand, confirming its role in energy conservation strategies.
- **ACH** has a pronounced effect on both heating and cooling demands, underscoring its importance in balancing internal air quality and temperature without excessively increasing energy consumption.
- **Irradiation and Temperature** impacts are more pronounced in cooling demand, which aligns with expectations regarding their influence on internal thermal gains.

Overall, the optimization process appears to have successfully identified settings that minimize energy consumption across different domains, providing clear pathways for implementing energy-efficient measures in building design and operations.

The correlation heatmap in Figure 7, displays the relationships between various building parameters and energy consumptions, offers a fundamental understanding of how these variables interact.

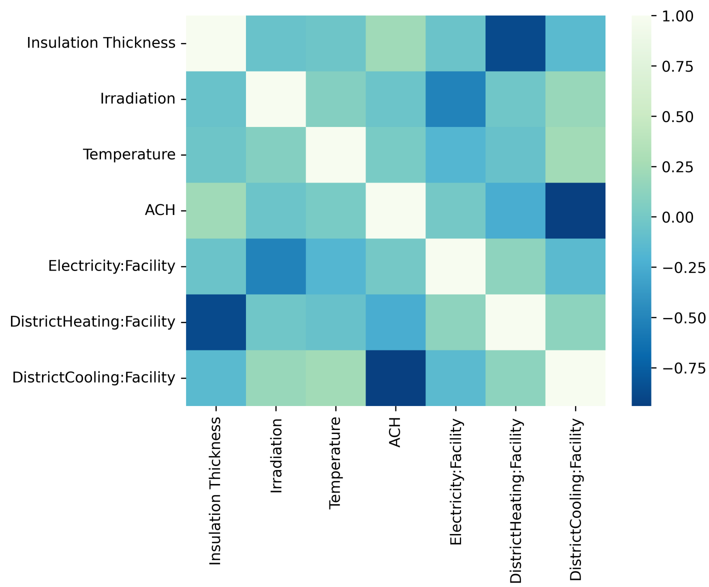


Figure 7: Correlation heatmap.

1. **Insulation Thickness**:
   - **Heating Demand**: Insulation thickness is strongly negatively correlated with heating demand, indicating effective thermal resistance that reduces heating needs.
   - **Cooling and Electricity Demand**: The correlation between insulation thickness and cooling/electricity demand shows varied effects; while generally minimal, in some cases, increased insulation can lead to slightly higher cooling demand due to trapped heat within the building environment.

2. **Irradiation**:

    - **Electricity Demand**: A strong negative correlation with electricity demand suggests that higher irradiation reduces the need for artificial lighting, potentially lowering electricity usage. However, this increased sunlight can also lead to higher cooling demands due to increased thermal gains, highlighting a complex interplay between natural light benefits and thermal load challenges.

3. **ACH**:

    - **Cooling Demand**: ACH is negatively correlated with cooling demand, demonstrating that more frequent air changes can effectively reduce the need for mechanical cooling by expelling warm indoor air. Nonetheless, excessive ACH might increase overall energy consumption by removing conditioned air, necessitating a balanced approach to ventilation settings.

4. **Seasonal Demand Variations**:

    - **Heating vs. Cooling**: There is a clear negative correlation between heating and cooling demands, reflecting typical seasonal variations where increased heating is required during colder months and more cooling during warmer months. This inverse relationship is crucial for planning energy management strategies that adapt to seasonal changes effectively.

Final physical criteria for achieving the lowest energy consumption are as follows:

Table 5: Parameters final values.

	Insulation Thickness	***Irradiation***	***Temperature***	***ACH***
Value	0.347823	81.923858	19.256269	5.597644

We substitute these in the original ".idf" file to create an optimized version for the next part of our work. Related objectives accomplished the following:

Table 6: objectives final values.

	Electricity [J]	***DistrictHeating [J]***	***DistrictCooling [J]***	***Total [J]***	***Dist [J]***
Value	1.404403e+10	1.430754e+10	1.163074e+10	3.998231e+10	2.317789e+10

5 Building management system

5.1 Visualization

In our project, we implemented an advanced Building Management System using a network of sensors to collect data on temperature, energy consumption (heating, cooling, and electricity), and window shading positions. This data is transmitted in real-time via the MQTT protocol with the broker "test.mosquitto.org" to facilitate rapid and reliable data handling.

We use InfluxDB as the MQTT subscriber to store this time-series data securely. Access to the InfluxDB is managed through a secure URL, authenticated with an account email and token, ensuring data integrity and accessibility. For visualization, we leverage Grafana, which connects directly to InfluxDB. This setup allows us to create dynamic visualizations that provide insights into energy usage patterns and operational efficiency.

Our integration of MQTT with InfluxDB and Grafana not only enhances our ability to monitor but also optimizes energy usage, with real-time data visualizations aiding in the proactive management of the building's energy performance.

5.2 Grafana

The graph in Figure 8 is a visualization from Grafana depicting the annual cycle of dry bulb temperatures in Turin for the year 2005. It demonstrates a clear seasonal pattern. Temperature peaks during the summer months, particularly noticeable in July and August, where temperatures frequently reach above 20 degrees Celsius. Conversely, the winter months, especially around January and December, show the lowest temperatures, dipping below 10 degrees Celsius.

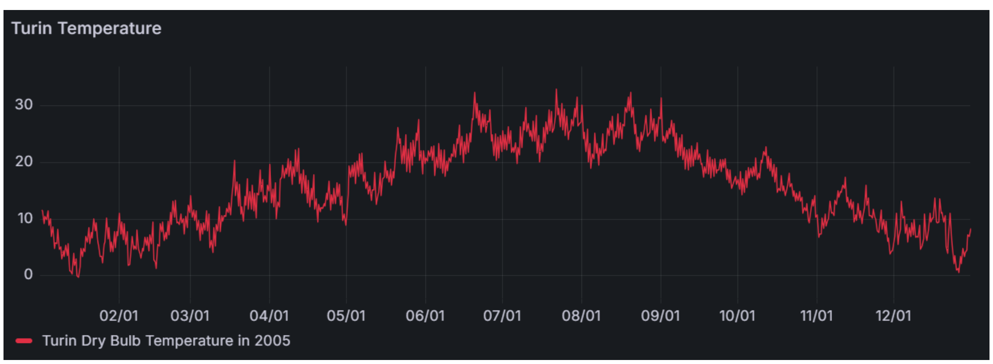


Figure 8: Turin City Temperature.

The graph in Figure 9 depicts the energy usage in terms of district cooling and district heating over the course of a year. The heating energy (gold) spikes are prominent during the colder months, starting to rise significantly in late autumn and peaking during the winter months. There's a visible increase in heating demand as the temperatures drop, which typically starts around late October and continues until early March. The cooling energy (blue) shows its highest usage during the summer months, with a sharp increase starting in late spring and peaking throughout the summer. This trend diminishes as the season transitions into autumn.

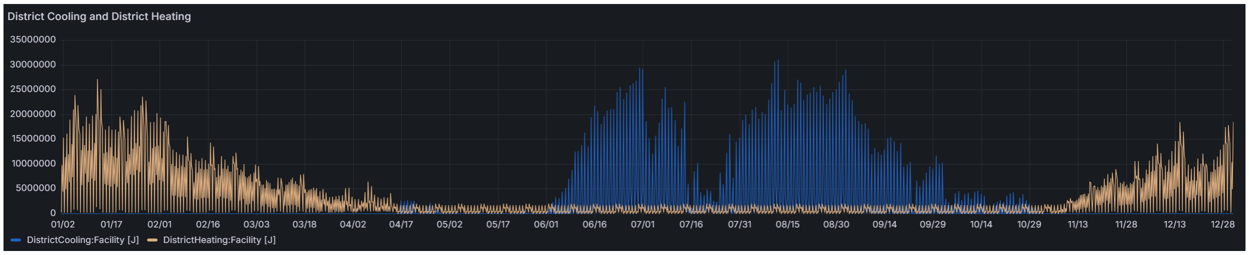


Figure 9: Districts Heating and Cooling.

The graph in Figure 10 shows the electricity consumption over a year. The graph displays pronounced daily spikes in electricity usage, indicating higher consumption during specific hours of the day. This pattern is consistent throughout the year, suggesting a regular daily cycle of peak and off-peak usage. Unlike heating and cooling demands, the electricity consumption does not show significant seasonal variability. The overall level of consumption remains relatively stable across different months, with daily peaks consistently occurring.

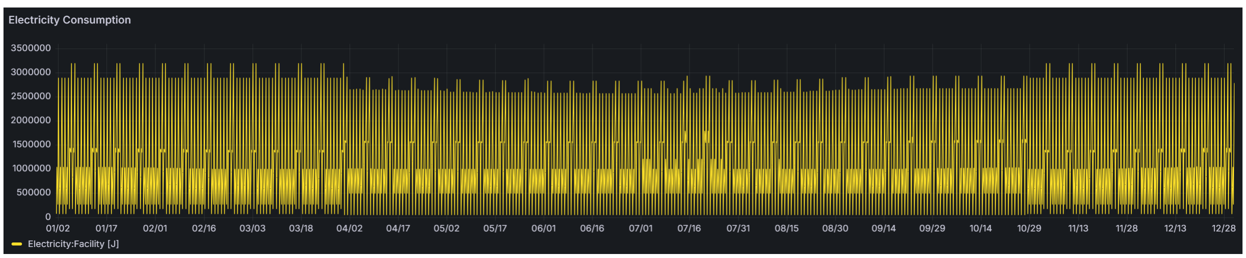


Figure 10: Electricity Consumption.

Figure 11 shows the Grafana dashboard, which displays sensor metrics visually. Visualizing metrics trends and behaviors through the dashboard facilitates monitoring and analysis.

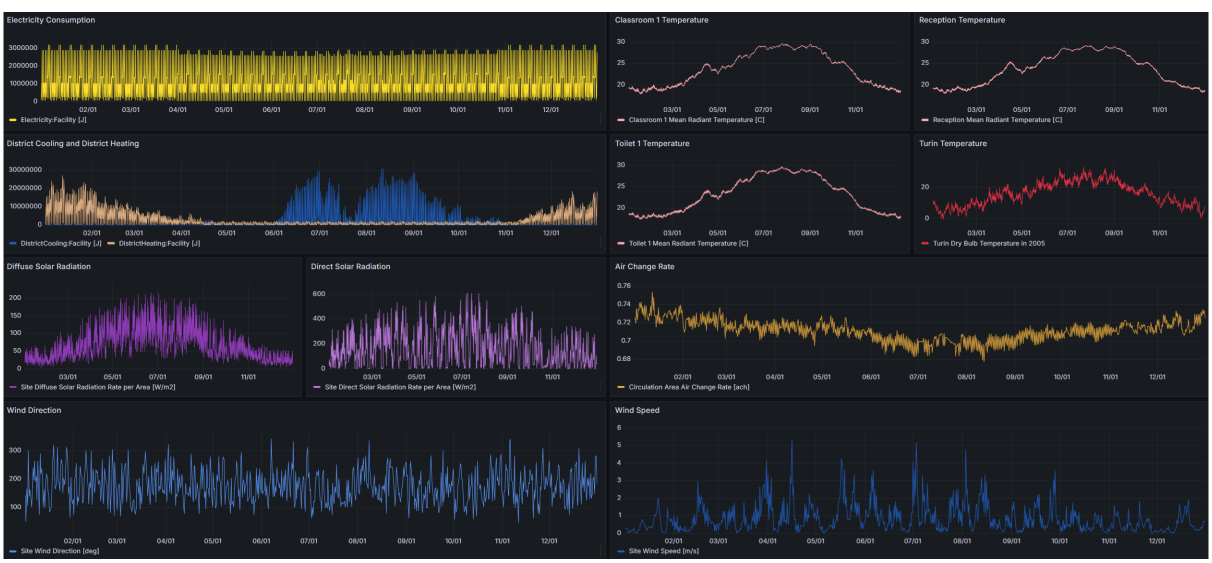


Figure 11: Grafana Dashboard.

5.3 Energy signature

A building's energy behavior is assessed using energy usage and climate information in the Energy Signature method. Regression analysis was done independently for the summer and winter seasons by excluding points from the dataset for the summer period that did not include any energy consumption for heating and, likewise, for the winter period that did not include any energy consumption for cooling. ΔT, as stated in Section 3.6, is the discrepancy between external and internal temperatures.

Figure 12 displays the energy signature of the building at various sampling frequencies. The data points in Figure 10a exhibit a high level of sparsity as a result of the dynamic influences of the building. Consequently, it is advisable to study data that has been averaged over a longer period of time. In Figures 12b, 12c, and 12d, the data points remain few, but the curve gradually aligns more closely with the points. A clear tendency can be seen in the points: while heating is rising, cooling is monotonically declining.

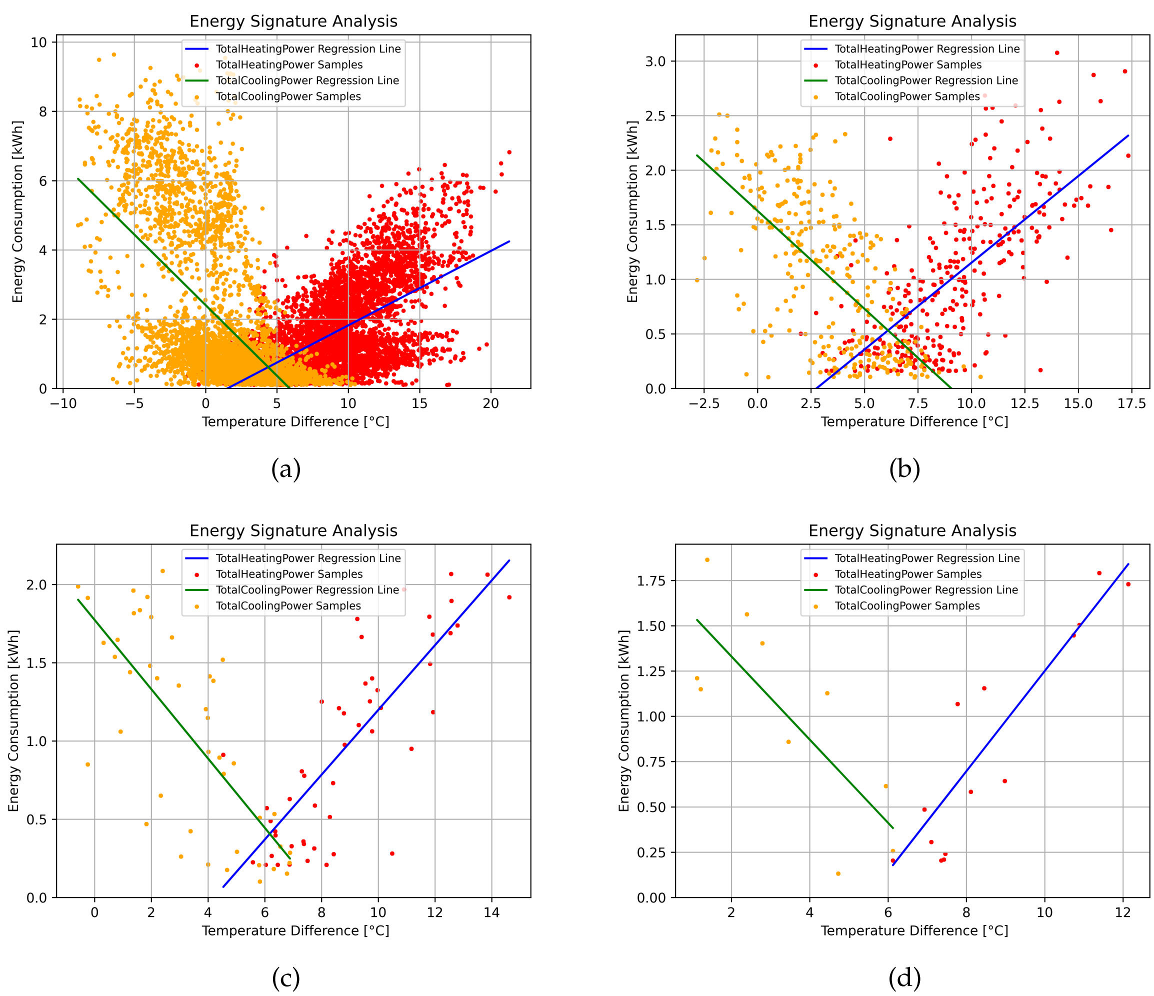


Figure 12: Energy Signature for summer and winter with (a) hourly samples, (b) daily sample, (c) weekly samples and (d) monthly samples.

The regression's performances are displayed in Table 7. Adjusting the time window helps the performances as predicted, indicating that noise from dynamic effects is progressively eliminated. This may be observed by the R^2 values. Through the process of estimating linear regression, it is feasible to establish the connection between energy and K.

$$P = K \times \Delta T$$

This relationship is defined by Equation above, where K represents the heat loss factor and corresponds to the slope of the regression line. Additionally, Table below presents the numerical values of the slope.

Table 7: Energy Signature results.

Period	***Sampling Frequency***	R^2	K
Winter	Hourly	0.344	-0.243
	Daily	0.482	-0.323
	Weekly	0.676	-0.231
	Monthly	0.821	-0.248
Summer	Hourly	0.372	0.192
	Daily	0.438	0.140
	Weekly	0.537	0.186
	Monthly	0.609	0.315

6 Prediction

We implemented a Long Short-Term Memory (LSTM) model, utilizing a Rectified Linear Unit (ReLU) activation function and an Adam Optimizer to enhance the neural network's performance. This model aimed to accurately predict the short-term energy consumption of our smart building, facilitating informed decision-making based on historical data trends.

6.1 Implementation and Configuration of the LSTM Model

To tailor the LSTM model to our needs, we considered several crucial hyperparameters: the length of historical data (number of hours back), epochs, batch size, and the number of neurons in each LSTM layer. Through iterative testing, we adjusted these parameters to optimize the model's accuracy, measured by Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). A sliding window approach was employed to manage time series data, allowing the model to continuously adapt to new data while maintaining a fixed window of historical input.

6.2 Training and Validation

The dataset was split into training and validation sets, comprising 66% and 34% of the data, respectively. This split was essential for training the model on a substantial portion of the data while validating its performance on unseen data. We developed distinct models for two specific datasets—cooling and heating energy consumption—to thoroughly analyze the energy usage patterns throughout different seasons.

Table 8: Cooling consumption prediction results.

Lags	*Step ahead*	*Epochs*	*Batch size*	*RMSE*	*MAE*
72	3	50	32	1.52e+06	1.52e+06
48	3	50	32	1.94e+06	0.66e+06
72	**3**	**60**	**64**	**1.34e+06**	**0.54e+06**
48	3	60	64	1.86e+06	0.78e+06

Table 9: Heating consumption prediction results.

Lags	*Step ahead*	*Epochs*	*Batch size*	*RMSE*	*MAE*
72	3	50	32	2.76e+06	1.58e+06
48	3	50	32	3.94e+06	1.76e+06
72	**3**	**60**	**64**	**1.24e+06**	**0.88e+06**
48	3	60	64	2.82e+06	1.35e+06

6.3 Observations and Outcomes

The analysis revealed that both heating and cooling energy consumptions exhibited similar patterns, which was expected given the consistent occupancy and operational conditions of the building throughout the year. However, as the prediction horizon extended (i.e., predicting further into the future), the RMSE and MAE values increased, indicating a decline in prediction accuracy. This trend underscores the challenges in long-term energy prediction due to increasing uncertainty with broader time horizons.

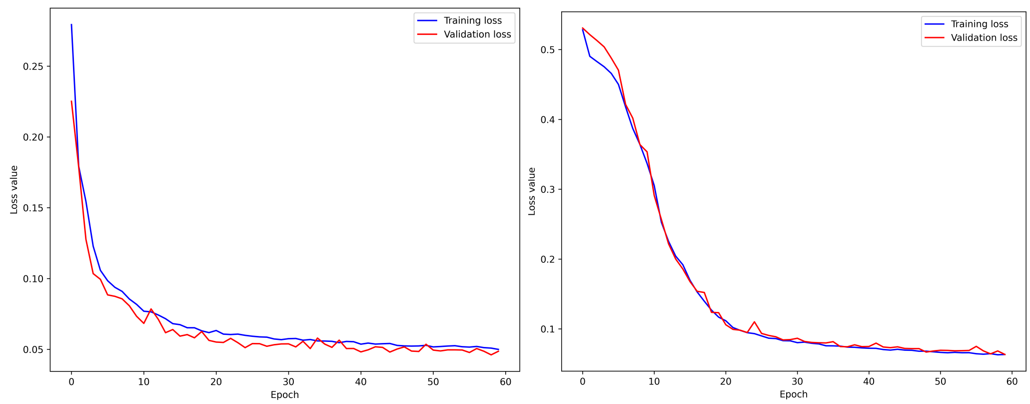
Using the optimal values, we conducted predictions for both datasets. The only variable we modified was the number of hours to predict, specifically 12, 24, and 72 hours. This was done to highlight a decrease in prediction accuracy as the number of predicted hours increased, which accorded with our assumptions.

Table 10: Cooling consumption prediction results changing only the step ahead parameter.

Lags	*Step ahead*	*Epochs*	*Batch size*	*RMSE*	*MAE*
72	3	60	32	1.48e+06	0.38e+06
72	12	60	32	2.66e+06	0.92e+06
72	36	60	32	3.06e+06	1.06e+06
72	72	60	32	3.58e+06	1.18e+06

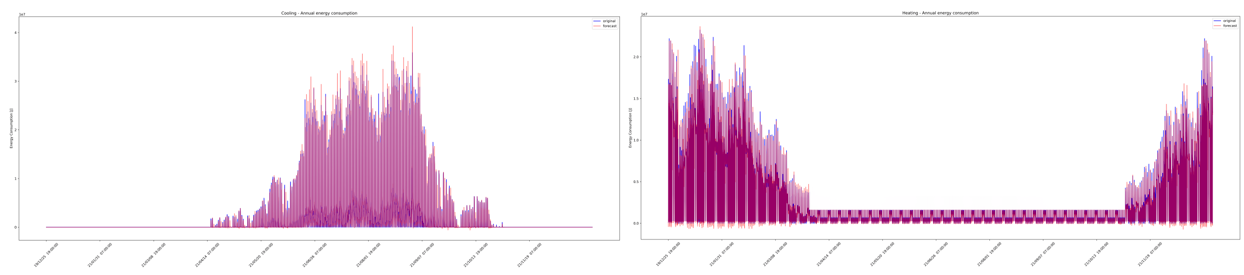
Table 11: Heating consumption prediction results changing only the step ahead parameter.

Lags	*Step ahead*	*Epochs*	*Batch size*	*RMSE*	*MAE*
72	3	60	32	1.33e+06	0.82e+06
72	12	60	32	1.94e+06	1.42e+06
72	36	60	32	2.34e+06	1.61e+06
72	72	60	32	3.12e+06	1.97+06



(a) (b)

Figure 13: Validation and Training losses for (a) Cooling and (b) Heating consumptions.



(a) (b)

Figure 14: (a) Cooling and (b) Heating consumption prediction with monthly view.

7 Conclusion

This study presents an analysis that suggests optimizing settings, emulating IoT sensors, computing energy signatures, and making predictions in a School building located in Turin. The use of IoT in the building industry has novel prospects for building management, while enhancing user experience through the utilization of intuitive data visualization. Regarding the optimization aspect, we observed that our optimal settings may result in increased expenses owing to the inclusion of double glazing windows and the thickness of the insulating layer. A potential compromise might be reached by opting for other glazing windows to reduce expenses, but at the expense of somewhat higher power consumption, and by picking a more straightforward model to prevent overly intricate scenarios. The assessment of the energy signature characterisation was conducted. Various sample rates were required to enhance the estimate. Upon analyzing the acquired values for R^2, it is evident that doing the regression with a weekly resolution yields superior outcomes. Discussing the predictive analysis, the LSTM model yields favorable outcomes when analyzing a three-hour future window, demonstrating satisfactory RMSE and MAE values. To enhance the neural network's performance, it would be beneficial to address any outliers in the initial data or to expand our training set. These adjustments are crucial as limited data and a small number of epochs could negatively impact the simulation results.

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