Modeling and Simulation of Electricity Consumption Profiles in the Northern European Building Stock

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Abstract

The electric power systems are currently being transformed through the integration of intermittent renewable energy resources and new types of electric loads. These developments run the risk of increasing mismatches between electricity supply and demand, and may cause non-favorable utilization rates of some power system components. Using Demand Response (DR) from flexible loads in the building stock is a promising solution to overcome these challenges for electricity market actors. However, as DR is not used at a large scale today, there are validity concerns regarding its cost-benefit and reliability when compared to traditional investment options in the power sector, e.g. network refurbishment. To analyze the potential in DR solutions, bottom-up simulation models which capture consumption processes in buildings is an alternative. These models must be simple enough to allow aggregations of buildings to be instantiated and at the same time intricate enough to include variations in individual behaviors of end-users. This is done so the electricity market actor can analyze how large volumes of flexibility acts in various market and power system operation contexts, but also can appreciate how individual end-users are affected by DR actions in terms of cost and comfort.

The contribution of this thesis is bottom-up simulation models for generating load profiles in detached houses and office buildings. The models connect end-user behavior with the usage of appliances and hot water loads through non-homogenous Markov chains, along with physical modeling of the indoor environment and consumption of heating and cooling loads through lumped capacitance models. The modeling is based on a simplified approach where openly available data and statistics are used, i.e. data that is subject to privacy limitations, such as smart meter measurements are excluded. The models have been validated using real load data from detached houses and office buildings, related models in literature, along with energy-use statistics from national databases. The validation shows that the modeling approach is sound and can provide reasonably accurate load profiles as the error results are in alignment with related models from other research groups.

This thesis is a composite thesis of five papers. Paper 1 presents a bottom-up simulation model to generate load profiles from space heating, hot water and appliances in detached houses. Paper 2 presents a data analytic framework for analyzing electricity-use from heating ventilation and air conditioning (HVAC) loads and appliance loads in an office building. Paper 3 presents a non-homogeneous Markov chain model to simulate representative occupancy profiles in single office rooms. Paper 4 utilizes the results in paper 2 and 3 to describe a bottom-up simulation model that generates load profiles in office buildings including HVAC loads and appliances. Paper 5 uses the model in paper 1 to analyze the technical feasibility of using DR to solve congestion problems in a distribution grid.

Keywords: Demand Response, Flexible loads, Building stock energy-use, Bottom-up simulation models, Load profiles, Non-homogenous Markov-chains, End-user behavior, Lumped capacitance models, HVAC system control, Smart Grid.

Sammanfattning

Integrering av förnybara energikällor och nya typer av laster i de elektriska energisystemen är möjliga svar till klimatförändringar och uttömning av ändliga naturresurser. Denna integration kan dock öka obalanserna mellan utbud och efterfrågan av elektricitet, och orsaka en ogynnsam utnyttjandegrad av vissa kraftsystemkomponenter. Att använda efterfrågeflexibilitet (Demand Reponse) i byggnadsbeståendet är en möjlig lösning till dessa problem för olika elmarknadsaktörer. Men eftersom efterfrågeflexibilitet inte används i stor skala idag finns det obesvarade frågor gällande lösningens kostnadsnytta och tillförlitlighet jämfört med traditionella investeringsalternativ i kraftsektorn. För att analysera efterfrågeflexibilitetslösningar är botten-upp-simuleringsmodeller som fångar elförbrukningsprocesser i byggnaderna ett alternativ. Dessa modeller måste vara enkla nog för att kunna representera aggregeringar av många byggnader men samtidigt tillräckligt komplicerade för att kunna inkludera unika slutanvändarbeteenden. Detta är nödvändigt när elmarknadsaktören vill analysera hur stora volymer efterfrågeflexibilitet påverkar elmarkanden och kraftsystemen, men samtidigt förstå hur styrningen inverkar på den enskilda slutanvändaren.

Bidraget från denna avhandling är botten-upp-simuleringsmodeller för generering av elförbrukningsprofiler i småhus och kontorsbyggnader. Modellerna kopplar slutanvändarbeteende med elförbrukning från apparater och varmvattenanvändning tillsammans med fysikaliska modeller av värmedynamiken i byggnaderna. Modellerna är byggda på en förenklad approach som använder öppen data och statistisk, där data som har integritetsproblem har exkluderats. Simuleringsresultat har validerats mot elförbrukningsdata från småhus och kontorsbyggnader, relaterade modeller från andra forskargrupper samt energistatistik från nationella databaser. Valideringen visar att modellerna kan generara elförbrukningsprofiler med rimlig noggrannhet.

Denna avhandling är en sammanläggningsavhandling bestående av fem artiklar. Artikel 1 presenterar botten-upp-simuleringsmodellen för genereringen av elförbrukningsprofiler från uppvärmning, varmvatten och apparater i småhus. Artikel 2 presenterar ett dataanalytiskt ramverk för analys av elanvändningen från uppvärmning, ventilation, och luftkonditioneringslaster (HVAC) och apparatlaster i en kontorsbyggnad. Artikel 3 presenterar en icke-homogen Markovkedjemodell för simulering av representativa närvaroprofiler i enskilda kontorsrum. Artikel 4 använder resultaten i artiklarna 2 och 3 för att beskriva en botten-upp-simuleringsmodell för generering av elförbrukningsprofiler från HVAC-laster och apparater i kontorsbyggnader. Artikel 5 använder modellen i artikel 1 för att analysera den tekniska möjligheten att använda efterfrågeflexibilitet för att lösa överbelastningsproblem i ett eldistributionsnät.

Nyckelord: Efterfrågeflexibilitet, Flexibla laster, Energianvändning i byggnadsstocken, Botten-upp-simuleringsmodeller, Elförbrukningsprofiler, Icke-homogena Markovkedjor, Slutanvändarbeteenden, Värmedynamikmodellering, Styrning av HVAC-laster, Smarta elnät.

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Stockholm, December 2015
Claes Sandels

Papers

List of included papers

Paper 1: **C. Sandels**, J. Widén, L. Nordström, "Forecasting household consumer electricity load profiles with a combined physical and behavioral approach" in *Applied Energy*, vol. 131, pp. 267-278, 2014.

Paper 2: **C. Sandels**, J. Widén, L. Nordström, E. Andersson, "Day-ahead predictions of electricity consumption in a Swedish office building from weather, occupancy, and temporal data" in *Energy and Buildings*, vol. 108, pp. 279-290, 2015.

Paper 3: **C. Sandels** and J. Widén and L. Nordström, "Simulating Occupancy in Office Buildings with Non-Homogeneous Markov Chains for Demand Response Analysis" in *PES General meeting*, Denver, USA, July, 2015.

Paper 4: **C. Sandels**, D. Brodén, J. Widén, L. Nordström, E. Andersson, "Modeling office building consumer load with a combined physical and behavioral approach: Simulation and validation" in *Applied Energy*, vol. 162, pp. 472-485, 2015.

Paper 5: D. Brodén, **C. Sandels**, L. Nordström, "Assessment of Congestion Management Potential in Distribution Networks using Demand-Response and Battery Energy Storage" in *IEEE PES Innovative Smart Grid Technologies Conference*, Washington, USA, February, 2015.

Author contributions

In [1], the model was developed by Sandels and Widén. Nordström supported and reviewed the research. The paper was fully authored by Sandels.

In [2], the general research concept was developed by Sandels, whereas the article was authored by Sandels. The data collection was assisted by Andersson. Widén and Nordström supported and reviewed the research.

In [3], the general research concept and model implementation were due to Sandels and Widén. The paper was mainly authored by Sandels, and presented by Sandels at the conference.

In [4], the main model development and authoring were done by Sandels.

In [5], the general research concept was due to Brodén, Sandels and Nordström. The authoring was done by Brodén and Sandels.

Publications not included in the thesis

Paper 6: C. Sandels, U. Franke, N. Ingvar, L. Nordström, R. Hamrén, "Vehicle to grid - Monte Carlo simulations for optimal aggregator strategies" in *POWERCON2010*, Hangzhou, China, October, 2010.

Paper 7: C. Sandels, U. Franke, N. Ingvar, L. Nordström, R. Hamrén, "Vehicle to grid - Reference architectures for the control markets in Sweden and Germany" in *IEEE PES Innovative Smart Grid Technologies Conference Europe*, Gothenburg, Sweden, October, 2010.

Paper 8: S. Hussain, N. Honeth, R. Gustavsson, **C. Sandels**, A. Saleem, "Trustworthy Injection/Curtailment of DER in Distribution Network maintaining quality of Service" in *16th International Conference on Intelligent System Applications to Power Systems*, Hersonisos, Crete, September, 2011.

Paper 9: C. Sandels, U. Franke, L. Nordström, "Vehicle to grid communication: Monte carlo simulations based on automated meter reading reliability" in *17th Power Systems Computation Conference*, Stockholm, Sweden, August, 2011.

Paper 10: C. Sandels, K. Zhu, L. Nordström, "Analyzing fundamental aggregation functions in power systems" in *IEEE PES Innovative Smart Grid Technologies Conference Europe, ISGT Europe*, Manchester, UK, December, 2011.

Paper 11: A. Jalia, N. Honeth, **C. Sandels**, L. Nordström, "A Local Market Model for Urban Residential Microgrids with Distributed Energy Resources" in *Proceedings of the 45th Annual Hawaii International Conference on System Sciences*, Hawaii, USA, January, 2012.

Paper 12: X. Hue, **C. Sandels**, K. Zhu, L. Nordström, "Empirical analysis for Distributed Energy Resources' impact on future distribution network" in *Energy Conference and Exhibition (ENERGYCON)*, Florence, Italy, September, 2012.

Paper 13: X. Hue, **C. Sandels**, K. Zhu, L. Nordström, "Modelling Framework and the Quantitative Analysis of Distributed Energy Resources in Future Distribution Networks" in *International Journal of Emerging Electric Power Systems*, ISSN 1553-779X, Vol. 14, no 5, 421-431, 2012.

Paper 14: M. Xie, **C. Sandels**, K. Zhu, L. Nordström, "A seasonal ARIMA model with exogenous variables for elspot electricity prices in Sweden" in *The 10th International Conference on the European Energy Market (EEM),*, Stockholm, Sweden, May, 2013.

Paper 15: F. Baccino, S. Massucco, **C. Sandels**, L. Nordström, "Technical analysis of an aggregator's operation for the Gotland power system" in *22nd International Conference and Exhibition on Electricity Distribution (CIRED)*, Stockholm, Sweden, June, 2013.

Paper 16: F. Baccino, S. Massucco, **C. Sandels**, L. Nordström, "Domestic heat load aggregation strategies for wind following in electric distribution systems" in *IEEE Power and Energy Society General Meeting (PES)*, Vancouver, Canada, July, 2013.

Paper 17: C. Sandels, U. Franke, L. Nordström, "Vehicle to grid: System reference architectures and Monte Carlo simulations" in *International Journal of Vehicle Autonomous Systems*, ISSN 1471-0226, Vol. 11, no 2-3, 205-228, 2013.

Paper 18: C. Sandels, M. Hagelberg, L. Nordström, "Analysis on the Profitability of Demand Flexibility on the Swedish Peak Power Reserve Market" in *IEEE PES Innovative*

Smart Grid Technologies Conference, Washington, USA, February, 2013.

Paper 19: G. Lebel, **C. Sandels**, S. Grauers, L. Nordström, "Household Aggregators development for Demand Response in Europe" in *22nd International Conference and Exhibition on Electricity Distribution (CIRED)*, Stockholm, Sweden, June, 2013.

Paper 20: Q. Lambert, **C. Sandels**, L. Nordström, "Stochastic evaluation of aggregator business models - Optimizing wind power integration in distribution networks" in *2014 Power Systems Computation Conference (PSCC)*, Wroclaw, Poland, August, 2014.

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Part I

Introduction

Chapter 1

Introduction

This thesis consists of two parts. The first part is composed by this introduction summarizing the second part which contains the research articles that constitute the core of the thesis. The introduction includes a motivation to the research, the design of the research project, used methods and materials along with results. The five papers in part 2 have either been published in peer-reviewed scientific journals (papers 1, 2, and 4), or presented at and published in the proceedings of peer-reviewed scientific conferences (papers 3 and 5).

1.1 Background and motivation

Future trends and challenges for power systems and electricity markets

Since the start of the industrial revolution the global energy-usage has increased with economic growth. The principal energy sources to power this development has been fossil fuels, in the form of oil, coal and natural gas. Over 80% of the global energy-usage came from these sources in 2014 [9]. Fundamentally, three problems are coupled with the use of fossile fuels. First of all, these sources are non-renewable which in the long run leads to resource depletion. Secondly, greenhouse gases are emitted when fossil fuels are burned. The accumulation of these gases is connected to warmer global temperatures, which in turn causes climate change. The International Panel on Climate Change (IPCC) predicts that the global mean temperature may increase between 1 °C and 6 °C depending on emission scenario [38]. Thirdly, consumption of fossil fuels creates an import dependency on countries which hold the resources. Hence, the problem concerns the security and resilience of energy supply as well.

Today, policy makers across the world are changing regulations to address these problems. In 2015, nearly 200 countries signed a climate action agreement in COP21 - aiming to limit the global temperature increase to under 2 °C [11]. Further, the European Union has manifested the following objectives for the year 2020: the renewable energy supply is 20% of the total generation mix, the overall energy consumption is decreased by 20% in comparison with forecast levels of 2020, and the greenhouse gas emissions are reduced by 20% with respect to 1990 levels [21]. There are even more ambitious goals for the year 2030 [22] and 2050 [23]. The electric power systems will be the key-enablers to meet these goals as a larger share of the energy supply will originate from Renewable Energy Resources (RES), such as wind and solar power. Converting energy from these sources to electrical energy is becoming a viable alternative to conventional electric power production in, e.g. coal based plants [83]. In Denmark, the installed wind power capacity has doubled between the years 2000 and 2013, and is now accounting for a 35% share of the total generation capacity. During the same period, the large-scale power plant capacity has decreased by 30% [81].

Moreover, an expanded electrification of the transport and building sector can be expected in the coming years due to technology advancements, along with the desire to make the distribution and end-use of energy more efficient. Because of improvements in battery technology, it is anticipated that the conventional fossil fuel car fleet will be more shifted to Electric Vehicles (EVs) [37]. As an example, EVs have a 10% market share of the new auto sales in Norway today. This process is driven by new attractive vehicle models that have been released on the market (e.g., Tesla motors [26]), and incentives from the government [82]. The sales of energy efficient heat pumps powered by electricity have grown in the previous years as well. 700,000 heat pumps have been sold in Sweden between 1995 and 2008 [87], and these have largely replaced conventional oil heating systems [74].

Integrating large volumes of RES and new type of loads will change how power systems and energy markets are planned and operated because of two reasons: (a) a considerable share of the resources are scattered in distribution grids instead of centralized locations in the transmission grids, e.g. solar photovoltaic (PV) panels installed on household rooftops [106] etc. (b) RES will only provide electricity during the right weather conditions, namely when it is windy or the sun is shining. If no countermeasures are applied, factors (a) and (b) will contribute to imbalances between supply and demand of electrical energy, which in turn affect the operation of the power systems when it comes overloading of power components (cables, transformers) and operational parameters [101]. Operating an AC power system involves strict requirements on keeping system frequency and voltage levels within their operational boundaries [43]. Ultimately, this is a matter of continuously balancing supply and demand of electricity on short term [40]. In a larger European synchronous power system area it is the Transmission System Operator (TSO) which is responsible for maintaining a secure operation in real-time [19].

To ensure the energy balance in the power system, as an example, the Nordic electricity market is composed by several markets on different time scales, namely a *day-ahead market*, an *intra-day market* and a *real-time market*. The day-ahead electricity prices are set according to a marginal pricing system, where the most expensive kWh needed to cover the expected demand determines the market price [52]. As these supply and demand curves are based on day-ahead forecasts, a market closer to the operational hour exist since more reliable forecast data is available for the producers and retailers on this time-scale (*intra-day market*) [51]. The mismatch cannot be completely eliminated, and, therefore, a *real-time market* exist which can manage real-time imbalances [2]. In general, it is the supply side that regulates its power output based on seasonal, diurnal and hourly variation of the system load [72], i.e. demand is considered an inelastic quantity. The Swedish TSO, Svenska Kraftnät, has historically regulated the Swedish power system at a low cost using hydropower [2]. However, if the volume of energy imbalances increase because of the aforementioned trends, it might be necessary for demand to be more elastic. This may also reduce the need for the electricity market to invest in expensive and environmentally unfriendly peak power plants, e.g. gas turbines [76].

Moreover, due to the fact that electricity production becomes more decentralized, i.e., connected directly to the distribution grids, problems are introduced for the Distribution System Operator (DSO) as well. The current distribution grid is primarily dimensioned according to the expected peak load - also denoted as a fit and forget investment strategy [100]. This approach assumes a unidirectional power flow from higher voltage levels, where the large power plants are connected, to lower voltage levels, where the passive end-users are connected. But if the fundamentals of how electricity is produced and consumed is changing in time and space, there is an increased risk that the current power systems cannot handle these changes without impacting reliability and quality of supply [8]. In other words, the new local supply and demand profiles can lead to power flows that overload individual network components at some occasions, resulting in power outages in worst case.

Addressing the challenges with smart grid solutions: Demand Response

In recent years, "smart grids" in general terms has emerged as a plausible approach to address the aforementioned problems [25]. Essentially, smart grid involves an increased usage of Information & Communication Technology (ICT) in the power systems. Advances in ICT offers the possibility to extend the observability and controllability by using and exchanging information between components and actors in the system, and, thus, allowing these entities to be more active in the operation. This approach opens up for implementation of new functions in the power systems and markets, e.g. advanced protection schemes [99], voltage regulation [97], and frequency control [30]. In the end, the smart grid concept is about optimizing grid and market operation by utilizing information for decision making in real-time.

To provide balancing power and storage solutions to the power systems, Demand Response (DR) is a proposed component within the smart grid framework [1] [68]. In short, DR refers to changing net-consumption of end-users (e.g., industries and households) by either moving it in time (load shifting), reducing it at specific points in time (load reduction) or using standby generated electricity [49]. The incentive for the end-users to alter their consumption could be economic or environmental, e.g. a CO_2 signal [75]. These signals are sent from an electricity market actor who wants to address specific market or technical power system challenges, as described earlier. In other words, DR involves the potential of influencing end-user consumption profiles, and to increase the efficiency and utilization rates in the electricity market. DR can be managed by the consumer himself or more commonly when the end-user is a small entity (e.g. a household), through an intermediary actor often referred to as aggregator [28]. The aggregator is primarily needed to fulfill energy market rules, e.g. minimum bid size requirements. Today, these requirements are usually on MW levels [2], meanwhile smaller end-users have consumption limitations in the size of kWs. Another motivation for the aggregator role is that flexibility actions of individual end-users will be seen as noise in a larger power system area. Thus, coordination of numerous end-users is needed to deliver flexibility that can make a real impact on the system [29].

Second to industrial loads, a large DR volume potential exists in the nation's building stock. This is valid due to several reasons. Firstly, the building stock constitutes a large share of the total electricity consumption. For example, in some European countries, the building stock represents over half of the electricity demand [90]. Secondly, the building stock contains appliances and consumption processes that could be suitable for DR, e.g. Heating Ventilation and Air Conditioning (HVAC) loads. These loads can take advantage of the thermal inertia of the buildings, i.e. energy stored in the building mass and its furniture, and be controlled through a thermostat without impacting the comfort of the occupants [63]. Thirdly, a vast majority of the buildings are connected directly to the distribution grids, where a number of the aforementioned problems will emerge. Fourthly, in recent years it is becoming more common that buildings are equipped with smart meters, where energy information can be accessed almost in real-time [20], and that new appliances have inherent communication and control capabilities [68]. Commercial buildings are often equipped with advanced Building Energy Management Systems (BEMS) [13], which have advanced data acquisition and control functions. This means that the required technical infrastructure to facilitate DR actions is evolving, and could be integrated with the processes in the power systems. Fifthly and finally, the building stock is typically not used for flexibility at present, as for some industrial end-users [15]. Hence, for the time being this DR volume is a non-utilized asset on the electricity market which may provide value in certain contexts.

Modeling is an alternative to analyze the feasibility of Demand Response

DR solutions from the building stock could be a viable alternative to traditional investments in the power sector, e.g. letting hydropower solely balance energy mismatches, expanding the power grids, connecting gas turbines for peak power generation, etc. However, as the flexibility is not used today, there are understandably some concerns regarding reliability and cost of proposed DR solutions. For analysis of traditional investments alternatives (e.g., refurbishing the networks), there are extensive experiences and knowledge how to assess the solutions with respect to impact on cost-efficiency, as it can be compared to similar investments done by the industry in the past. This is not valid for DR as no large-scale implementations are available for examination. Hence, electricity market actors lack necessary information and models to assess the feasibility of these investment options. This aspect needs to be addressed for smart grid solutions to have an opportunity to compete with traditional alternatives.

Mathematical modeling is an approach to addressing complex questions related to end-user flexibility and DR. The approach involves the development of models that can capture key properties of a system - in this case end-use flexibility - where subsequently experiments (i.e., simulations) can be performed with different sets of input data [104]. The results from the experiments are used to analyze complicated DR scenarios with varying boundary conditions and prerequisites. Then, the output from the simulations can be compared with other possible options to confirm the validity of the proposed solution for the market actor. Note, for the models to be useful as decision support, it is important to validate the simulation results against either real measurements or expert knowledge, i.e. estimating model accuracy.

A market actor who uses DR wants to understand how a larger volume of flexible demand behaves with respect to incentive signals. Preferably, these dynamics would be described by simplified price elasticity curves of the demand, where a certain price will result in a specific change of aggregated demand [24]. This is a top-down modeling approach, where no disaggregation of individual building energy-use is taken into account [79]. However, the flexibility of the energy-use in individual buildings is complicated to estimate as the consumption is a process governed by many variables. These variables include end-user behavior, weather dynamics, building properties, and available appliances in the building [104]. For example, occupancy is a necessary condition for some electricity consumption, such as appliances and lighting [55]. This usage, along with the occupancy generates internal heat gains, which together with the weather affect the indoor temperature. The HVAC system will consume electricity to output the required heating/cooling energy to stabilize the temperature according to thermodynamic properties of the building and the occupants' comfort constraints. These types of load characteristics are highly dynamic, and will vary in time (both seasonal and diurnal), and between end-users. Consequently, this will put prerequisites on the potential of being flexible. In addition, a certain control strategy of the heating system will have an implication on load levels in other time points. If the heating output is reduced for a couple of hours, the heating demand will increase at the end of the period to bring the temperature back. This phenomena is known as the payback effect [7] and adds more complexity to the problem as the control mechanism needs to manage these side-effects.

Bottom-up simulation models are needed to capture consumption processes on load-level [79]. As opposed to top-down models, bottom-up models start from the lowest level of components (e.g., an appliance), outputs load profiles from these, and, subsequently, aggregates the profiles to reflect total load in buildings, neighborhoods, cities, etc. The main advantage of a bottom-up approach is that characteristics of individual loads can be represented. This is important in DR analysis as the flexibility ultimately is provided by single loads, e.g. EV batteries, dishwashers or heat pumps. On the other hand, modeling electricity consumption processes in buildings with a bottom-up approach is challenging because of two reasons. Firstly, to perfectly predict the heating dynamics and temperature variation for a specific point in a building, a model with an infinite set of partial differential equations has to be formulated [60]. To model these low-level heating dynamics detailed building based software is essential, e.g. EnergyPlus [18] or DOE-2 [14]. However, these software tools require extensive knowledge about the building parameters, and the resulting models tend to be computationally cumbersome and difficult to scale [61]. Secondly, as individual buildings only can contribute with a small volume of flexibility, a larger group of buildings is needed to reach the required capacities. Every building is unique with respect to building design, used materials, orientation in the landscape, household behaviors, etc. Hence, detailed and accurate models have to be developed for each individual building, implying a huge modeling effort, which may lead to significant costs in both time and money.

Based on the above arguments, it becomes obvious that neither a price elasticity model (simplified top-down approach) nor a building based model (advanced bottom-up approach) will be applicable for DR analysis. Modeling the consumption of individual buildings is not relevant for analysis of market impact of DR, as only the performance of the aggregated flexibility is of interest. However, as the flexibility is provided by individual households and loads, this perspective must be respected as well. Ultimately, it is the comfort and behavioral constraints of end-users that determine the available flexibility. In order to balance these two tradeoffs, it is appropriate to develop bottom-up models which makes it possible to represent many building objects (i.e., reflecting aggregations), and at the same time capturing the consumption processes of individual buildings and households. Thus, a compromise in detail level of the modeling approach is necessary to generate data required for DR analysis, thereby simplifying the modeling process so to that aggregations of buildings can be simulated without impacting the cost and time effort. In addition, the models should be able to reflect important differences between individual households with a reasonable accuracy. Preferably, these models are simplified and standardized to minimize the demand for input data, estimation of parameter values, and model assumptions [103].

Figure 1.1 summarizes the challenge of choosing an appropriate detail level of the consumption models, with respect to differences in interest between the electricity market actors and the end-users.

1.2 Scope of the thesis

Based on the reasoning in the previous section, the main purpose of this thesis is to investigate and present simplified bottom-up simulation load models of different building types, representative for Northern Europe. The models are mainly delimited to Northern Europe because of the high availability of electric heating in the residential sector. With these models, it should be possible to generate load profiles for detached houses and office buildings with respect to variation in weather conditions and end-user behavior. Here, the model approach should allow aggregations of different buildings to be simulated. The models

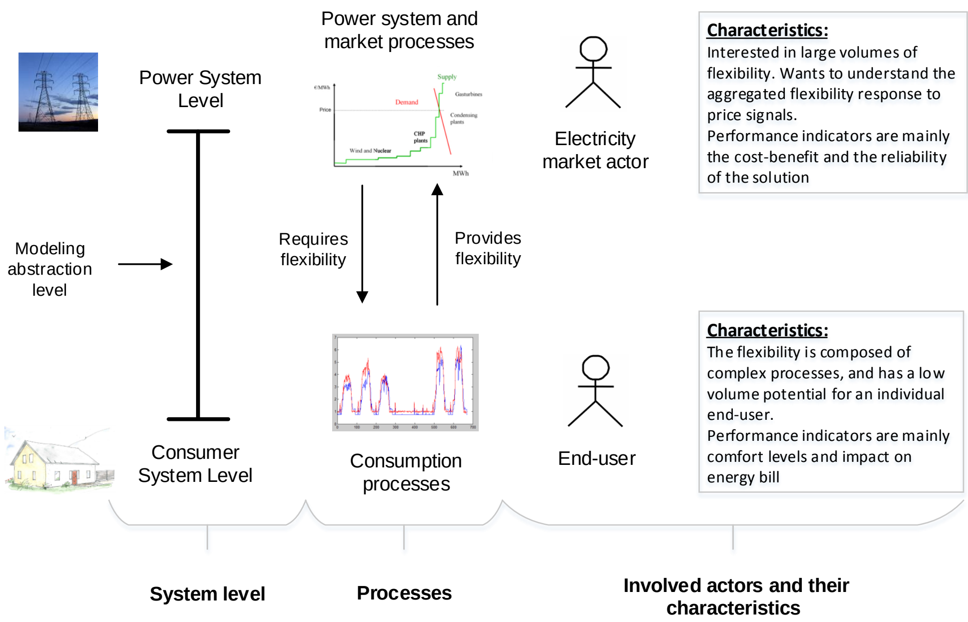


Figure 1.1: A diagram which gives an overview of motivation of the PhD thesis.

will primarily be used for decision support analysis regarding demand flexibility for various market actors in the power sector. In addition, the models could potentially be utilized to forecast demand flexibility on short term, e.g. day-ahead, for market or power system operation applications.

Moreover, the models should be built on a bottom-up model approach, which takes advantage of openly available data and statistics, along with a set of standardized assumptions. Because of the simplified approach, an important component of the research is model validation. The validation constitutes comparisons between generated load profiles and measured load data collected from various sources. The validation should confirm the feasibility of the model approach, and, thereby, that the models can be used for the intended purposes.

An additional component of the thesis is to demonstrate the applicability of using the bottom-up simulation models as decision support for a electricity market actor in a DR case. This refers to a justification that the consumer models generate load flexibility data necessary for the assessment of DR investment options.

Research Questions

The purpose of the thesis can be broken down into two concrete Research Questions (RQs), that are listed below:

- RQ1: Can a simplified detached house bottom-up simulation model generate load profiles and energy-use values that are representative[1] for the consumption of an aggregation of detached houses?

[1]Meaning that the models have similar prediction accuracies as established models in literature.

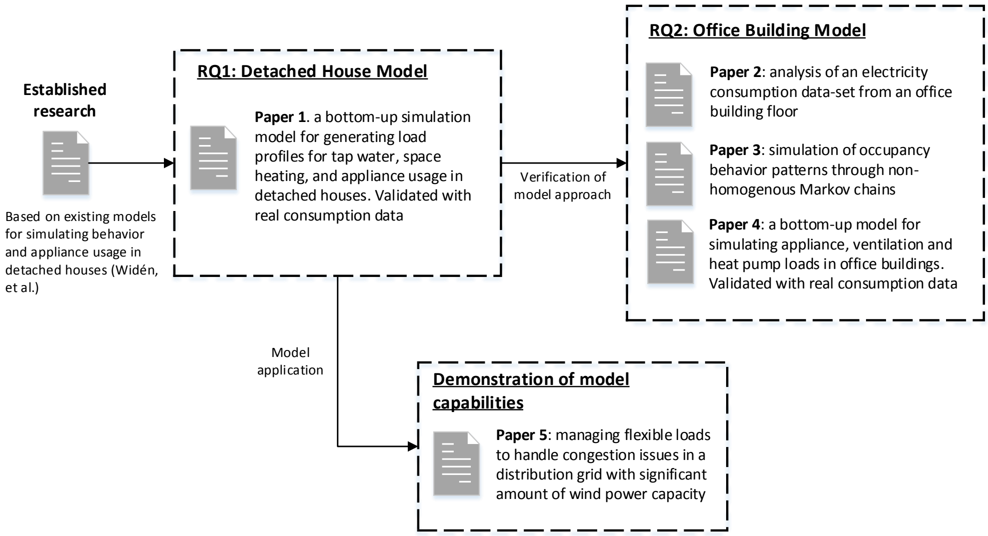


Figure 1.2: An overview of the contributions of the thesis in relation to the research questions.

- RQ2: Can a simplified office building bottom-up simulation model generate load profiles and energy-use values that are representative[2] for the consumption of an aggregation of office buildings?

The RQ structure is shown in Figure 1.2. RQ1 concerns the validity of using a bottom-up simulation approach to generate load profiles connected to heating, Domestic Hot Water (DHW), and appliances in a population of detached houses. This model builds partly on the work in [103], [104] and [105]. By addressing RQ1, a verification of the modeling approach is done, and opens up for the possibility to extending the modeling approach to consumption processes in office buildings as well, i.e. RQ2. More fundamental research needs to be performed to address RQ2 as no prior work is available for modeling office buildings in this case. The fundamental research includes analysis of an extensive office building consumer data-set, along with the development of a model that can estimate employee behavior in these buildings. In the end, RQ1 and RQ2 aim to answer the questions whether the bottom-up simulation model approach is valid, and, subsequently, can be useful for analysis of DR solutions - see lower box of Figure 1.2.

Main contributions in relation to Research Questions

Below, the main contributions of the thesis in relation to the RQs are listed:

- **RQ1:** A bottom-up simulation model that can generate electricity load profiles for space heating, DHW and appliance loads in detached houses with a combined behavioral and physical approach has been developed and it is presented in paper 1. The simulation model has been validated using hourly consumption data from a distribution grid substation with a group of detached houses. The validation confirms that

[2]Meaning that the models have similar prediction accuracies as established models in literature.

the model can generate representative load data since the error results are comparable to related models in literature and energy-use values from national statistics.

- **RQ2:** An extensive data-set has been collected from an office building floor, including energy measurements on load-level, occupancy in individual office rooms, and weather measurements. Firstly, exploratory data analysis, along with correlation analysis between pair-wise variables are performed to gain insight to the properties of these type of data-sets, e.g. temporal aspects of the consumption, variation in occupancy and its linkage to appliance use, etc.

  Secondly, using the occupancy data, a non-homogenous Markov chain model to estimate occupancy patterns in individual office rooms was developed. Validation of the occupancy model on a test data-set (i.e., occupancy data not used for model development) confirms that the model can generate realistic occupancy patterns. The outcome of the data analysis and the Markov-chain modeling were both used in the development of the bottom-up simulation model that can generate electricity consumption profiles from HVAC and appliance loads in office buildings with a combined behavioral and physical approach. The simulation results have been validated against the consumption data-set from the aforementioned office building floor, along with load data from a population of office buildings connected to a distribution grid substation. The validation of the two data-sets show error results in alignment with related models and national energy statistics. Hence, the model can generate representative load profiles for office buildings.

In addition to the development of the simulation models to address the RQs, a third objective has been guiding the work. This concerns the practical usability of the modes in a DSO setting. In paper 5, a demonstration of using the detached house model in a DR solution to handle events of congestion in a distribution grid due to excess supply of wind power is therefore performed. The technical impact of the DR solution on the grid operation of the DSO is quantified. Data from the Smart Grid Gotland project [70] has been used to generate the case. For more elaborate results, analysis and discussions see chapter 4.

Chapter 2

Related Work

The main contribution of this thesis is simulation models for generating load profiles in buildings which can be used for analysis of DR potential. Hence, the related work described in this chapter concern the subject of electricity consumer load modeling that can generate consumption profiles on load-level. This means that consumer models based on top-down approaches, as explained further in section 1.1, are out of the scope of this work [79]. As the thesis concerns modeling aspects for electricity consumption processes connected to the physical indoor environment and end-user behavior, this chapter is split into three sections: (i) approaches to model physical indoor environment and operation of HVAC loads, (ii) alternatives to model end-user behavior and appliance usage, and (iii) holistic end-user electricity consumption models, i.e. combining approaches (i) and (ii) to represent total loads in buildings. Additionally, resulting error rates of the predictions in the related papers from model validations of (iii) are compiled. These error rates will be used as a benchmark for the validation of the consumer models presented in this thesis, i.e. connected to RQ1 and RQ2.

2.1 Models of physical indoor building environment and HVAC loads

As HVAC load constitutes a large share of the total building load it is important to study it. Analysis of flexible control of HVAC systems[1] require good understanding of the heating dynamics in buildings [81]. This is because the flexibility to a large extent is determined by how fast the indoor temperature responds to changes in the HVAC system output. Here, heating dynamics refer to a representation of how energy flows and temperatures interrelate in a building environment. To predict these processes and behaviors, i.e. how temperature varies over time at different places in a building, a model is required. As mentioned in section 1.1, it is problematic to develop accurate models that capture all aspects in the heating balance as these are complex, computationally heavy and require extensive input data regarding the buildings, i.e. not appropriate for analysis of DR potential in large clusters of buildings. Thus, simplified models which reduce complexity levels and increase user friendliness are necessary. These models must however be still representative and capture the systematic variations in the indoor environment due to the impact of various energy processes, and its relation to HVAC loads - in order to output data that with a sufficient detail level for DR availability assessment.

[1] Domestic heating is in this work included in the term HVAC system.

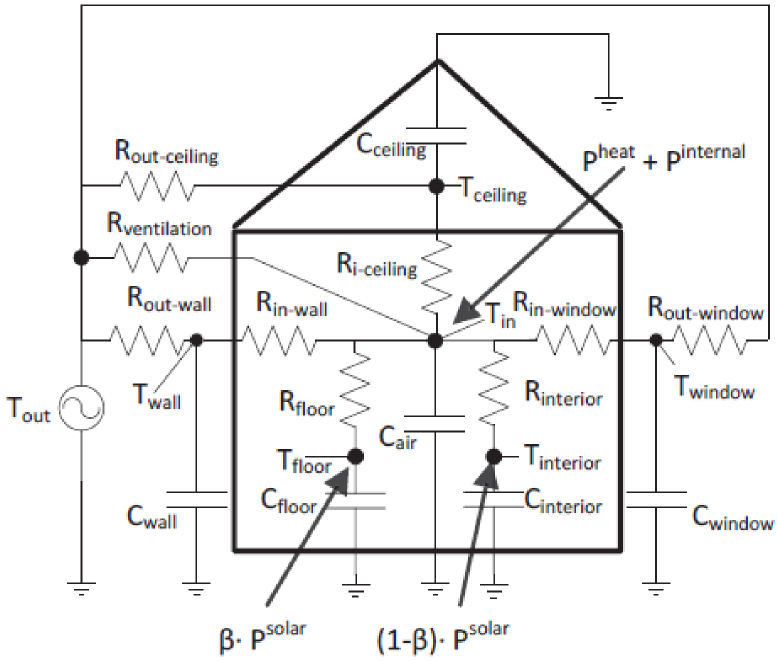


Figure 2.1: A circuit diagram of a lumped capacitance model of a building [72].

In essence, three classes of simplified building models exist [42], viz.: (i) white box physical models, (ii) black box models which are completely data-driven, and (iii) gray models which are a combination of the previous two. Lumped capacitance models is a common white box modeling approach, and is a direct analogy to modeling of electric circuits [42]. These models have a direct physical meaning of the indoor climate, where specified temperature nodes (lumps) are connected to thermal resistances (insulation) and capacitances (thermal masses), represented by different parts of the building (walls, windows, etc.). Note, the HVAC system is seen a provider of heating/cooling energy to the nodes, where the efficiency of this process is measured by its Coefficient of Performance (COP) factor [73]. In Figure 2.1 a graphical example of a lumped capacitance model is displayed. The complexity level of the model and, thus, the achievable accuracy level is determined by the number of included capacitance nodes, which then influence the indoor climate dynamics to a set of corresponding differential equations. The indoor temperature varies with the energy flows interacting with the building, e.g. heat gain from solar radiation, occupants, heating system, along with the thermal properties of the building envelope [81]. Normally, first order lumped capacitance models are applied for analysis of HVAC load control in the power systems [72]. Usually these models only consider the indoor temperature as in [56], [31], [59], or also the building interior temperature [47], [114], [57]. The advantage with lumped capacitance models is that a physical understanding of the heating system can be obtained in a straightforward way. An additional strength is that modifications of the model can be easily implemented to capture the effect of retrofits or inclusion of new technologies [79]. This is valuable when the aim is to analyze future developments in the building stock. The drawback with the approach is that parameter values need to be identified for the model by, e.g. fitting procedures from measured data [61] or construction data.

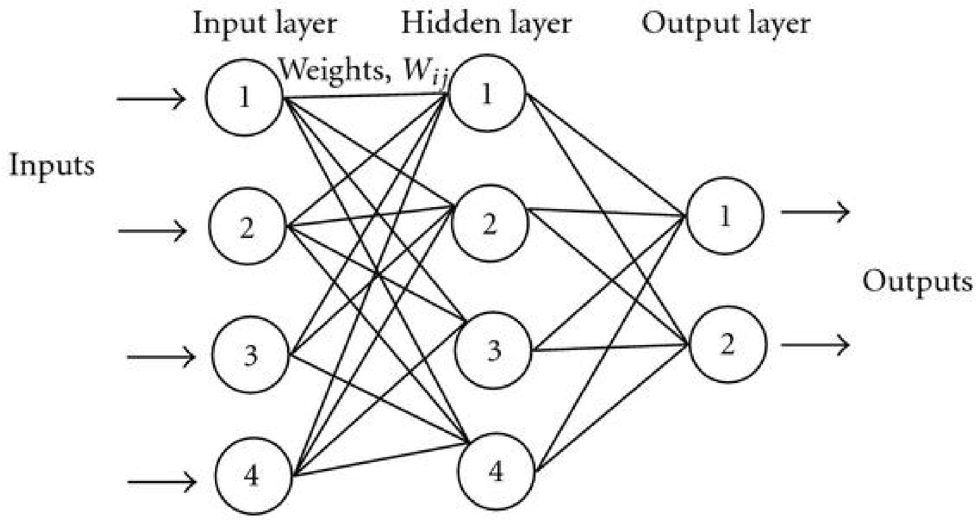


Figure 2.2: A graphical example of a ANN network configuration [34].

A common black box model is Artificial Neural Networks (ANN) [42]. This is an adaptive and self-learning data driven approach, which can capture complex non-linear processes in measured data. In short, ANNs are constructed by the same principles as the human brain, i.e. through a network of neurons, layers and interactions between these - see Figure 2.2. The modeler designs the network so that issues related to over-fitting are minimized (aiming to have a simple network structure), meanwhile obtaining good predictability of the measured data [35]. Example studies that have used ANNs to predict a building's thermal behavior and HVAC load consumption can be seen in [3], [4], [64], [78]. In [3], an optimal schedule of HVAC load is computed based on day-ahead electricity prices and the heating usage predicted from ANN models. The ANN is trained using simulated data from a heating model implemented in TRNSYS [93]. When comparing the resulting indoor temperature profiles between the two models, the error is always lower than 1 $°C$. The model however shows poor prediction performance on a test data-set, i.e. predictions made on a new set of observations. This implies that ANN needs training data from a wide range of building objects to perform accurate predictions for new sets of data. The main advantage with ANNs is that no information about the physical properties of the buildings is required. This is beneficial as smart meters can provide substantial amount of load data, but no physical information about the building itself [79]. However, to appreciate DR potential from such models, other type of data needs to be included and correlated with the load data as well, e.g. indoor temperature, occupancy etc. It can become problematic to collect this data with respect to cost and privacy issues. In addition, ANNs must be calibrated with data from multiple sources (i.e., buildings) in order to appreciate differences between individual buildings, and thus be able to identify models that can represent average buildings. Another disadvantage with the ANN approach is that the building cannot be characterized by its parameters, and, therefore, lacks physical meaning of the building physics [42]. This can cause problems when, for instance payback effects need to be respected in the HVAC system control.

Linear parametric models, such as regression and ARMAX models, are examples of a gray box models which combine physical knowledge about the buildings and empirical data [42]. These models are also data-driven, but can provide benefits over black box techniques as few model parameters are typically needed when theory and knowledge of how energy usage is connected to various determinants can be exploited [36], and the model can be connected to physical features of the system. The main disadvantage of linear parametric models is the risk of poor prediction performance in non-linear settings [39], and the dependency of having access to input data. Example studies that have used a gray model approach to model energy usage from HVAC systems in buildings can be found in [44], [46], [50].

2.2 Models of end-user behavior and appliance usage

In contrast to HVAC loads which are primarily dependent on building parameters and weather dynamics, the electricity consumption from appliances[2] is mainly effected by: (a) the available setup of appliances in the building, (b) the load parameters of these, and (c) the actual usage of the appliances. The third factor is the most difficult to estimate as it is related to behavioral attributes of the end-users, such as whether the individual is present or not [104]. Thus, stochastic models which can reproduce behaviors of occupants are an important aspect of bottom-up load modeling. Here, different approaches are available in literature. The end-user behavior and appliance model presented in Capasso et al. [10] is the most commonly cited example. This model connects consumer behavior, socioeconomic background data, with statistics on appliance ownership collected from extensive surveys, in order to estimate probability functions which can output load profiles for a given day. Similar models based on a bottom-up statistical approach can be found in [54] and [94]. These models can generate data with high resolution regarding factors (a)-(c) for individual households. However, the main drawback concerns practical implications of implementing such models as they have a complex structure and require a substantial amount of socioeconomic and demographic data [12].

To overcome these practical issues, standardized behavioral models which utilize Time Use Data (TUD) as input have been proposed in [62], [107], [53] and [104]. In short, TUD is based on diaries recorded by study participants with a high time resolution (e.g. 5 minutes) for several days [104], which then provide a rich description of peoples' everyday lives. By translating the raw behavior data into predefined energy usage activity types (TV watching, taking showers, etc.), deterministic load profiles can be generated for an individual or a household, by formulating mathematical expressions which converts an activity into a specific energy-use [104]. With the TUD, stochastic non-homogenous Markov chain models can also be constructed [103]. These models output random activity and energy-use profiles on a minute resolution for an individual household member based on probability estimates derived from the TUD. The main advantage of this approach is that the model structure is kept simple; meanwhile it can produce complex results, e.g. unique occupancy patterns of household members. The main disadvantage is the demand for TUD, which is costly to collect and might not be available for the nation/region of interest.

Other types of data besides TUD can be used as input to non-homogenous Markov Chain models for generating end-user behavior. For example, Page et al. [55] uses occupancy sensor data as input to generate occupancy patterns of employees in individual office rooms. Other studies that focus on prediction occupancy in offices with sensor data can be found

[2] Loads that are used directly by end-users to fulfill their needs, e.g. dishwashers, servers, computers, lighting, etc.

Table 2.1: The references and their fulfillment of the five criteria.

Criteria/ reference	(i) building type	(ii) combined approach	(iii) aggregations	(iv) hourly resolution	(v) validation
Killian [48]	✓	✓	✓	✓	✓
Steen [73]	✓	✓	✓	✓	–
Yao [109]	✓	✓	✓	✓	✓
Baetens [5]	✓	✓	✓	✓	–
Shao [66]	✓	–	✓	✓	–
Yamaguchi [108]	✓	–	✓	✓	✓
Shimoda [67]	✓	✓	✓	✓	✓
Zhou [113]	✓	–	✓	✓	✓

in [45] and [102]. However, these works do not incorporate detailed end-user activities, but only their occupancy. Hence, explicit assumptions between occupancy and appliance usage must be made in order to emulate consumption profiles. Furthermore, in [112], a survey with employees in an UK office building is presented, where questions related to their energy usage are addressed, e.g., kitchen usage habits and whether appliances are turned office when people leave the room. With this information, different end-user behavior is in the paper simulated using agent based logic. The occupants move between various zones in the building over the day, and electricity consumption from lighting and computers is triggered by their activities.

2.3 Holistic consumer models: combined physical and behavioral models

In this section, consumer models based on a combined physical and behavioral approach to reflect total loads in buildings are reviewed. To include a reference in the review, the proposed consumer model should fulfill the following criteria: (i) The model captures energy consumption processes in either detached houses (residential sector) or office buildings (commercial sector). (ii) The modeling approach must encompass both physical and behavioral attributes of the consumption. (iii) The approach must be simplified and based on a bottom-up simulation methodology, meaning that aggregations of buildings can be simulated, and still be able to produce results on building level. (iv) The model can generate load results on at least an hourly resolution, i.e. relevant for DR applications. (v) The model has been validated with either real load measurements, national/regional energy statistics, or on other simulation models, so that objective accuracy comparisons can be performed. Eight references from the literature fulfilled a subset of the criteria (i)-(v), and are described below. See Table 2.1[3] for more information concerning the evaluation of the included references.

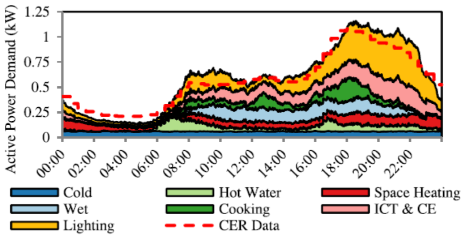
McKenna, et al. [48] presents a dynamic pricing framework to influence residential consumer load levels to optimize the operations of low voltage networks. The model simulates occupancy and appliance usage through non-homogenous Markov chains with TUD from Ireland [53] as input. DHW loads are modeled through a two layered thermal equation, and the space heating is composed by a first order RC network with indoor temperature

[3] To fulfill criteria (v) in the table, error rate results must have been presented in the validation.

as the only temperature node. Data from an Irish residential distribution feeder with 85 buildings is then simulated for a typical winter day. To validate the reference load model, i.e. loads not influenced by price variations, simulation results for the winter day are compared against typical Irish load profiles derived from national statistics. Here, a Root Mean Square Error (RMSE) of 7.6% is achieved. See the left subplot in Figure 2.3 for graphical comparison between generated load profile and the national statistics profile - divided with respect to load category. No model validations are performed for other day types e.g. winter days vs. summer days, weekday vs. weekends etc. Furthermore, the DR simulations show a negative technical impact for the DSO operation as the load diversity between end-users decrease as the load becomes more correlated with price, and less with individual behavior. Another study focusing on the impact of distribution grids by applying different pricing schemes on active residential consumers can be found in Steen et al. [73]. This model has a deterministic approach, where the usage of appliances and DHW system are determined by energy measurements performed at appliance level for 20 Swedish residential end-users [115]. The heating model is composed by a lumped capacitance model with two temperature nodes, viz. indoor and building mass temperature. The authors of this paper aim to reproduce the load data of a 10 kV transformer station in Gothenburg, Sweden with 100 customers connected, assigning the composition of detached houses with a least squares method. Only a graphical comparison between the two yearly profiles is provided, i.e. no error rate results are produced. The comparison shows that the real load has less variance than the estimated load as the latter quantity is based on a lower number of customers than the real load. The simulated load however follows the seasonal variation of the measured load well as seen in the right subplot of Figure 2.3.

Yao et al. [109] presents a simple consumption model which simulates the daily household load for four different dwelling types in UK. The purpose of the model is to generate aggregated load profiles which can be used for the planning and design of RES systems, i.e. adapting the RES system to the demand of the residential sector. In short, the model includes a significant amount of gathered national statistics, such as appliance ownership, energy-use characteristics of these, household sizes, etc. Occupancy patterns are modeled through five standardized scenarios, which depend on number of occupants, when the first person get up in the morning, the last individuals go to bed at night, and the period that the building is unoccupied over the day. For example, retired people are assumed to be home at all day, while young working couples are away between 9 a.m. and 4 p.m. on weekdays. By combining appliance statistics and occupancy profiles with a random uniform probability distribution function, daily load profiles can be simulated for an individual household. Then, the individual random load profiles are aggregated to a total load profile representative for a district of buildings. Space heating is modeled through a simplified RC-network introduced in [110]. The model has one temperature node, and accounts for conduction and ventilation heat losses and heat provision from internal gain and solar radiation. The control of the heating output is adapted after the occupancy profile, i.e. increasing the indoor temperature set-point when people are present. The model is validated on a statistical load profile from 100 household supplied by the UK Electricity Association Load Research [95]. The correlation coefficient between the two profiles is 0.84. The daily consumption is 10 kWh for the modeled data and 13 kWh for the measured load, i.e. an error of 30% of the daily energy consumption. A validation of the heating model is not conducted.

Baetens et al. [5] studies the implications on voltage quality in a LV grid serving a residential neighborhood of nearly Zero-Energy Buildings (ZEB). The ZEBs are mainly characterized by the presence of high efficient energy technologies, and integration of RES. A holistic energy model is proposed to replicate thermal and electric process in the buildings, with models for PV production, occupancy behavior based on Markov chains [62],



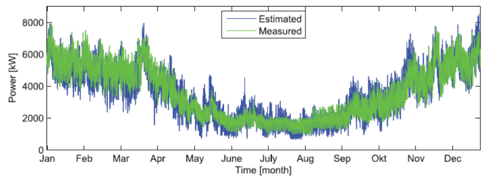


Figure 2.3: Left subplot: Model validation on a standard Irish daily winter load profile in McKillan et al. [48]. Right subplot: comparison between measured and simulated annual load profiles in Steen et al. [73].

and general appliance consumption is mainly based on Belgian statistics. DHW usage is composed by a Becker profile [6], which is an averaged hot water consumption profile based on measurements in 110 single-family homes in US. The thermal building model is based on a finite volume method. Four different dwelling types which are representative of the Belgian building stock are proposed. Additionally, a neighborhood of 33 Belgian ZEBs is simulated with respect to energy consumption features, along with voltage impact at the substation level. The simulated energy consumption for the respective building is compared against national energy statics on the appliance level. The simulated load profiles are not validated, instead these are only compared with annual energy figures. The overall simulation results show a consistent correspondence with the load statistics. It is shown that the voltage quality of the LV grid may be affected if no curtailment strategy of the PV systems is applied.

For DR analysis purposes, stochastic physical-based bottom-up models for detached houses in US are investigated by Shao et al. [66]. Here, emphasis is put on developing simple models of individual loads, where aggregations of buildings can be simulated through parameter distributions estimated from national statistics. Typical appliances are classified according to information in a national database, and then modeled with respect to physical and operational attributes. Thermostat controlled space heating/cooling loads are modeled through first order RC-networks with indoor temperature as the temperature node. DHW systems are represented by simple energy storage models, with reference hot water use profiles and tank parameters as inputs. No behavior is simulated, only reference usage gathered from statistics. By instantiating distributions of values for the model parameters, various building objects can be created. Hourly load profiles are then simulated for a larger distribution system with 780 buildings, and validated against consumption measurements from the network. No error rate results for the distribution grid case are presented, but only a graphical comparison - see right subplot of Figure 2.4. As seen in the figure, the load follows the diurnal variation of the measured data.

A dynamic energy demand model where energy-use can be generated for a larger district of office buildings is presented by Yamaguchi and Shimoda [108]. The main purpose of the model is to understand how building determinants and policy instruments affect the energy demand of buildings (heat, gas and electricity), and their interconnection with CO_2 emissions, primary energy consumption, heat release and utility peak power demand. The model is composed by two bottom-up sub-models: an energy demand and source model, respectively. The energy demand model simulates the load on floor level and then presents the results in an aggregated form. In the energy-demand model, representative Japanese

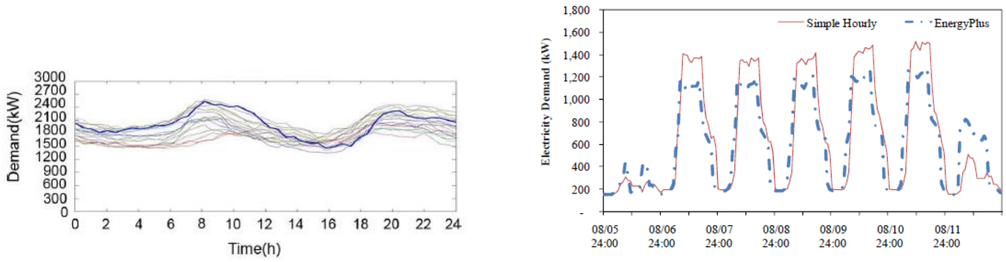


Figure 2.4: Left subplot: Winter day load validation between simulated and measured aggregated data in Shao et al. [66]. Right subplot: comparisons between summer week office building load profiles generated from the simple consumer model and the advance EnergyPlus model in Zhou et al. [113].

commercial buildings are modeled from input data of climate conditions, distribution of building properties, configuration and operation of HVAC system, occupants behavior, etc. Space heat load is dynamically calculated using a weighting factor method, which is in essence, a simplified RC-network. Appliance and lighting loads are computed by an operation schedule, i.e. no advanced occupancy patterns are produced. In order to be able to simulate various scenarios concerning the energy source sub-model, multiple databases are created regarding properties for different cooling technologies, e.g. heat source type and energy efficiency measures. The model is validated against monthly electricity and gas consumption data from 31 office buildings. The building input parameter values are estimated based on questionnaires to the land-lords in the geographical area. The validation shows a 3.0% and 9% difference in the annual electricity and gas consumption, respectively. Only a graphical examination between the load profiles is done.

A similar study approach is presented by Shimoda et al. [67], but for residential end-users instead. Here, the annual energy consumption is estimated on a city-level using a simulation platform. The platform includes stochastic schedules of occupants through probability distributions quantified from a Japanese TUD study. Weather data and energy efficiencies of appliances and thermal properties of different building envelopes are also accounted. Hourly consumption of electricity use is simulated for the city of Osaka and compared against the city's energy statistics. It is shown that the model underestimates the annual energy consumption by 18%. The authors of [67] argue that the mismatch is because no consideration is taken to consumption that is not strictly rational with regards to the end-users simulated behavior, e.g. leaving the lights on although the building is unoccupied.

An assessment of electricity market impact of DR actions from large-scale aggregations of commercial buildings in US is performed by Zhou et al. in [113] and [114]. To do the analysis, a simplified agent based framework for simulating load profiles from different types of commercial buildings is developed. The consumer models are based on a quasi-steady-state first order RC-network with three temperature nodes (indoor air, interior, and supply air) according to ISO 13790 standard to generate hourly consumption curves from the HVAC system. Usage of lighting and appliances is modeled through assumed occupancy schedules. Building stock statistics are collected from the Commercial Building Energy Consumption Survey (CBECS) [96] to categorize representative different building objects (e.g. offices, supermarkets) based on different energy consumption characteristics. A twelve story office building with a total floor area of 40,000 m2 with natural gas as the primary heating source is modeled in the EnergyPlus simulation software to validate the simplified modeling approach. The results show that the annual electricity consumption error is 2% between the two models. NB: no validation is performed with measured load data from commercial buildings. For hourly load profiles the simple hourly model overestimates the peak load by 30% in the summer time (warm months), and underestimates the peak demand by 20% for the other months (cold months). See right subplot of Figure 2.4 for a graphical comparison between the two load profiles during a summer week.

2.4 Contribution in relation to related work

This section discusses the main differences between the bottom-up simulation models presented in this thesis, and the related work models introduced in this chapter. Firstly, the reviewed models are not general in that sense that they can simulate consumption processes in different building types, e.g. detached houses and office buildings. The models that are presented in this thesis are based on such a generic approach.

Secondly, the related work models have not been validated as completely as the models in this thesis. The former models are commonly validated on reference load profiles or energy-use statistics provided by national databases. The model validation in this thesis has been made using load measurements from real end-users in combination with national energy-use statistics. Using real consumption data makes the validation setup more realistic, where also insightful conclusions concerning strengths and limitation of the model approach can be drawn.

Thirdly, the models presented in this thesis concern holistic consumption of the building along with its end-user, where the mathematical modeling aspects of end-user behavior and the connection to consumption from all common loads is defined and motivated. In general, the related work models have not been described and handled in detail with respect to structure and functioning as for the models proposed in this thesis. Fourthly, none of the related work office building models incorporate advance modeling of employee behavior, and its implication on the electricity consumption and the operation of HVAC loads.

Chapter 3

Method and Materials

In this section, the methods and materials used for the development of the bottom-up consumer models for detached houses and office buildings are introduced, respectively. This is followed by a review of building stock data.

3.1 Bottom-up simulation models for detached houses and office buildings

The consumer load models developed and presented in this thesis are based on a bottom-up model methodology. The models are constituted of three separate modules: (i) end-user behavior, (ii) appliance and hot water usage which are mainly driven by behavior, and (iii) HVAC system load which is primarily driven by weather dynamics and building properties. With these models it is possible to simulate load profiles at a load level for a single occupant, a group of individuals in a building (e.g., a household) and an aggregation of buildings. In Figure 3.1 a conceptual diagram showing the main principles of the modeling approach used to simulate the load in detached houses and office buildings is shown. As seen in the top-right part of the figure, a building is instantiated and in turn populated by a random number of individuals. Each individual has a stochastic occupancy behavior which will in turn correlate with an energy-use of appliances and DHW, along with the need to heat, cool and ventilate the building. The methods used in development of these modules are described below.

Behavioral module: Non-homogenous Markov chain models

The behavior of the individuals is simulated through non-homogenous Markov chains. A Markov chain X is a time-discrete stochastic process which describes how courses of action evolve over time by transiting between a set of states E_1, E_2, ..., E_N with certain probabilities. Between time steps t and $t+1$, an individual can change its current state E_i to a new state E_j with probability p_{ij}. This process is described by the following equation:

$$p_{ij}(t) = P(X_{t+1} = E_j | X_t = E_i). \tag{3.1}$$

In other words, the probability for transiting to a certain state at time $t+1$ is only dependent on the outcome of the previous time step t. This is denoted as the Markov property, i.e. the process has no memory [111]. Further, in a non-homogenous Markov chain these transition probabilities change over time. This feature is required to capture a process which alters behavior over time, such as an occupancy pattern in an office room

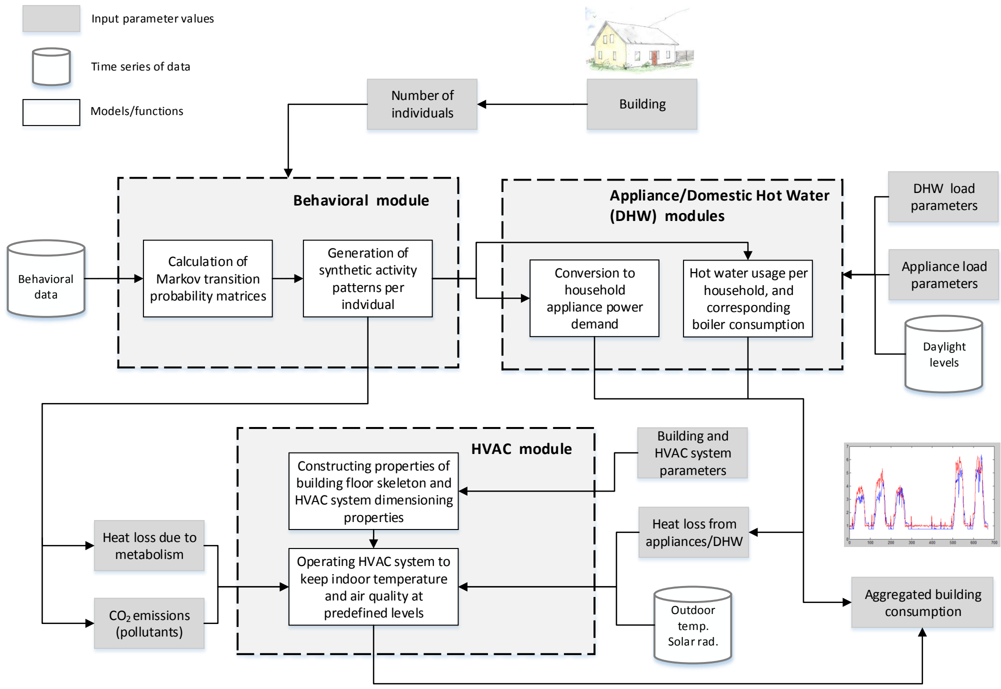


Figure 3.1: The conceptual diagram shows the functioning, interrelationship, and data requirements of the different modules of the model.

where it is less probable to show up at the office in the night time, etc. [55]. By estimating transition probabilities between all possible states and time steps, a transition matrix $M(t)$ can be defined. In short, $M(t)$ is a quadratic matrix where the size of each matrix is determined by the number of states. Then, N number of $M(t)$ is defined, i.e. one matrix for each time step. The Markov chain probabilities are sampled from behavior data by first determining the number of empirical transitions n_{ij} between states and then calculating the transition probability p_{ij} as:

$$p_{ij}(t) = \frac{n_{ij}(t)}{n_{ii}(t) + n_{ij}(t)}. \tag{3.2}$$

How the actual Markov chain is designed differs between the detached house and office building model as different behavioral data has been available for the calibration. This is described more thoroughly in the upcoming subsections.

Detached house: design of behavior model with usage of appliances and DHW

In the detached house model, there are two parallel non-homogenous Markov chains to synthetically generate activity behavior for appliance and DHW usage, respectively. The activity behavior Markov chain for appliance usage is taken from [103] and consists of nine states, namely: *away*, *sleeping*, *cooking*, *dishwashing*, *washing*, *TV watching*, *computer usage*, *audio listening*, and *other*. The seven last activities infer that the individual is at home and active, and consumes electricity through appliance usage. An individual can be in

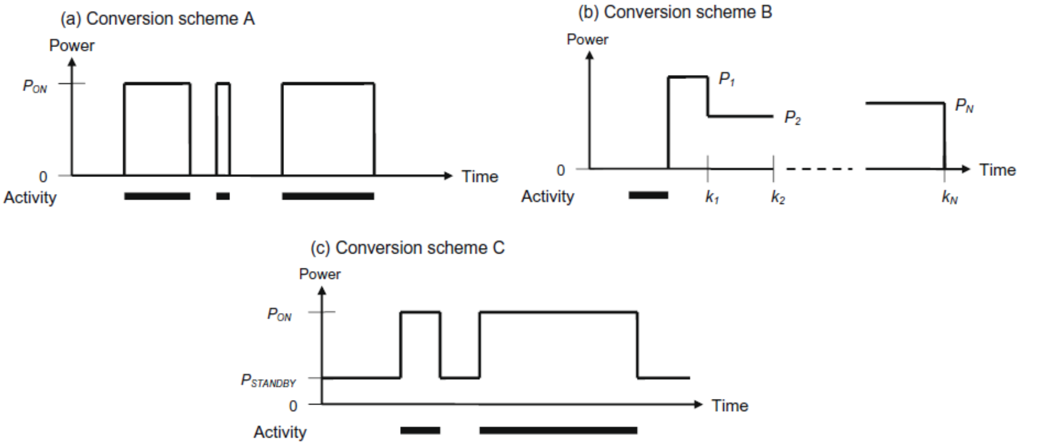


Figure 3.2: The three schemes to convert activities of the individuals to an usage of appliances [103].

only one of these states in any given time slot. Furthermore, the non-homogenous Markov chains were calibrated with TUD from a Swedish study performed by Swedish Statistics Bureau (SCB) in the year 1996 [16]. This study consisted of energy measurements and interviews with 463 individuals in the age span of 10 to 97 years in 176 households of various compositions, e.g. singles, pairs, families with children, etc. The participants wrote dairies with a five minute time resolution to keep track of their daily activities for one ordinary weekday and weekend day, respectively. This included information about which activity that was being performed, where it was performed, and if it was performed collectively. The data-set was complemented with information that stated whether the household lived in a detached house or an apartment. In this thesis, only the data for people living in detached houses is used for the Markov chain calibration. With the defined appliance Markov chain and the TUD it is possible to generate synthetic activity data of the individuals living in detached houses.

In the next step, the activity data is converted to electricity usage. Widén et al. [104] defines three classes of models which can transform an activity type into load profiles from various appliances: (a) electricity consumption that is constant during an activity, e.g. refrigerators/freezers, (b) a variable load cycle which is started directly after an activity is finished, e.g. dishwasher, and (c) a constant electricity consumption during the activity, e.g. TV watching and a stand-by consumption during non-use. In addition, these models take into account to energy-usage activities that are done collectively. For example, if two individuals in a household watch TV at the same time, there will only be energy-use from one TV set. See Figure 3.2 for graphical representations of the three conversion schemes. For lighting-use, a separate model is proposed which is dependent on occupancy patterns of the individuals, along with the daylight levels. Hence, the seasonal and diurnal variation of lighting load are accounted for in the model [105]. Subsequently, by assigning reasonable load parameter values and run times for the appliances, electricity consumption profiles can be generated with the aforementioned activity data for an arbitrary number of households and time frame. The model framework has been validated against electricity measurements from a subset of the participating households in the TUD study. The validation showed that the models can generate load profiles that are comparable with the measured consumption

[104].

Moreover, a non-homogenous Markov chain with the following states is proposed for DHW processes: *away*, *sleeping*, *bathing*, *showering* and *other*. Only the states *bathing* and *showering* imply a usage of DHW. As for the appliance usage, synthetic activity data can be generated by utilizing the aforementioned TUD. The Markov chains for appliance and hot water usage are run in parallel and independently of one another. This implies that an individual can perform two energy usage activities at the same time, e.g. both showering and cooking. However, it is expected that this simplified approach will have a limited impact on the model accuracy, as compared to the increase of complexity by merging the two Markov chains. Further, the DHW model connects hot water consumption processes from the bath and shower activity states, with thermal processes in the DHW tank. The DHW tank is represented as an energy storage equipped with a thermostat with the objective to maintain a specific reference temperature (T_{tank}^{ref}). This temperature will deviate from the reference point in time due to the hot water use emulated by the Markov-chain state changes, along with energy losses from the tank to the surroundings. It is assumed that the electric boiler will supply energy to the tank at full capacity (P_{boil}) as soon as the tank temperature T_{tank} departs from the reference value. The total energy demand of the tank (Q_i^{drain}) at time step t is determined by:

$$Q_{drain}(t) = V_a^{flow}(t) \cdot C_{p,water} \cdot (T_{outlet} - T_{inlet}), \quad [W], \tag{3.3}$$

where $C_{p,water}$ is the specific heat capacity of water. T_{outlet} and T_{inlet} are the temperatures of the inlet and outlet water, respectively. V_a^{flow} is the total hot water flow to serve the current DHW activity a of the household member (showers or baths). In the end, the DHW tank is an energy storage where discharge of energy is a result of usage and losses, and the recharge is performed by the boiler.

Office building: design of employee behavior model and usage of appliances

In parallel to the models developed for household behavior, a model for generating occupancy patterns of employees in individual office rooms has also been proposed. This model is composed by non-homogenous Markov chain with only two states - occupant or vacant. The occupancy behavior does only concern single office rooms, not joint office areas, e.g. corridors, lunch rooms, etc. Behavior in joint office area has not been modeled in detail because it is much more complicated to quantify occupancy patterns and energy-use in these areas as it can be occupied by several employees simultaneously. In addition, no occupancy data has been available for these room types. Therefore, a simpler model for appliance use in other rooms has been proposed - where the usage only depends on time schedules. Furthermore, the model approach for generating occupancy patterns in individual office rooms is composed by two steps: (i) estimating probability distributions of number of employees showing up to the office during the day, i.e., account for people who are sick, on business trips, vacations, etc., and (ii) calibrate Markov transition matrices to reflect occupancy patterns in office rooms for the employees that have shown up. To estimate values for (i) and (ii), occupancy sensor data has been collected from 47 single office rooms for a time period of 17 months from an office building floor located in the southwest of Sweden.

Synthetic occupancy profiles for an arbitrary number of employees can be generated with this approach. These occupancy profiles are then connected to an electricity use from appliances in the office rooms. As no detailed behavioral data is available for office buildings (as compared to the detached house TUD), statistics for commonly used appliances in office rooms is collected, and assumptions on how occupancy and usage of these appliances are correlated are made. Three types of appliances are identified as common from a larger office building survey conducted in Sweden [86], namely: lighting, computer and server usage. It is assumed that the consumption of these appliances correlates perfectly with occupancy, except for lighting which also depends on daylight levels. For appliance usage in other building areas, i.e. the area that does not constitute single office rooms, two groups of electricity consumption classes are proposed: (i) a base load that is independent of time, and (ii) consumption that is coupled with work schedules. These two consumption posts are proportionate to the floor area. See paper 4 for more mathematical details on the models for occupancy and appliance use.

HVAC module: Lumped capacitance model of physical indoor environment

Again, in parallel to the behavioral models in detached houses and office buildings, simplified lumped capacitance models has been formulated to describe the heating and cooling dynamics in the two building types. These lumped capacitance models constitute the HVAC module in Figure 3.1. The main objective of the HVAC module is to regulate the quantity of heating/cooling energy supplied by, e.g. a heat pump, to maintain a predefined indoor temperature (T_{ref}). The indoor temperature (T) will deviate from this set point value due to the following disturbances: (i) outdoor temperature (T_{out}), (ii) solar radiation (G_{sun}), and (iii) internal heat gains from occupants and appliances (G_{int}). Ambiance leakage, i.e. disturbance (i), is the only factor that can drain energy from the building, and the others disturbances can be seen as energy providers to the system. The leakage amount transferred between indoor and outdoor environment is determined by the conduction properties of the building skeleton (transmission losses), along with an amount of indoor air that is released from the building (leakage/ventilation losses). The transmission losses Λ_{trans} are defined by:

$$\Lambda_{trans} = \sum_j \mathrm{U}_j \cdot \mathrm{A}_j, \quad \left[\frac{\mathrm{W}}{^\circ C}\right], \tag{3.4}$$

where U_j is the transmission coefficient of each building component j, and A_j is the total area of that component. Further, the leakage losses Λ_{vent} are determined by:

$$\Lambda_{vent} = V_b \cdot N_{vent} \cdot C_p \cdot (1 - \alpha_{rc}), \quad \left[\frac{\mathrm{W}}{^\circ C}\right], \tag{3.5}$$

where V_b is the total volume of the building, N_{vent} is the air exchange rate. C_p is the specific heat capacity of air, and α_{rc} is the heat recycle coefficient. Then, the heating/cooling losses Q_{loss} are quantified by:

$$Q_{loss}(t) = (\Lambda_{trans} + \Lambda_{vent}) \cdot (T(t) - T_{out}(t)), \quad [\mathrm{W}]. \tag{3.6}$$

As stated earlier, energy is supplied to the indoor environment through solar radiation and internal heat gains, i.e. disturbance (ii) and (iii). Quantifying the heating gain from solar radiation is a complex procedure. Hence, a simplified model has been used that includes only the solar radiation against a vertical area (G_{sun}), the total window area per building side (A^{side}_{window}) and a reduction factor (α_{red}), where the solar radiation is shaded by e.g. surrounding trees and buildings, etc. The heat contribution from solar radiation G_{sun} is:

$$G_{sun}(t) = \alpha_{red} \cdot A^{side}_{window} \cdot P_{sun}(t), \quad [\mathrm{W}]. \tag{3.7}$$

The internal heat gain from appliances and occupants G_{int} at time step t is determined by the stochastic output of the behavior, DHW and appliance usage modules as follows:

$$G_{int}(t) = P_{met} \cdot N_{occ}(t) + \gamma_{app} \cdot P_{app}(t) + \gamma_{DHW} \cdot P_{DHW}(t). \quad [W], \tag{3.8}$$

where N_{occ} is the number of occupants, P_{met} is the heat loss through metabolism, and P_{app} is the electricity usage from appliances. Further, P_{DHW} is the energy loss through DHW usage, γ_{app} and γ_{DHW} are coefficients that determine how much of the heat losses that are actually absorbed by the indoor environment. Evidently, as all of these energy flows will not be in balance to provide a stable indoor temperature, a HVAC system exists that can compensate the energy imbalances. Such a system could be a heat pump or a direct electrical heating system etc. The HVAC system's capacity to supply heating/cooling energy Q_{reg} is dependent on the installed power capacity P_{reg}, along with the COP indicator of the system. COP defines how much of the electrical energy input that is converted to heating/cooling energy. For example, for direct electric heaters the COP is 1, and typical air-air heat pumps have COP values between 2 and 3.5 [91]. These values vary with respect to model type, compressor power, outdoor temperature, etc. The installed capacity of the heating/cooling system (P_{reg}) is mainly dependent on the thermal inertia of the building (C_{in}), and historical outdoor temperature data of the region (T_{DWT}).

As a consequence of all the aforementioned processes, there will be a net flow of energy from/to the building that will affect the indoor temperature T between time step t and $t+1$ according to:

$$T(t+1) = T(t) + \frac{1}{C_{in}} \cdot (Q_{reg}(t) + Q_{sun}(t) + Q_{int}(t) - Q_{loss}(t)), \quad [°C]. \tag{3.9}$$

Hence, the indoor temperature for the next time step is dependent on the temperature value of the previous time step, the net flow of energy and the thermal properties of the building. Subsequently, the heuristic controller in the thermostat aims to keep $T(t+1)$ close to T_{ref}. For more detailed information about the bottom-up simulation models, see papers 1 and 4.

3.2 Description of used data-sets and statistics

In this section, the materials used, such as building stock statistics, along with data for weather and end-user behavior is described.

Statistics on national building stock

To be able to instantiate building objects which are representative for the different segments in the Nordic building stock in the bottom-up simulation model, statistical data from various sources was collected. Different types of statistics need to be included to find the wide range of parameter values required by the consumer models. This includes statistics for: (i) the building stock composition and its energy-use characteristics, (ii) the building properties, e.g. U-values, time constants, (iii) HVAC-system configurations, (iv) occupant size distributions, and (v) typically used appliances.

Detached house statistics

The total energy-use for space heating and tap water purposes in detached houses was 32.5 TWh in Sweden in the year of 2012. The number of houses is slightly under 2 million, with

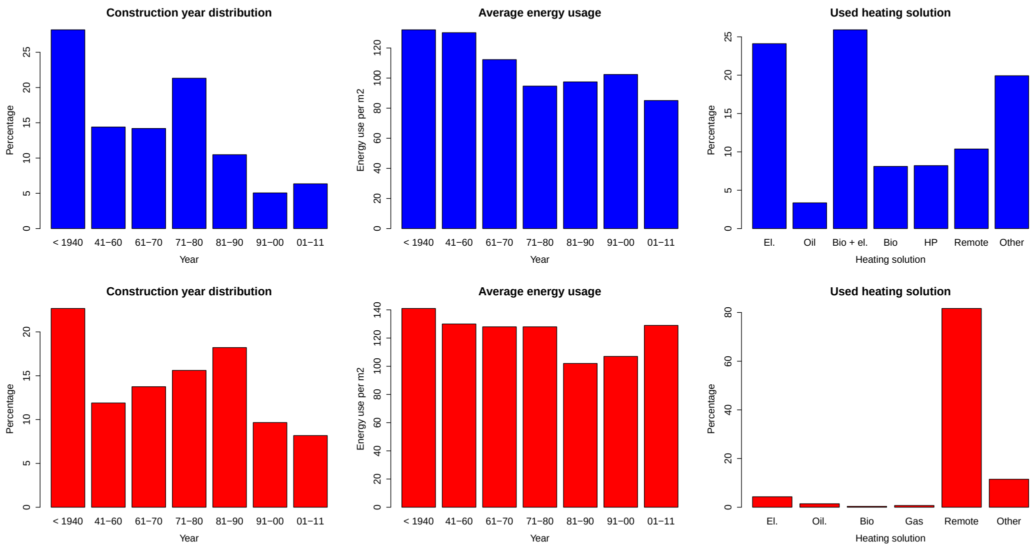


Figure 3.3: Building stock statistics for detached houses (upper row) and office buildings (lower row), respectively. The statistics include relative number of buildings and average energy-use per decade and distribution of used heating technology.

a total floor area of 287.6 million m^2 [89]. The average detached house consumes around 23 MWh annually, where heating stands for 13 MWh (approx. 60% of total use), and 4.3 MWh is DHW (approx. 20%) [17]. This implies an average consumption of 113 kWh/m^2, year for these two posts together. In older buildings, the consumption is 50% higher than in buildings constructed between the years 2000 and 2011 [89].

In the upper half of Figure 3.3, the following statistics for detached houses are shown: relative number of buildings per decade, average energy-use from heating and DHW per decade, along with the distribution of used heating technologies. As seen in the upper-left subplot, approx. 80% of the detached houses are built before the 1980s, and 28% is constructed prior the 1940s. This implies that the exchange rate of the detached house stock is slow, i.e. detached houses are used for many years, and newly constructed buildings are few in relation to the entire population. Furthermore, the average energy usage per m^2 has decreased steadily between the years 1940 and 1980. However, this consumption increases again between the years 1981 and 2000, until it drops again significantly after the year 2001. These developments are mainly due to applied building standards, e.g. used building materials and window-to-wall ratios.

Heating technologies which use electricity as the main energy source, e.g. electric heating[1], combined bio fuel and electric heating systems or heat pumps, stands for a 60% share of the heating solutions in detached houses. Heat pumps are more common in newly built houses, where the house manufacturer often recommend to install an exhaust air heat pump [32]. Remote heating only represents a 10% share of the heating supply. As remote heating is an uncommon heating solution for detached houses, the hot water is normally supplied locally by a separate DHW tank with an electric boiler [72]. Energy-use for cooling is not common in Swedish detached houses, and, therefore, the statistics for this consumption post is not communicated here. Further, 90% of the buildings constructed before 1975 are

[1]Either through direct heating or hot water systems

naturally ventilated. For buildings built after 1975, it is common that mechanical ventilation systems are installed, such as exhaust air fan systems (F-system), both exhaust and supply air fans system (FT-system), or systems with both exhaust and supply air fans, along with heating exchange (FTX-system). Only 10% of the buildings established after 1985 are naturally ventilated [84].

Statistics on typical appliances in detached houses are taken from [103]. The included appliances are dishwashers, cold and cooking devices, lighting, TV-sets, stereos, and washing/drying machines. The average annual electricity-use from appliances in detached houses was 6.2 MWh in 2012 [89]. This implies that appliances represents approx. 20% of the total energy-use in these buildings. The consumption post has increased by 63% since the year 1970.

When it comes to representative household sizes, background data from the aforementioned TUD study is used [16]. Here, household sizes between 1 and 7 individuals are defined in the form of a probability distribution, estimated from the study data. For more information about the parameters in the detached house consumer model see paper 1.

Office building statistics

The total stock of office buildings in Sweden consumed around 3.5 TWh for space heating and hot water applications in 2012. In total, there are 17,109 office buildings according to [88] with a total floor area of 27.8 million m^2. Thus, the average floor area per building is 6,800 m^2. The variation in floor area between buildings is however significant, where some buildings are over 40,000 m^2 in size, and others can be as small as 500 m^2 [86]. As for detached houses, a majority of the office building floor area is established before the 1980s - in this case over 64% of the total area. Between the decades 1981-90 and 1991-2000, a noteworthy drop in construction of new office floor area can be noticed in the bottom-left subplot of Figure 3.3. This drop can according to [77] be explained by the financial crisis that struck Sweden in the early 1990s.

In average, an office building consumes 128 kWh/m^2 per year for space heating and cooling [88]. There is a variation in energy-use depending on construction decade, where older office buildings in general consume more. However, the downward trend in energy-use over the decades changes after 1991 when it begins to rise. The reason for this shift is two fold: firstly, newer buildings have a higher window to wall ratio, and secondly, it is more common that these buildings are equipped with comfort cooling. Further, 81% of the total office floor area is district heated. Electric heating is the second most common solution with a share of 4.3% [88]. In other words, district heating has a very dominant role in the heating of office buildings. However, the situation is opposite for the cooling of offices. In a thorough energy-review of 123 office buildings presented in [86], it is concluded that 84 of the buildings are equipped with cooling machines powered by electricity, i.e. a 68% share. Additionally, 29 buildings are connected to a district cooling infrastructure. It must be noticed that a high proportion of the investigated buildings are located in metropolitan areas. So this share of district cooling may not be representative for smaller cities. The average energy-use for cooling is 10.6 kWh/m^2 per year for the investigated buildings [86]. Finally, energy-use from hot water is limited, with an average of consumption 2 kWh/m^2 per year. This can be compared to detached houses which have an average consumption of 20 kWh/m^2 per year for hot water [85].

The way that the heating/cooling energy is supplied has an impact on HVAC system design. Heating energy is most often distributed to the office room area via water based radiators. A share of the heat can also be delivered from the ventilation system by preheating the supply air. Cooling energy is commonly exchanged to the office environment by water based system in the ceiling - denoted as cooling panels, or by cooling the supply air in the ventilation system [32]. In general, mechanical ventilation systems are very common in office buildings, where the investigated buildings in [86] either have variable air ventilation or constant air ventilation systems. The average annual consumption from ventilation load is 17.9 kWh/m^2 in the investigated buildings.

Usage of appliances represents one third of the total electricity consumption in office buildings. Roughly, the energy-use from appliances can be split into two categories: either consumption originating from processes in the business or in the building. The former category includes consumption posts related to everyday business operation of the tenants, such as IT-equipment and lighting, etc. The latter post compromises energy processes connected to the actual use of the buildings, e.g. elevators. In total, the average energy consumption from appliances is 66.7 kWh/m2 per year in Swedish office buildings [86]. The most significant consumption comes from lighting, PC and server usage. For more information about the parameters in the office buildings consumer model see paper 4.

Behavioral and Weather data

As mentioned earlier, the detached house behavioral data is taken from a Swedish TUD study with 463 participants [16]. The raw TUD has been transformed into two separate non-homogenous Markov chain matrices (appliances and DHW use), with the size $10 \times 10 \times 1440$, for one ordinary weekday and one weekend day, respectively. The matrices are dimensioned after the number of possible activity states in the Markov chain (i.e., 10 by 10) along with a one minute time resolution of the simulated behavior, i.e. 1440 minutes per day.

The office building behavioral data has been collected in the form of occupancy sensor data from 47 single office rooms in Borås, Sweden [65]. The sensor data is binary and event based. This means that the sensor unit registers a time stamp and a corresponding variable value whenever the occupancy state has changed, such as going from vacant (= 0) to occupied (= 1). This data has been measured for the time period of November 2010 to April 2014. A significant amount of data processing has been applied on the raw occupancy data to convert it into a discrete time series of vacant/occupant values with a one minute resolution. The processed data has then been used to estimate the non-homogenous Markov chains according to same method as for detached house model - but with only two states instead, i.e. a matrix with size of 2 by 2.

Both day-ahead forecasts and observed data for outdoor temperature and solar radiation have been collected from the Swedish weather institute SMHI [92]. The observed values have an hourly time resolution, and the prognosis data has a six hour resolution. Further, complementary data for observed daylight levels and outdoor temperatures with a 15 min time resolution have been gathered from a weather station located at the office building floor in Borås.

3.3 Model validation

As the proposed consumer models are based on numerous assumptions and predefined parameter settings – model validation on real load measurements is an important component of the project. In order to validate the developed models data has been collected from two data sources: the Swedish utility company Vattenfall [98] and an office building in Borås [65] housing parts of the research institute SP. The Vattenfall data consists of hourly load measurements for two separate substations for an entire year. The first substation is located in a suburb of Stockholm, and serves 41 detached houses. The second substation is located

Table 3.1: Description of the data-sets collected in the project.

Data-set description	**Time resolution**	**Area**	**Used in Paper**
Household behavior: Markov matrices based on TUD-data from a larger SCB study in 1996	1 min	Numerous of locations in Sweden	1
Office room occupancy: Sensor data from 47 individual office rooms	Event based	Borås	2, 3, 4
Observed weather data for outdoor temperatures, solar radiation, and wind speeds	1 h	Stockholm, Uppsala, Gotland	1, 2, 4, 5
Day-ahead weather forecast data for outdoor temperatures and solar radiation	6 h	Borås	3
Substation load data: measured electricity consumption data from two substations	1 h	Stockholm, Uppsala,	1, 4
Office building data: power consumption data from heat pump, ventilation and appliance loads. In addition, data for indoor temperatures, outdoor temperatures and daylight levels	15 min	Borås,	2, 3, 4
Day-ahead electricity prices from Nordpool	1 h	SE3 price area	1
Distribution grid data: Total measured system load and production data	1 h	Gotland	5
Day-ahead and hour-ahead forecast data for wind power production	1 h	Gotland	5

in Uppsala, Sweden, and serves seven office buildings with district heating. The substation load data does only reveal the aggregated consumption of the buildings, and, therefore, load characteristics of individual households and appliances are not known in this case. Only information concerning (i) geographical area, (ii) time period of measurements, (iii) number of connected buildings, and (iv) used heating solution is available. The second data-set, gathered at SP consists of consumption measurements for heat pump, ventilation and appliance loads, respectively - with a 15 min time resolution during one year. For this data-set, measurements for indoor temperature from two office rooms with a 15 min time resolution have also been collected. This data has been used to validate the individual simulation modules presented in paper 4.

Chapter 4

Results and Discussions

This chapter summarizes the main results of each appended paper which together answer the Research Questions (RQs) of the thesis. Paper 1 contains the simulation results for the detached house consumer model and is connected to RQ1. Analysis of an extensive analysis office building data-set is reported in paper 2. Paper 3 presents the non-homogenous Markov chain model which can simulate occupancy patterns in single office rooms. These two papers provide important input to the development of the office building consumer model communicated in paper 4, which relates to RQ2. The final section presents results from simulations of a DR case related to congestion management in distribution grids where the detached house consumer model is used.

4.1 Detached house bottom-up simulation model results

For simulating hourly detached house load, weather and electricity price data for the time period, along with parameter values for an average Swedish detached house has been instantiated in the detached house consumer model. Using this input simulations are performed for a whole year using a Monte Carlo approach, where the DHW and appliance modules are simulated with a one minute resolution, and the HVAC module is simulated on an hourly resolution. The simulations are repeated 20 times, and then the load data from the samples are averaged with a one hour resolution. A Monte Carlo approach with 20 samples is applied to output the average outcome of the process, and, therefore, minimizing the expected difference to the measured load data. The load results are shown both on a seasonal and an intraday time scale, and statistically compared to the measured substation load data with 41 detached houses.

Seasonal load variation

The upper subplot of Figure 4.1 shows the simulated and the measured daily average electricity consumption of the population of detached houses over the year, i.e. the seasonal load variation. As seen, the simulated load profile follows the empirical data well, where the seasonal variation with respect to consumption magnitude and phase is captured. The RMSE becomes 10.9% between the two profiles. However, there are two periods that are significantly inaccurate, namely: the consumption in the first weeks of February and April, respectively. The mismatch in February may be due to extreme electricity price peaks observed in the lower subplot. These price peaks are so severe that media covered the events [33], and the end-users acted accordingly. The model does not take price sensitivity into ac-

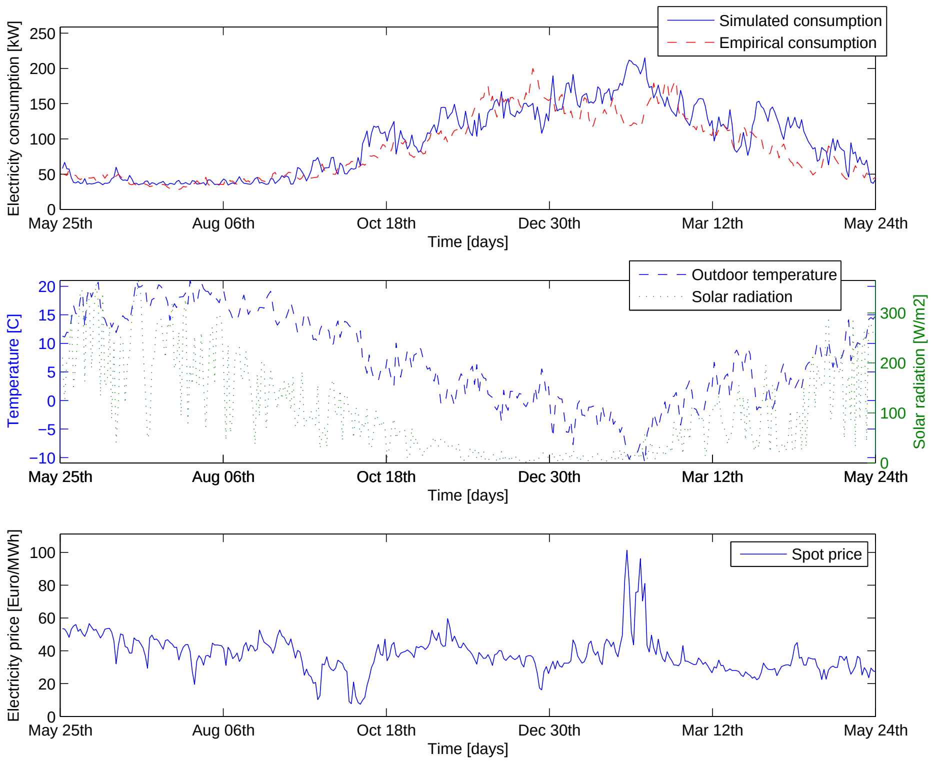


Figure 4.1: The upper plot shows the daily mean load simulated and measured for one year (May 25th 2011 to May 24th 2012). The middle plot depicts the outdoor temperature and solar radiation for the same period. The lower plot shows the electricity prices.

count, and assumes that the end-users are price takers. Hence, the simulated consumption is mainly influenced by the low outdoor temperatures (see middle subplot). The second mismatch in April is more difficult to explain. One possible explanation is that the model underestimates the heating contribution from solar radiation. Furthermore, during summer time, the simulated load follows the measured load closely. This implies that the DHW and appliance modules provide realistic forecast of the measured consumption as the space heating module is inactive most of the times.

In order to quantify the correlation between the model results and the real measurements, a linear regression model is fitted between the two hourly load quantities for the whole year, i.e. 8760 pairwise data points. The fitted model has a regression coefficient β of 0.73. In other words, when the load increases by 1 kW in the model, the empirical load tends to increase by 0.73 kW. The obtained R^2 and RMSE for the regression is 67.8% and 18.0%, respectively. The total simulated energy-use per building for the time period is 21.0 MWh, where space heating stands for 13.0 MWh (63% of the total), DHW is 3.2 MWh (10% of the total), and appliance use is 4.8 MWh (22% of the total). This output corresponds well to national energy statistics documented in [89] which states a total energy-use of 23 MWh per year for an average detached house, where space heating is 13.0 MWh, DHW is 4.3 MWh and appliance use is 6.2 MWh of the total share. Therefore, the total consumption differs with 9.5% between the simulated values and the national statistics. For space heating consumption, there is no difference at all. The simulated DHW energy-use is underestimated by 34% in comparison to the statistics. One explanation could be that the model only considers two DHW activities, i.e. baths and shower. In reality, there are additional activities that increase the DHW consumption, such as manual dishes, hand wash, etc. For example, according to [104], making dishes cross tube and running water can require 39 liters of hot water, resulting in a 2.0 kWh energy-use. This energy-use does almost correspond to a 5 min shower. If manual dishes are done like this on a daily basis, the annual DHW consumption will increase by 22.8%.

Lastly, the appliance use is underestimated by 29%, and the reason to this could be what is included as appliance usage in the statistics. Here, consumption posts such as pumps, floor heaters, and ventilation units are included. Such posts are considered to be HVAC loads, and not appliances in the consumer model. In addition, the appliance-use model is based on TUD from 1996. It is obvious that IT-equipment is used differently today, and may impact the average consumption. Based on the previous documentation of results it is concluded that detached house simulation model can reproduce seasonal energy-use figures that are aligned with the national statistics. In addition, the error between the simulated and the measured annual energy consumption for the substation is around 10%. This result is better than the validation of annual energy-use of the residential consumer model presented in [108], where an error rate of 18% is received. For summarizing statistics from the seasonal simulation results, see upper part of Table 4.1.

Intraday load variation

In order to assess how well the consumer model captures the intraday variation of the measured substation load, the simulated and measured load profiles are compared against each other on daily time scale. To make the results easier to interpret, the load profiles are split according to the following categories of days:

- *Winter day*: The daily mean outdoor temperature is below 5 $°C$, and the daily average solar radiation is under 50 W/m^2. 105 days meet these requirements
- *Spring/Fall day*: The daily mean outdoor temperature is between 5 and 15 $°C$, and the daily average solar radiation is between 100 and 200 W/m^2. 40 days meet these requirements
- *Summer day*: The daily mean outdoor temperature is over 15 $°C$, and the daily average solar radiation is over 200 W/m^2. 40 days meet these requirements

Note, days with average electricity prices over 60 €/MWh are filtered out to remove potential reactions to extreme prices. The categories are also further divided with respect to weekday and weekend days. In Figure 4.2, averaged 24 h consumption profiles for the different categories of days are plotted. These are the key-findings from the subplots. (i) The model captures the systematic load variation between the category days, i.e. higher consumption in winter vs. lower consumption in spring. (ii) The simulated data is generally more volatile between the hours than the measured data, e.g. bigger load difference between peak and valley points. This is especially true for summer days, where the load variance over the day is limited for the measured data. (iii) The simulated evening peak load is generally lagging the measured peak with one or two hours - in particular valid for colder days. The main explanation to the limited variation for measured load in (ii) could be a changed

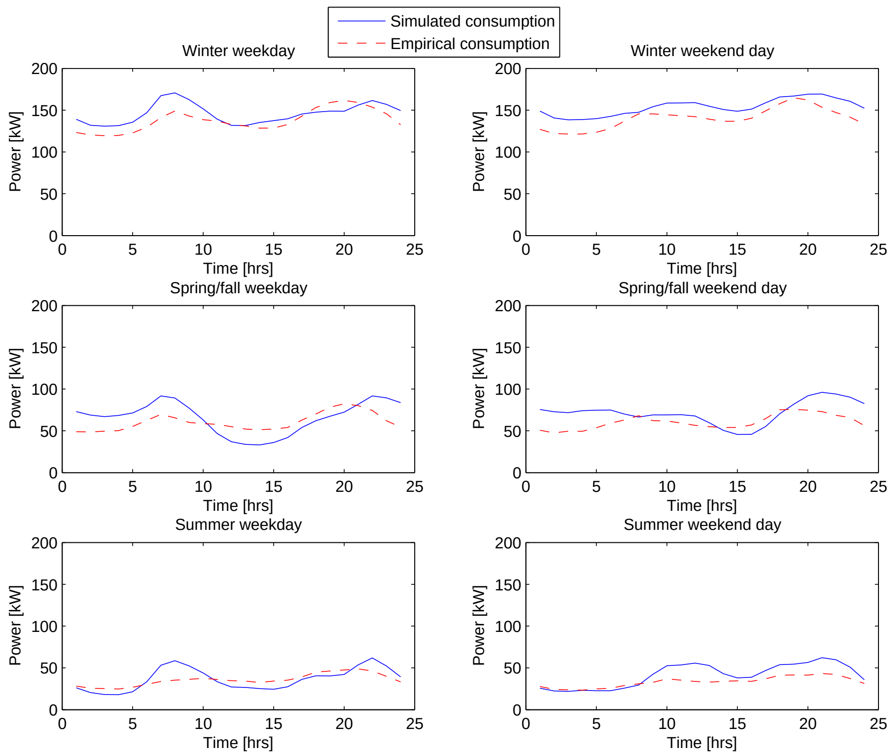


Figure 4.2: The 24 h average consumption profiles for the three type days. The subplots to the left are weekdays, and the subplots to the right are weekend days.

end-user behavior during summer time. For instance, the non-occupancy may increase due to trips etc., which results in more consumption from appliances in standby mode (fixed consumption), and less with actual usage from occupants (variable consumption). For (iii), a reasonable explanation to the difference in results could be due to the operation logic of the heating system. As the heating system is mainly functioning according to the outdoor temperature in the model, the consumption will tend to increase later in the evening due to an expected temperature drop. However, the real heating system might be operated much slower and/or the individuals are interacting with it in another way.

Moreover, a RMSE of 8.0% is obtained for the winter weekday load profile. This is consistent with the error results communicated by McKillan, et al. in [48], which yielded a RMSE of 7.6% for a winter day load profile. However, the validation in [48] was carried out on average load profiles from an Irish national database. The validation of the consumer model in this thesis is composed by load data from real consumers, which is believed to be influenced more by uncertainty. For example, this is confirmed when the end-users changed their behavior during extreme prices. Such events are not included in the national load profile, which instead reflects a reference case under stable conditions. Yao, et al. [109] validated their consumer model on national load data without space heating consumption. Yao, et al. obtained an R^2-value of 84.0% between the simulated and the reference load profile, along with a 30% error for the daily energy consumption. To compare these figures with the error results from this model, it is decided to compare the results for when the

Table 4.1: Summary of the seasonal and daily load results for the detached house consumer model. Note: SH stands for space heating and App stands for appliances.

Detached house model	Regression stats		Energy-use stats per building [MWh]			
Seasonal load	R^2	RMSE	Total	SH	DHW	App
Simulated load			21.0	13.0	3.2	4.8
	67.8%	18.0%	-	-	-	-
Measured load			18.5	-	-	-
National stats [89]	-	-	23.5	13.0	4.3	6.2
Daily load	R^2	RMSE	Total [kWh]			
Simulated winter load			86.5	-	-	-
	63.4%	8.0%	-	-	-	-
Measured winter load			81.0	-	-	-
Simulated summer load			21.8	-	-	-
	65.6%	10.7%	-	-	-	-
Measured summer load			20.5	-	-	-
McKillan [48]	-	7.6%	-	-	-	-
Yao [109]	84.0%	-	10.0	-	-	-

space heating load is inactive, i.e. for the summer type day. For the summer days an R^2 of 65.6% is obtained, and in average the daily energy usage is overestimated by 11.1% in comparison to the measured substation load. As mentioned earlier, it is believed that the lower accuracy of the model is mostly linked to the used validation data-set, where the measured load data is less predictable as it has connection with end-user behavior during, e.g. summer vacation. The consumer model does not take changed behavior due to vacation and holidays into account, and thus is less reliable when such events occur. For summarizing statistics from the intraday simulation results, with comparisons of related work models, see lower part of Table 4.1. Additional simulation results can be seen in appended paper 1.

Answer RQ1: The results of the validation show that the output from the model is aligned with Swedish energy statistics and error results from comparable models in the literature. The model obtains a RMSE of 8.0% for winter days, and a R^2 of 65.6% during summer days between the simulated and measured load profiles. McKillan receives a RMSE of 7.6% for their validation of winter day profiles, and Yao, et al. obtained an R^2-value of 84.0% for validation excluding space heating. However, these two aforementioned studies are using reference load profiles for model validation - and not real consumption data as in this thesis. Considering that a significant amount of information is unavailable regarding the actual buildings, e.g. house dimension, used materials, household types living in the neighborhood, exact data on behavior of the individuals, it is considered that the model can produce load profiles which are reasonable and representative for the intended consumer cluster. The model has an advantage in the usage of openly available data and statistics.

4.2 Office building models results

The results of the office building studies is constituted by three separate parts, viz. analysis of an office building data-set to retrieve more knowledge about such consumption data, a model for generation of occupancy patterns, and finally a bottom-up simulation model to generate load profiles in office buildings. As only the bottom-up simulation model is directly connected with RQ2, the two former parts will be handled briefly, i.e. only the key-findings will be described. For more results from these two, see appended papers 2 and 3.

Analysis of an office floor data-set

Exploratory data analysis is performed on the office building floor data-set introduced in the previous chapter. Appliance, ventilation and heat pump loads, along with occupancy ratios and outdoor temperatures are plotted in boxplots with respect to three different time horizons in Figure 4.3. As seen in the upper row, the variation in loads and occupancy is practically zero on weekends. A low variance is also seen on holidays and bridge days for these variables. Due to the limited variation, these day types are excluded in the upcoming plots. In the middle row, the monthly variation is depicted for the aforementioned variables. Here, it can be seen that the heat pump load only operates during the summer months. This is because the heat pump serves the floor with cooling when the daily average outdoor temperature exceeds 15 $°C$. The ventilation load also increases during the summer months while the consumption is more stable during the other months. This is tied to the fact that the ventilation system distributes the cooling produced by the heat pump to the office rooms. The appliance load and occupancy ratio variables follow each others' patterns, where the levels peak during the winter months, and notable drops can be detected in the months of July and August because of summer vacation times. Further, from the bottom row of subplots, it is obvious that the HVAC loads are time controlled. Both the heat pump and the ventilation load increase drastically at 6 a.m., consume energy over the day and then shut off at around 7 p.m., i.e. operates according to expected occupancies. The appliance load shows a similar pattern, but has more variation over the day which appears to be linked to occupancy. In summary: the energy-use and the occupancy levels are insignificant on weekends. The HVAC system consumes differently in the summer (warm months) as compared to the other months (cold months). The day operation of the HVAC system operation is based on time schedules. The appliance load is linked with the occupancy on a daily and a seasonal time scale.

Moreover, based on the temporal attributes, the data is split by month type - warm vs. cold months. Thereafter, correlation analysis is performed between all pair-wise variables for the two respective data-sets, during work hours only, i.e. 6 a.m. to 7 p.m. on ordinary weekdays. The main finding from this analysis is that appliance load is linearly dependent on occupancy for both data-sets, with an average correlation coefficient of 0.86 (p-val $<$ 0.001). Ventilation load has a weaker non-linear relationship with outdoor temperature during the other months, and is considered to be valid as the ventilation system can provide with free-cooling to the office floor when it is required. For the warm months, strong non-linear correlations are detected between heat pump load and ventilation load (correlation coefficient: 0.79), heat pump load and outdoor temperature (correlation coefficient: 0.82), along with ventilation load and outdoor temperature (correlation coefficient: 0.70). All of these correlation coefficients are statistical significant at a 0.1% confidence level. In other words, the HVAC system is associated with outdoor temperature in a non-linear fashion. This is most likely because the air-air heat pump and the ventilation loads work less efficiently at higher outdoor temperatures. All of these results are important input to

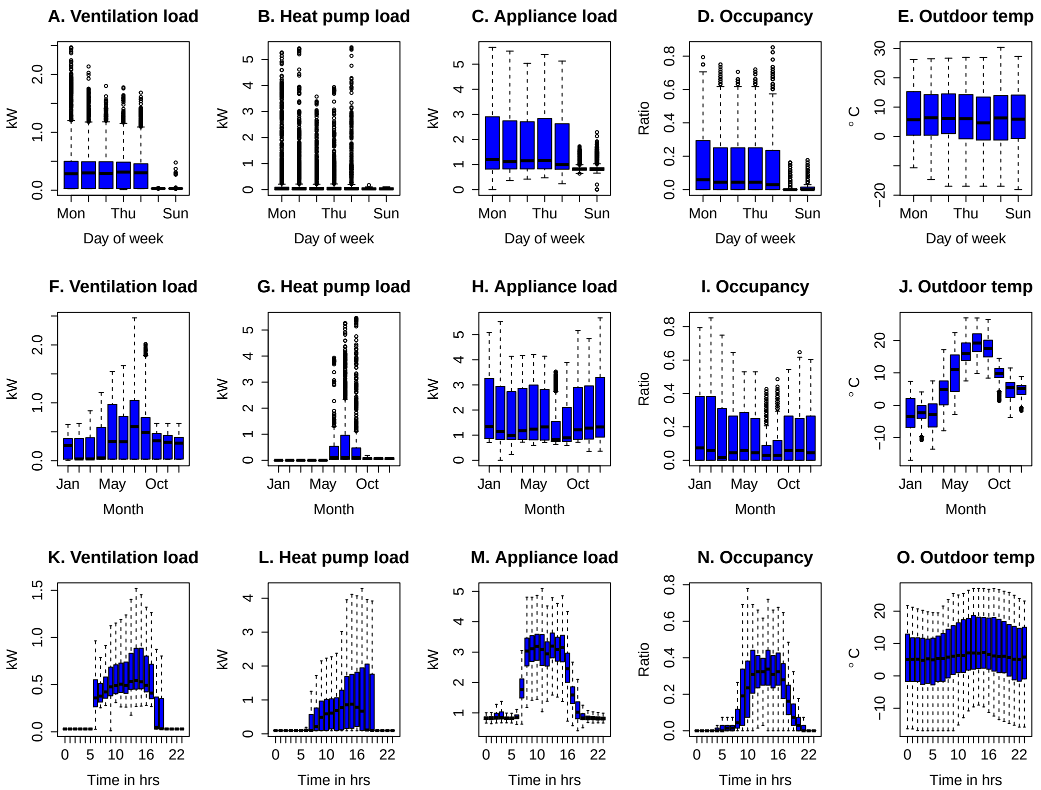


Figure 4.3: The upper subplots depict variations in the HVAC load, appliance load, occupancy and outdoor temperature variables with respect to weekday type in boxplots. The second row subplots show the seasonal variation for these variables in boxplots. The third row subplots illustrate hourly variation in boxplots. The bold points are outliers.

the bottom-up simulation model, e.g. temporal aspects of the consumption, variation in occupancy and its relation to appliance use, etc.

Behavior module for occupancy patterns in office rooms

The Markov transition matrices for the office room behavioral model are calibrated with occupancy data from 24 randomly chosen office rooms (51% of all rooms), for a time period of 327 weekdays from the office floor data-set described in the previous section. Weekend days are excluded due to low occupancy levels. As no clear differences in intraday occupancy profiles can be distinguished between different weekdays - transition matrices are calibrated for an overall weekday only. In other words, it is not necessary to calibrate Markov chain matrices for a Monday and a Friday, separately. However, the probability for an employee to arrive to the office during *sometime* in the day varies with day type. ANOVA tests [41] are performed to deduce whether there is a difference in mean values of showing up to the office depending on month and weekday. Here, it is shown that Mondays are significantly different from other weekdays (p-val < 0.001), and June and August are significantly different from other months (p-val < 0.001) and each other ($p = 0.0495$). Thus, six normal probability distributions are fitted with respect to type of month and weekday.

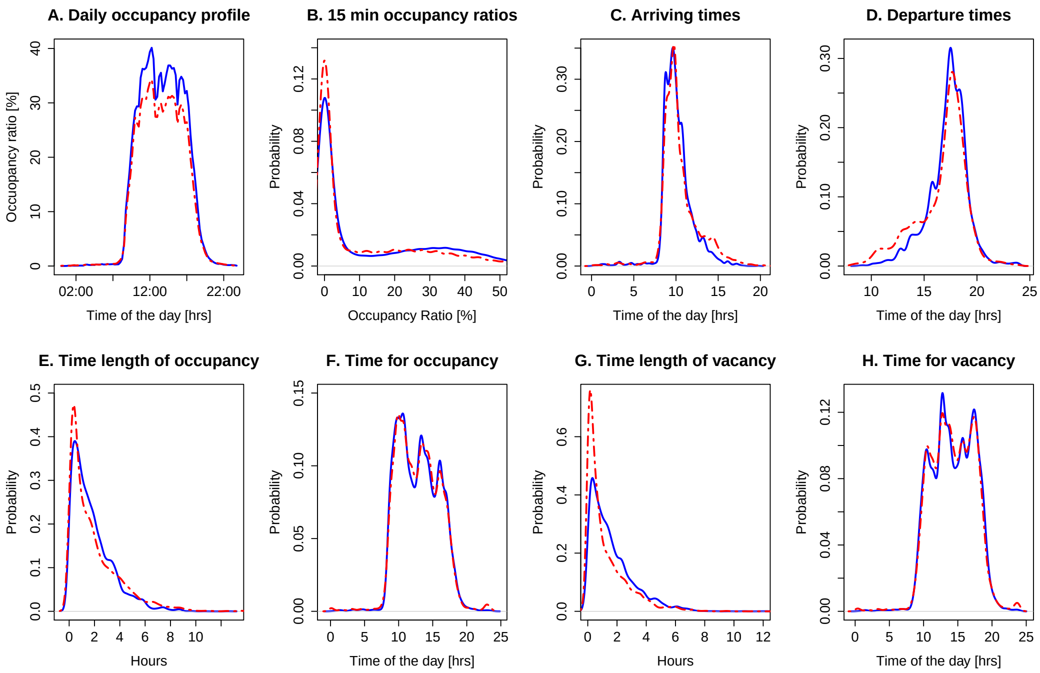


Figure 4.4: Plots of the statistical properties of the simulated and test occupancy data, respectively. The solid curves are the simulated data, and the dashed curves are the test data.

The remaining occupancy sensor data, i.e., from the 23 other rooms, is used as test data to verify that the model can generate representative occupancy profiles.

Occupancy profiles are simulated for the whole time period with a one minute resolution by combining the probability functions for showing up at the office and the calibrated Markov-chain matrices. To be able to say that the model can generate representative occupancy profiles, a number of occupancy/vacancy properties for the simulated and measured data are plotted against each other in Figure 4.4. The main conclusion from the analysis is that the model can reproduce key-statistical properties of the real occupancy data, as the curves follow each other rather well for all properties. In general, the real occupancy data has higher variance than the simulated data. This is however expected as the Markov chain matrices are averaged with data from many days, and the test data is composed by occupancy values from individual days.

Office building bottom-up simulation model: results

The office building bottom-up simulation model has been validated against two data-sets. Data-set 1 is composed by quarterly electricity energy measurements on load level, i.e. appliances, ventilation and cooling loads, for an office building floor. This data-set is described more elaborate in section 4.2. Data-set 2 represents aggregated hourly load values at substation level with seven connected office buildings. These buildings have remote heating and are not equipped with cooling loads. The validation will be presented with respect to each data-set.

Data-set 1 validation: one office building floor

Data-set 1 is represented by load data from 205 full days in the year of 2013. Some days are excluded due to missing or inconsistent observations. For example, for a majority of the days in April and September the BEMS is down and not registering any measurements. The consumption processes is simulated on load level (heat pump, ventilation and appliances) in the bottom-up model by input data for outdoor temperatures, solar radiation and occupancy ratios for the actual time period. Note, in this data-set validation, deterministic time series of the occupancy levels from the office floor are used in the simulations. This is done to be able to verify that the model can capture the impact of occupancy on consumption. Hence, the Markov chain occupancy model is deactivated in this validation.

In Figure 4.5, the daily averaged values for simulated and measured total load of the office floor, outdoor temperatures, solar radiation, and occupancy ratios are plotted in order to depict the seasonal variation. As seen, both the simulated and measured load follows a cyclic function with five days of high load, and then two consecutive days of low load. The daily load pattern is quite similar over the seasons, except for the summer period. Here, the average daily load increases drastically in comparison to the other months due to higher outdoor temperatures (middle subplot) and ensuring the need for cooling. In general, the model captures the load variation during these months well, except for the fact that the simulated load has a higher consumption spike in the beginning of each cycle (i.e., every Monday) than the measured consumption. This is because of inaccuracies in the thermal behavior of the indoor climate due to model simplifications - where the simulated HVAC system becomes slower than the real system to bring the temperature back to the set-point value when it has been inactive over the weekend period. Lastly, lower occupancy ratios can be noted for the summer months. However, this does not have a significant impact on the consumption, as the load during the summer is more dependent on the weather variables than the behavior of the employees. For example, the warmest day of the year (daily average of 20.5 C) results in the highest HVAC system load (daily average of 4.1 kW), which coincides with the lowest registered occupancy level of the whole time period (daily average of 4.3%). In other words, no adaption of the HVAC system operation is done for low occupancy during summer.

Moreover, in the left subplot of Figure 4.6, averaged 24 h load profiles in the cold months (i.e. the days when the cooling load is inactive due to low outdoor temperatures) are shown for the simulated and measured data, respectively. As seen, the two load profiles have a similar shape, although the simulated load is higher than the measured load in the morning hours (between 6 a.m. and 8 a.m.) and the evening hours (7 p.m. to 9 p.m.). One possible reason behind this is the fact that energy-use in the other room area, i.e., floor area besides individual office rooms, is fixed and only dependent on time schedules in the model. In reality, the consumption is most likely correlated with occupancy as well and, thus, more variable. Further, the simulated load is underestimated as compared to the measured consumption for the midday hours.

During the cold months, electricity usage only comes from appliances and ventilation since the building is district heated. When regression analysis is applied on the quarterly simulated and measured load values, the appliance and ventilation loads obtain an R^2 of 81.2% and 78.6%, along with a RMSE of 7.8& and 11.6%, respectively. The total energy use for the time period[1] is 29.5 MWh for the simulated data, and 29.2 MWh for the measured data, i.e. an error rate less than 1.0%. An average energy-use of 150.2 kWh/day (71.3 kWh/m^2 per year) and 151.5 kWh/day (71.9 kWh/m^2 per year) for the simulated and measured appliance load data are output, respectively. The ventilation load con-

[1] In total 155 days for the cold month period.

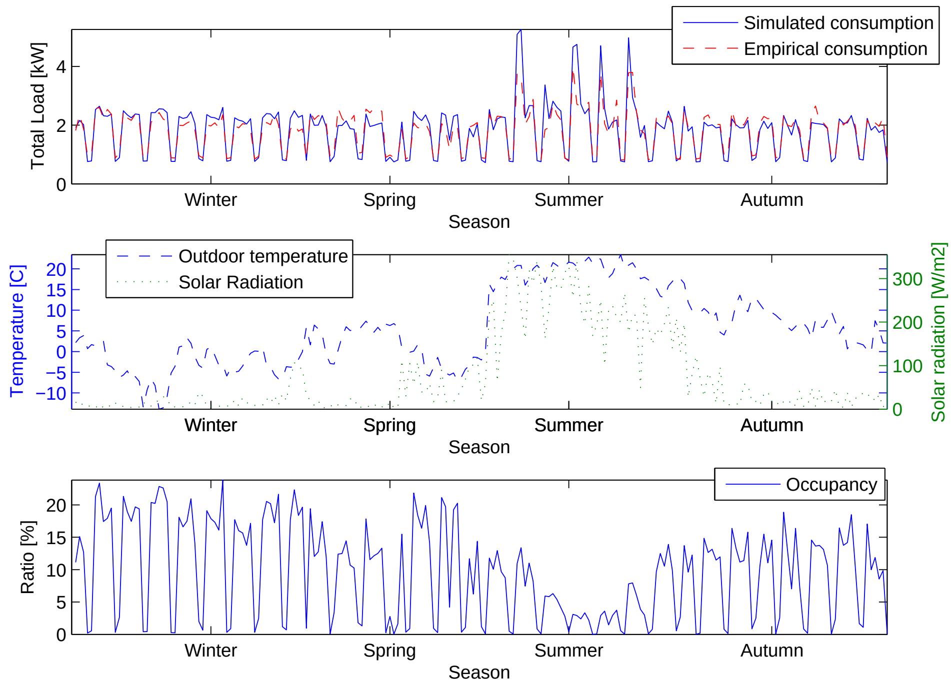


Figure 4.5: The upper subplot shows the simulated and measured daily mean load for the four seasons (winter, spring, summer and autumn). The middle plot depicts the outdoor temperature and solar radiation for the same period. The lower plot shows the occupancy ratio for the office floor.

sumes 16.0 kWh/day (7.6 kWh/m^2 per year) for the simulated quantity, and 16.7 kWh/day (7.9 kWh/m^2 per year) for the measured quantity. All together, these values correspond quite well with national statistics in [86], where average energy-use from appliances of 66.7 kWh/m^2 per year, and 17.9 kWh/m^2 per year for ventilation are declared. NB: the modeled office building floor has unique characteristics. Therefore, it is not surprising that the ventilation energy-use is not equal to the national statistics as, e.g., building parameters, HVAC system configuration and comfort constraints from employees will impact the ventilation load differently. These results are summarized in the upper part of Table4.2.

In the right subplot of the same figure, the 24 h load profile is displayed for the warm month time period, i.e. when the cooling load is operating[2]. As seen, this load profile is different from the cold month load profile. Here, the simulated consumption increases continuously over the day, and is subsequently reduced drastically after 7 p.m. This is connected to the increasing outdoor temperature and solar radiation over the day, which then impacts the need to cool the building. In other words, the load profile is more adapted to changes in weather than in end-user behavior. The measured load has a comparable profile, but is not changing as fast as the simulated load in the morning and afternoon hours. One possible explanation for the differences is that the real thermal environment is not fully represented by the simplified model, which may imply that less cooling energy is

[2]In total 50 days for the warm month period.

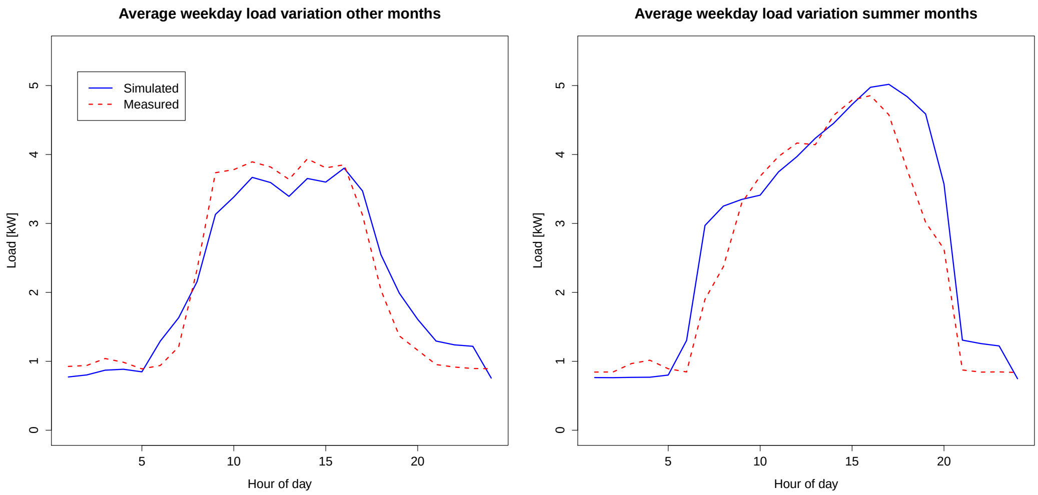


Figure 4.6: Left subplot: average weekday load variation for simulated load and measured load during other months (appliance load and ventilation load). Right subplot: average weekday load variation for simulated load and measured load during summer months (appliance load ventilation load and cooling load).

required to bring the indoor temperature back to the reference value.

The total energy-use for the period is 10.6 MWh for the simulated data, and 9.9 MWh for the measured data. This implies that the model overestimates the energy-use by 9.3%. Further, the cooling load consumes 54.4 kWh/day in average (roughly 8.9 kWh/m^2 per year[3]). This value is in line with national statistics which states average consumption from cooling loads by 10.6 kWh per m^2 and year [86]. The difference in energy-use can potentially be explained by several factors, e.g. different weather conditions at the site, a more efficient cooling machine is used, the average internal heat gain is lower, etc.

The ventilation load has a daily average consumption of 38.2 kWh, i.e. the consumption is increased by 240% as compared to the cold months. This is because the ventilation system distributes the cooling energy to the office space, which in turn raises the overall electricity consumption. Finally, the appliance load has a daily energy-use of 120.9 kWh which is ca. 20% lower than the cold month period. This is connected to lower occupancies during the summer vacations.

Regression analysis between the simulated and measured load data outputs R^2 values of 55.2%, 71.0% and 57.0%, and RMSE values of 12.1%, 12.6% and 16.2% for cooling, ventilation and appliance load, respectively. In other words, the warm month period yields less accurate results than the outcome for the cold months. This is connected to the simplified approach in the modeling of the indoor environment, which cannot capture all complex thermal processes in the real office building floor. These results are summarized in the middle part of Table4.2. Zhou et al. [113] validated their bottom-up simulation model with HVAC system consumption on a model implemented in the EnergyPlus simulation software. During the warm months, these authors' model overestimated the peak load by 30% as compared to the load data retrieved by the EnergyPlus model. For the model presented in this thesis, the peak load is in average overrated by 18.9%, and, thus, better

[3]Based on the assumption that the cooling load is used 1/4th of the weekdays in one year.

Table 4.2: Summary of simulation results for office building consumer model. The results are split with respect to data-set 1 (an office building floor) and data-set 2 (group of office buildings). Note: app stands for appliances, vent stands for ventilation.

Data-set 1	Regression stats		Energy-use stats
Cold months	R^2	RMSE	Total [kWh/m^2 and year]
Simulated app load			71.3
	81.2%	7.6%	-
Measured app load			71.9
National stats app load [86]	-	-	66.7
Simulated vent load			7.6
	78.6%	11.6%	-
Measured vent load			7.9
National stats vent load [86]	-	-	17.9
Warm months	R^2	RMSE	Total [kWh/m^2 and year]
Simulated app load			57.4
	55.7%	12.1%	-
Measured app load			52.9
Simulated vent load			18.1
	71.0%	12.6%	-
Measured vent load			19.0
Simulated cooling load			8.9
	57.0%	16.2%	-
Measured cooling load			8.3
National stats cooling load [86]	-	-	10.6
Data-set 2	R^2	RMSE	Total [kWh/m^2 and year]
Simulated total load			83.7
	88.9%%	8.6%	-
Measured total load			85.5
National stats [86]			84.6

on estimating the peak load in relation to the related work model. NB: Zhou et al. modeled an office building with 40,000 m^2 of aggregated space[4] which could be a reason to the higher error rate due to more complex consumption patterns in larger buildings.

Moreover, a general source of error for both data-sets is the fact that the validation is performed on 15 min load values. This means that unexplained random variations in the load will have a bigger impact on the accuracy, as consumption data with higher resolution is less smooth. If the data is averaged to, e.g., an hourly resolution, the error results will be improved, as the load profile will be more homogenous and predictable.

Data-set 2 validation: population of office buildings

Data-set 2 is composed by hourly load data from seven office buildings with district heating and no cooling machines. A validation is on this data-set to test the model's performance on an aggregation of office buildings where limited background information is available. The consumption is simulated with a Monte Carlo approach where data for day-light levels and

[4]Almost 50 times larger than the modeled office floor presented in this section

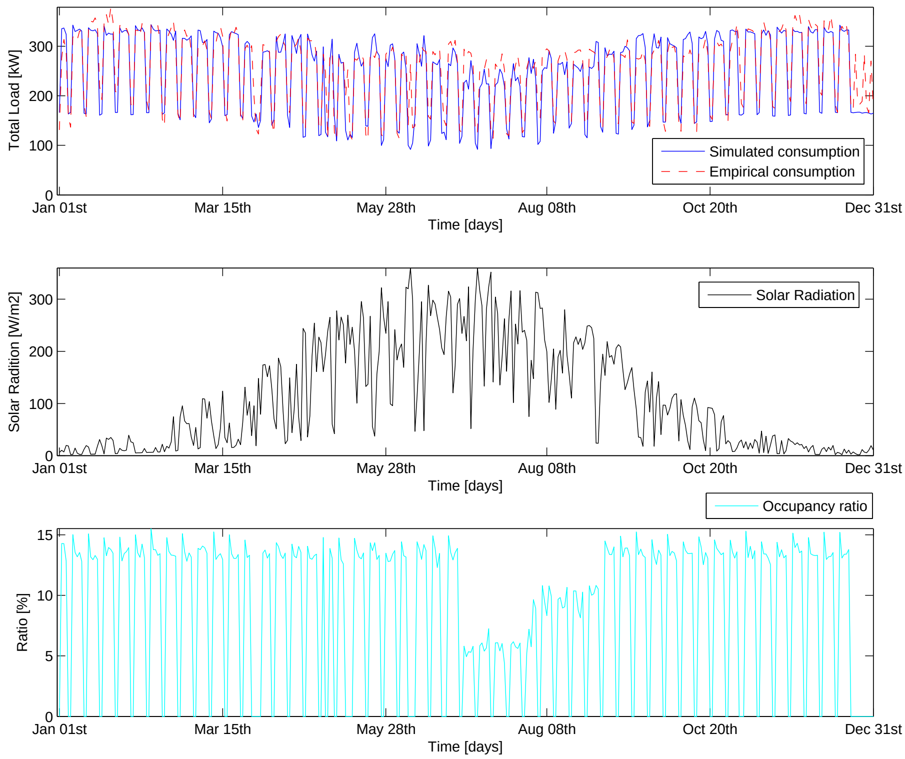


Figure 4.7: The upper subplot shows the simulated and measured daily mean load for the four seasons (winter, spring, summer and autumn). The middle plot depicts the outdoor temperature and solar radiation for the same period. The lower plot shows the occupancy ratio for the office floor.

occupancy levels from the Markov chain model is input. Additionally, as no detailed information is available for the real office building, building parameters have to be estimated. These values are taken for an average office building given in [74]. In the upper plot of Figure 4.7, the daily simulated and measured consumption is plotted for the whole year. As seen, the simulated load follows the measured consumption pattern well, with a five weekday high consumption cycle, followed by two weekend days of low consumption. The model also captures some seasonal variation of the real load, where the average consumption tends to follow the seasonal changes in the solar radiation and the reduced need for lighting (see middle subplot). The model also captures the general decrease in energy-use during the summer period due to a lower occupancy (see lower subplot). Moreover, the simulated annual energy-use is 2095 MWh, while the measured value is 2143 MWh, i.e., an error of 2.2%. The authors of [108] and [113] obtained an error rate of 3.0% and 2.0% respectively when they validated the annual electricity consumption from their bottom-up simulation models against office building load data. Thus, this error rate is consistent with the related work models. Further, based on the size of the office buildings instantiated in the model (3200 m^2 per building), an average consumption of 83.7 kWh/m^2 per year for the

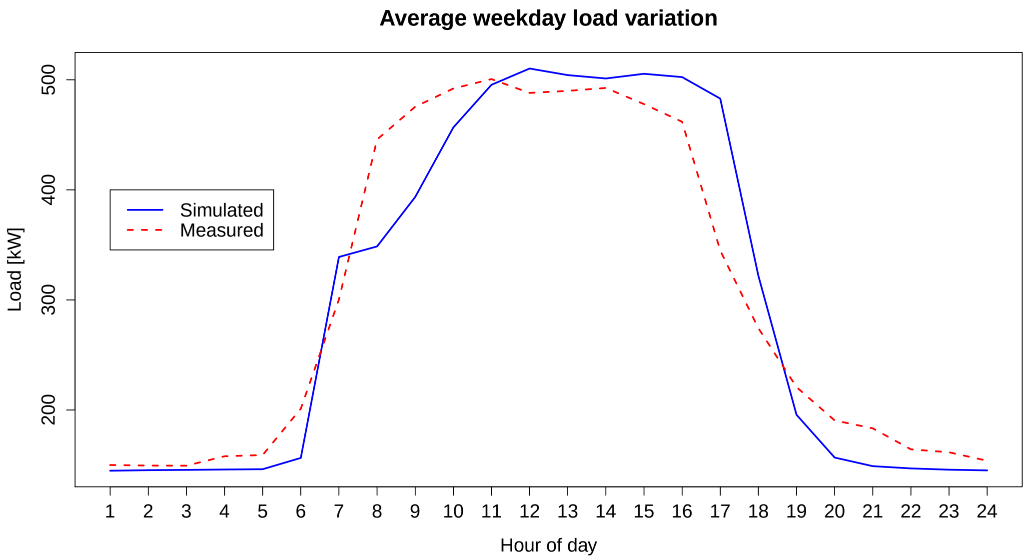


Figure 4.8: The plot shows the 24 h weekday load profiles for simulated load and measured load for the substation load data-set.

ventilation and appliance loads is yielded. This can be compared to the Swedish national energy statistic for office buildings in [86] which presents a mean annual energy-use of 84.6 kWh/m^2 for their investigated buildings. In other words, the simulated consumption data is corresponding well with the energy statistics for a population of office buildings.

In Figure 4.8, the simulated and measured 24 h weekday load profile for the time period is displayed. As seen, the overall load shape is comparable for the two data-sets. However, the measured consumption increases faster during the morning hours than the simulated load, and starts to decrease earlier in the afternoon. One explanation could be that the real employee behavior in data-set 2 is different from the one in data-set 1, i.e. the occupancy data which is used for simulating the employee behavior. For example, the office hours may be based on other time schedules with respect to type of business, organization, work culture, etc. Other reasons for the differences in results could be that the real consumption of appliances are based on more complicated interactions with the employees than what the model assumes, or that other types of loads exist in the office buildings which are not represented in the model. Regression analysis between the simulated and measured hourly load values gives a R^2 value of 88.9% and a RMSE of 8.6%. Hence, the office consumer model receives a higher explanation factor than the detached house model. The main reason for this is that the office building load is more homogenous, and that no space heating/cooling loads are included. These results are summarized in the lower part of Table4.2. For further results and discussions see paper 4.

Answer RQ2: The results of the validation show that the model can generate load profiles that correspond well with measured load data for appliances, ventilation and cooling load for an office building floor (data-set 1). This regards 15 min consumption profiles for individual loads during cold months (RMSE: 7.8% - appliances, 11.6% - ventilation) and warm months (RMSE: 12.1% - appliances, 12.6% - ventilation, 16.2% - cooling), along with total energy-use figures (error: 1.0% - cold months, 9.3% - warm months). No comparable validation for consumption profiles on load-level has been conducted for the related work models.
The simulated yearly load profile of the population of office buildings (data-set 2) coincided well with the measured substation data (RMSE: 8.6%). The yearly energy-consumption was well aligned with the measured consumption data (error: 2.2%) and the accuracy of related work models (error: 2.0% in [113] and 3.0% in [108]). Additionally, the yearly electricity consumption was close to the national energy-use statistics for ventilation and appliance electricity consumption together (83.7 vs 84.6 kWh/m^2 and year). Considering the limited amount of information that is available for the office buildings connected to the substation, e.g. used appliances, exact behavior of the employees, it is justifiable to claim that the model can generate load profiles which are reasonable and representative for the intended consumer cluster, although there are several possible error sources affecting the model accuracy.

Note: the error rate is reduced substantially for the office building model as compared to the detached house model. The main reasons are: (i) the consumption in office buildings is generally more homogenous, and (ii) no space heating/cooling loads are available.

4.3 Demonstration of model capabilities in analysis of a DR application

To demonstrate the capabilities of the proposed consumer models - the models have been used to assess a DR case in the Smart Grid Gotland (SGG) project [70]. The SGG project started in 2012 with participating project partners such as Vattenfall and ABB. In short, Gotland is an island located in the Baltic Sea - around 100 km east from the Swedish mainland. The island's distribution grid is connected to the Nordic transmission system by two submarine HVDC-cables with a total capacity of 260 MW. The distribution grid can be viewed as an isolated system with a radial structure. The island has favorable wind conditions which have resulted in a significant installation of wind power in the previous years. In 2013, the island had 186 MW of installed wind power capacity with an annual energy supply of 382 GWh [80], and is the predominant supply of local electricity. This can be compared to the system load which has an average consumption of 107 MW, a peak load of 196 MW and an annual electricity use of 942 GWh [27]. Gotlands 18,000 detached houses account for approx. 20% of the total electricity use on the island [71].

The main goal of the SGG project is to use novel smart grid technologies in the existing distribution grid to: (i) Increase the hosting capacity of wind power. (ii) Improve the power quality in rural parts of grids with large quantities of connected wind power. (iii) Create possibilities for end-users to participate on the electricity market by shifting their consumption between hours. In connection to project objectives (i) and (iii), a study is conducted to analyze whether it is technically feasible to implement a DR solution for detached houses on Gotland to balance wind power supply at times when the export cable

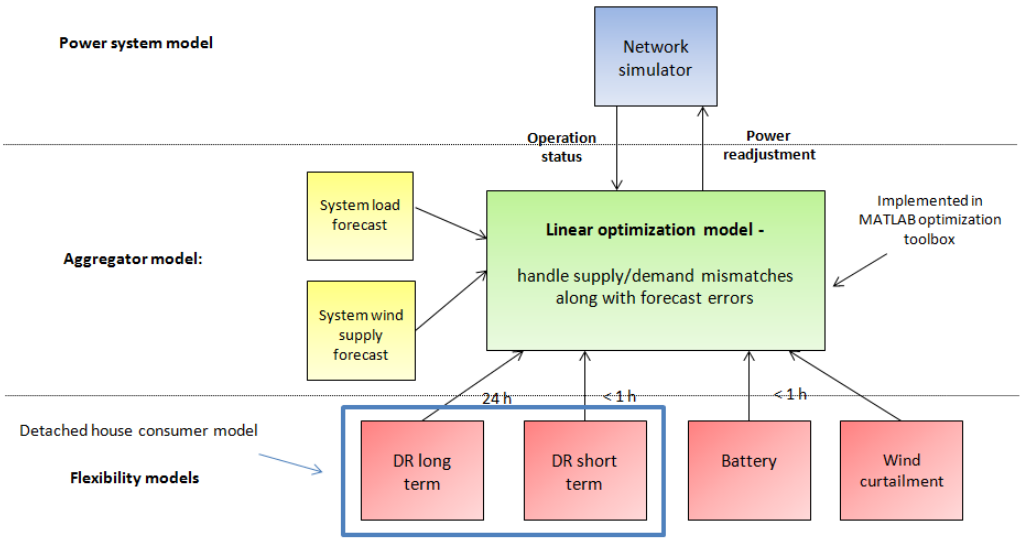


Figure 4.9: The communication channels of the optimization framework. The linear optimization model operates the flexibility tools every time there is an anticipated export problem. The information is exchanged to a power system model (could be implemented in a detailed power system simulator, e.g. PSS/E [69]) to verify the feasibility of the power flow in the network. The power system simulator sends readjustment signals to the optimization model if power flow limitations are experienced.

to the overlaying power system is congested. The study suggests that investments should be made on smart grid solutions (in this case DR from buildings) instead of traditional solutions, i.e. typically an expansion of the distribution grid. The DR solution must be dimensioned so that the reliability of supply is not impacted. In other words, the DR solution should be able to handle worst case conditions in the distribution grid operation, i.e. regulate the excess supply during congestion with sufficient amount of flexible load capacity. Central questions related to the technical feasibility of the DR solution is how many detached houses that are required to solve the congestion events, and how the comfort of the occupants are affected by the load control.

To answer these question, the aforementioned setup is modeled in a linear optimization framework where three classes of models are considered, viz. a power system model, flexibility models (primarily represented by the detached house consumer model), and an aggregator model which coordinates the consumption flexibility of end-users and the constraints of the power system. See Figure 4.9 for a diagram of the optimization framework. The optimization framework makes it possible to input and analyze various operation scenarios relevant for congestion issues and DR solutions in detached houses, e.g., various system load and production cases and availability of DR capacity for different weather situations. The model classes are described more in detail below:

- *Physical power system model*: A model which represents steady-state power system processes, such as power flows, losses, voltage magnitudes, etc. No short term dynamic behavior of the power system operation is considered, e.g. transient events. In this particular simulation setup, the system is modeled as a simplified one bus radial system which is connected to the overlaying power system with a transmission cable. Thus,

Table 4.3: A summary of simulation results of required DR participants and total load shifted for the different scenarios.

Scenario	Day	Total load shift [MW]	Managed congestion hours	Number of day-ahead buildings	Number of hour-ahead buildings
Winter	1	5	2 out of 2	1,000	100
Winter	2	4	1 out of 1	1,200	100
Winter	3	19	7 out of 7	1,300	500
Spring	1	14	5 out of 5	1,000	500
Spring	2	10	2 out of 2	800	100
Spring	3	16	4 out of 4	1,600	100
Summer	1	4	1 out of 1	700	100
Summer	2	5	1 out of 1	600	100
Summer	3	5	1 out of 1	600	200
Summer	1	5	1 out of 1	700	100
Summer	2	17	6 out of 6	800	700
Summer	3	5	1 out of 1	800	100

no power flow and voltage variation can be quantified in the Gotland distribution grid, only the power exchange with the overlaying network.

- *Flexibility model*: DR flexibility is modeled with the equations and necessary input-data described in section 3.1. The participating detached houses are divided in two separate clusters - which either are controlled based on day-ahead forecasts concerning congestion issues (i.e., 12-36 h ahead) or on hour-ahead. This division is implemented to handle forecast errors on the timing of congestion events. The purpose of the stationary battery system is to balance real-time mismatches between supply and load, i.e. handle the forecast error of the hour-ahead DR control. Curtailment of wind power is available as last resort if the battery cannot absorb the supply due to a high state of charge.

- *Aggregator model*: The aggregator model aims to handle events of congestion by solving a linear optimization problem that accounts constraints from the aforementioned model classes, e.g. comfort levels, the power rating of space heating and thermal behavior of the indoor environment, etc. The objective function is to maximize the consumption from space heating and DHW systems in detached houses during hours of export congestion, while not increasing the daily energy-use of the detached houses or violating comfort constraints.

Simulations are then performed by input relevant data-sets and parameter values for the Gotland use case in the optimization framework. Four scenarios are defined to account for the seasonal variations in flexibility potential in space heating. Each scenario consists of a three day period with known congestion problems. The following results are output from the simulations for the respective scenarios. (i) The required number of DR participants to solve anticipated congestion events based on either day-ahead or hour-ahead forecast data. (ii) The total amount of shifted load by DR actions compared to the number of congestion hours managed. (iii) The comfort zone variations for indoor and DHW temperature in the buildings.

In Table 4.3, the results from the simulations divided with respect to scenario is listed. An overall conclusion from the results is that it is technically feasible for a DR solution on Gotland – as it could manage all congestion problems with a maximum number of 1,600 participating detached houses. This maximum number of buildings is required during spring because of a generally higher wind power supply and lower consumption flexibility from the space heating units due to higher outdoor temperatures and more intense solar radiation. This number is significantly lower than the total number of detached houses on Gotland which is approximately 18,000 [71]. The indoor comfort constraints are always within $\pm 1\,^{\circ}$C from the reference indoor temperature in all scenarios. The water temperature in the DHW system shows strong variations from the reference temperature. However, the comfort constraints for baths and showers are fulfilled at all times - which is defined as a tank temperature of at least $60\,^{\circ}$C.

For more details regarding the optimization framework along with simulation results see appended paper 5.

Chapter 5

Concluding remarks and future work

The scope of this thesis is to present bottom-up models that can generate electricity load profiles in buildings on load-level. The models are intended to be used for analysis of DR investment alternatives for electricity market actors. DR solutions in the building stock may become a viable alternative to traditional investments in the power sector due to an increased share of RES, new electrical loads, and developments in ICT.

To make the models useful in analysis of DR options on electricity markets, it must be possible to simulate flexible consumption in aggregations of buildings. However, as the flexibility is supplied by individual buildings and loads, where the end-users will be affected in terms of comfort and cost of the DR control, the building view must be respected as well. Preferably, the former interest requires a simplified top-down approach to appreciate the flexibility potential of an aggregated load, while the latter interest demands detailed building based software to accurately predict the consumption processes. In order to make a compromise between the conflicts of the two approaches, a simplified bottom-up simulation model which utilizes openly available data and statistics is developed. The model accounts for consumption processes in the buildings on load level connected to both physical and behavioral attributes. The end-user behavior is modeled through non-homogenous Markov chains, which then relates to an electricity-use of appliances and DHW loads. To simulate the heating dynamics in the buildings, and the resulting need to heat and cool the buildings, lumped capacitance models are used.

As the models are based on several assumptions, along with parameters estimations taken from statistics, model validation is an important component of the thesis. The validation constitutes comparisons between simulated load profiles and measured load data collected from various sources. The resulting error rates are then compared to related work models identified from literature and energy-use statistics from national databases.

Hourly load profiles from the detached house model are simulated using data from a secondary substation with 41 buildings connected. The error rate between hourly simulated and measured load is 18.0% for the full year. The results are aligned with Swedish energy statistics and error results from comparable models in the literature. The office building model is simulated using two separate data-sets: (i) a data-set with 15 min energy measurement on load-level from an office building, and (ii) hourly load data from a secondary substation with seven office buildings. By comparing the simulated load from (i) with the measured 15 min consumption data on load-level, the following error rates are obtained: 7.8% for appliance load and 11.6% for ventilation load during cold months, along with 12.1% for appliance load, 12.6% for ventilation load, and 16.2% for cooling load during warm months. No comparable validation for consumption profiles on load-level has been conducted for the models described in literature. The simulated yearly load profile of the population of office buildings coincided well with the measured substation data (RMSE: 8.6%). The yearly energy-consumption was well aligned with the measured consumption data, the accuracy of related work models, along with national energy-use statistics.

Considering the limited amount of information that is available for the buildings in general, such as available appliances, house dimensions, used materials, exact behavior of the occupants, it is concluded that the model can generate load profiles which are reasonable and representative for the consumer clusters - and that it can be used for the intended purposes. Finally, to demonstrate the capabilities of the developed models in analysis of DR solutions, the detached house model is used in the analysis of a DR case which aimed to technically solve congestion issues is distribution grids. It was also concluded that the model could provide information required for the analysis.

5.1 Future work

During the research process a couple of interesting topics for future work have been identified.

Additional model validation using other consumption data-sets

To increase knowledge on model advantages and limitations, it would be valuable to validate the model using other consumption data-sets from the two building types. By conducting such validations, general conclusions can be drawn whether the consumer models are representative in a wider range of contexts and scenarios. For example, in this thesis, the physical environment was simulated with parameter estimations based on average building stock statistics. Hence, the validity of this important assumption could be more rigorously tested if multiple consumption data-sets were used for examination. In addition, it would be valuable to include consumption data-sets outside the Northern European context to see if the consumer models were generalizable for other countries.

Include other modules in the model framework to represent future consumers

A relevant extension of the models could be to attach simulation modules for, e.g. electric vehicles, PV-panels, solar collectors, stationary batteries, etc. Also building and HVAC system parameter settings could be adapted to passive building standards - where efficient heating technologies and improved insulation techniques are implemented [58]. This together makes it possible to model and simulate future developments in the building stock, and analyze their potential of being flexible in the consumption. If such modules are developed, validation on real consumption data from these types of end-users would be valuable.

Use models in stochastic simulations of DR solutions

Finally, it would be interesting to perform system analysis of DR solutions using a strict stochastic simulations approach, instead of the partly deterministic approach presented in paper 5. This refers to inclusion of stochastic variation and uncertainty in the electricity-usage in the building from unknown end-user behavior, thermodynamic characteristics in different buildings, and its connection to unique comfort constraints of occupants - by instantiating random building related parameter values from probability distributions instead of just mean values. Also, such analysis should include both detached houses and office buildings as the consumption of heating in detached houses and cooling in office buildings could offer interesting synergy effects in the availability of flexibility.

Bibliography

[1] M. Albadi and E. El-Saadany. Demand response in electricity markets: An overview. In *Power Engineering Society General Meeting, 2007. IEEE*, pages 1–5, June 2007. doi: 10.1109/PES.2007.385728.

[2] S.-L. Andersson, A. Elofsson, M. Galus, L. Göransson, S. Karlsson, F. Johnsson, and G. Andersson. Plug-in hybrid electric vehicles as regulating power providers: Case studies of sweden and germany. *Energy Policy*, 38(6):2751 – 2762, 2010. ISSN 0301-4215. doi: http://dx.doi.org/10.1016/j.enpol.2010.01.006. URL `http://www.sciencedirect.com/science/article/pii/S0301421510000121`. The Role of Trust in Managing Uncertainties in the Transition to a Sustainable Energy Economy, Special Section with Regular Papers.

[3] D. Atabay, S. Herzog, F. Sanger, J. Jungwirth, and V. Mikulovic. Self-adapting building models and optimized hvac scheduling for demand side management. In *Electricity Distribution (CIRED 2013), 22nd International Conference and Exhibition on*, pages 1–4, June 2013. doi: 10.1049/cp.2013.1119.

[4] M. Aydinalp, V. I. Ugursal, and A. S. Fung. Modeling of the appliance, lighting, and space-cooling energy consumptions in the residential sector using neural networks. *Applied Energy*, 71(2):87 – 110, 2002. ISSN 0306-2619. doi: http://dx.doi.org/10.1016/S0306-2619(01)00049-6. URL `http://www.sciencedirect.com/science/article/pii/S0306261901000496`.

[5] R. Baetens, R. D. Coninck, J. V. Roy, B. Verbruggen, J. Driesen, L. Helsen, and D. Saelens. Assessing electrical bottlenecks at feeder level for residential net zero-energy buildings by integrated system simulation. *Applied Energy*, 96:74 – 83, 2012. ISSN 0306-2619. doi: http://dx.doi.org/10.1016/j.apenergy.2011.12.098. URL `http://www.sciencedirect.com/science/article/pii/S0306261912000037`. Smart Grids.

[6] B. Becker and K. Stogsdill. Development of hot water use data base. *ASHRAE transactions*, 96:422 – 7, 1990.

[7] R. Belhomme and et al. Deliverable 1.1 address technical and commercial conceptual architectures. Technical report, EDF, 2009.

[8] M. Bollen, Y. Yang, and F. Hassan. Integration of distributed generation in the power system - a power quality approach. In *Harmonics and Quality of Power, 2008. ICHQP 2008. 13th International Conference on*, pages 1–8, Sept 2008. doi: 10.1109/ICHQP.2008.4668746.

[9] British Petroleum. Bp statistical review of world energy june 2013. Technical report, British Petroleum, 2013.

[10] A. Capasso, W. Grattieri, R. Lamedica, and A. Prudenzi. A bottom-up approach to residential load modeling. *Power Systems, IEEE Transactions on*, 9(2):957–964, May 1994. ISSN 0885-8950. doi: 10.1109/59.317650.

[11] COP21. `http://www.cop21paris.org/`, December, 2015.

[12] S. D and et al. Characterising and managing domestic electrical demand: a literature review. In *In 3rd Annual TSBE EngD Conference Proceedings*, 2012.

[13] N. Djuric and V. Novakovic. Identifying important variables of energy use in low energy office building by using multivariate analysis. *Energy and Buildings*, 45(0):91 – 98, 2012. ISSN 0378-7788. doi: http://dx.doi.org/10.1016/j.enbuild.2011.10.031. URL `http://www.sciencedirect.com/science/article/pii/S0378778811004762`.

[14] DOE2. `http://www.doe2.com/`, August, 2015.

[15] Elforsk. `http://www.elforsk.se/Documents/Market%20Design/seminars/DemandResponse/4.pdf`, September, 2015.

[16] K. Ellegard and M. Cooper. Complexity in daily life a 3d-visualization showing activity patterns in their contexts. *Electron Int J Time Use Res*, pages 37 – 59, 2004.

[17] Energiaktiv. `http://www.energiaktiv.se/sv/smahus/`, November, 2015.

[18] EnergyPlus. `http://apps1.eere.energy.gov/buildings/energyplus/`, August, 2015.

[19] ENTSOE. Towards smarter grids: Developing tso and dso roles and interactions for the benefit of consumers. Technical report, European Network of Transmission System Operators for Electricity (ENTSOE), 2015.

[20] European Commission. `http://ses.jrc.ec.europa.eu/smart-metering-deployment-european-union`, September, 2015.

[21] European Regulators Group for Electricity & Gas. Position paper on smart grids an ergeg conclusions paper. Technical report, ERGEG, 2010.

[22] European Union. `https://ec.europa.eu/energy/en/topics/energy-strategy/2030-energy-strategy`, November, 2015.

[23] European Union. `https://ec.europa.eu/energy/en/topics/energy-strategy/2050-energy-strategy`, November, 2015.

[24] S. Fan and R. J. Hyndman. The price elasticity of electricity demand in south australia. *Energy Policy*, 39(6):3709 – 3719, 2011. ISSN 0301-4215. doi: http://dx.doi.org/10.1016/j.enpol.2011.03.080. URL `http://www.sciencedirect.com/science/article/pii/S0301421511002771`.

[25] H. Farhangi. The path of the smart grid. *Power and Energy Magazine, IEEE*, 8(1):18–28, January 2010. ISSN 1540-7977. doi: 10.1109/MPE.2009.934876.

[26] Forbes. `http://www.forbes.com/sites/brookecrothers/2015/07/13/tesla-most-popular-u-s-electric-vehicle-in-q1-while-norway-leads-globally-says-ihs/`, September, 2015.

[27] GEAB AB. `http://www.gotlandsenergi.se/omgeab.pab`, September, 2015.

[28] L. Gkatzikis, I. Koutsopoulos, and T. Salonidis. The role of aggregators in smart grid demand response markets. *IEEE Journal on Selected Areas in Communications*, 31(7): 1247–1257, 2013. URL `http://dblp.uni-trier.de/db/journals/jsac/jsac31.html#GkatzikisKS13`.

[29] C. Guille and G. Gross. A conceptual framework for the vehicle-to-grid (v2g) implementation. *Energy Policy*, 37(11):4379 – 4390, 2009. ISSN 0301-4215. doi: http://dx.doi.org/10.1016/j.enpol.2009.05.053. URL `http://www.sciencedirect.com/science/article/pii/S0301421509003978`.

[30] S. Han, S. Han, and K. Sezaki. Development of an optimal vehicle-to-grid aggregator for frequency regulation. *Smart Grid, IEEE Transactions on*, 1(1):65–72, June 2010. ISSN 1949-3053. doi: 10.1109/TSG.2010.2045163.

[31] H. Hao, Y. Lin, A. Kowli, P. Barooah, and S. Meyn. Ancillary service to the grid through control of fans in commercial building hvac systems. *Smart Grid, IEEE Transactions on*, 5(4):2066–2074, July 2014. ISSN 1949-3053. doi: 10.1109/TSG.2014.2322604.

[32] J. Heier. *Energy Efficiency through Thermal Energy Storage Possibilities for the Swedish Building Stock*. PhD thesis, Royal Institute of Technology, 2013.

[33] Helsingborgs Dagblad. `http://hd.se/ekonomi/2012/02/06/`, August, 2013.

[34] Hindawi. `http://www.hindawi.com/journals/aai/2011/686258/fig1/`, December, 2015.

[35] H. Hippert, C. Pedreira, and R. Souza. Neural networks for short-term load forecasting: a review and evaluation. *Power Systems, IEEE Transactions on*, 16(1):44–55, Feb 2001. ISSN 0885-8950. doi: 10.1109/59.910780.

[36] R. Homod. Review on the hvac system modeling types and the shortcomings of their application. *Journal of Energy*, 2013:10, 2013. doi: http://10.1155/2013/768632.

[37] IEA. Global ev outlook understanding the electric vehicle landscape to 2020. Technical report, The International Energy Agency (IEA), April, 2013.

[38] IPCC. Climate change 2007: Synthesis report. contribution of working groups i, ii and iii to the fourth assessment report of the intergovernmental panel on climate change. Technical report, Intergovernmental Panel on Climate Change (IPCC), 2007.

[39] G. James, D. Witten, T. Hastie, and R. Tibshirani. *An Introduction to Statistical Learning*. Springer, 2014.

[40] W. Kempton and J. Tomic. Vehicle-to-grid power fundamentals: Calculating capacity and net revenue. *Journal of Power Sources*, 144(1):268 – 279, 2005. ISSN 0378-7753. doi: http://dx.doi.org/10.1016/j.jpowsour.2004.12.025. URL `http://www.sciencedirect.com/science/article/pii/S0378775305000352`.

[41] S. Korner and L. Wahlgren. *Statistisk Dataanalys*. Studentlitteratur, 2006.

[42] R. Kramer, J. van Schijndel, and H. Schellen. Simplified thermal and hygric building models: A literature review. *Frontiers of Architectural Research*, 1(4):318 – 325, 2012. ISSN 2095-2635. doi: http://dx.doi.org/10.1016/j.foar.2012.09.001. URL `http://www.sciencedirect.com/science/article/pii/S2095263512000647`.

[43] P. Kundur, J. Paserba, V. Ajjarapu, G. Andersson, A. Bose, C. Canizares, N. Hatziargyriou, D. Hill, A. Stankovic, C. Taylor, T. Van Cutsem, and V. Vittal. Definition and classification of power system stability ieee/cigre joint task force on stability terms and definitions. *Power Systems, IEEE Transactions on*, 19(3):1387–1401, Aug 2004. ISSN 0885-8950. doi: 10.1109/TPWRS.2004.825981.

[44] T. Leephakpreeda. Grey prediction on indoor comfort temperature for {HVAC} systems. *Expert Systems with Applications*, 34(4):2284 – 2289, 2008. ISSN 0957-4174. doi: http://dx.doi.org/10.1016/j.eswa.2007.03.003. URL `http://www.sciencedirect.com/science/article/pii/S0957417407001212`.

[45] C. Liao, Y. Lin, and P. Barooah. Agent-based and graphical modelling of building occupancy. *Journal of Building Performance Simulation*, 5(1):5–25, 2012. doi: 10.1080/19401493.2010.531143. URL `http://dx.doi.org/10.1080/19401493.2010.531143`.

[46] D. Loveday and C. Craggs. Stochastic modelling of temperatures for a full-scale occupied building zone subject to natural random influences. *Applied Energy*, 45(4):295 – 312, 1993. ISSN 0306-2619. doi: http://dx.doi.org/10.1016/0306-2619(93)90002-7. URL `http://www.sciencedirect.com/science/article/pii/0306261993900027`.

[47] N. Lu. An evaluation of the hvac load potential for providing load balancing service. *Smart Grid, IEEE Transactions on*, 3(3):1263–1270, Sept 2012. ISSN 1949-3053. doi: 10.1109/TSG.2012.2183649.

[48] K. McKenna and A. Keane. Residential load modeling of price-based demand response for network impact studies. *Smart Grid, IEEE Transactions on*, PP(99):1–1, 2015. ISSN 1949-3053. doi: 10.1109/TSG.2015.2437451.

[49] N. Motegi. Introduction to commercial building control strategies and techniques for demand response. Technical report, Lawrence Berkeley National Laboratory, 2011.

[50] G. Mustafaraj, J. Chen, and G. Lowry. Development of room temperature and relative humidity linear parametric models for an open office using {BMS} data. *Energy and Buildings*, 42(3):348 – 356, 2010. ISSN 0378-7788. doi: http://dx.doi.org/10.1016/j.enbuild.2009.10.001. URL `http://www.sciencedirect.com/science/article/pii/S0378778809002394`.

[51] Noordpool. `http://www.nordpoolspot.com/How-does-it-work/Intraday-market/`, September, 2015.

[52] NordPool Spot. `http://www.nordpoolspot.com/TAS/Day-ahead-market-Elspot/Price-calculation/`, November, 2015.

[53] O. Nue and et al. High resolution space - time data: Methodology for residential building simulation modelling. In *13th Conference of International Building Performance Simulation Association,*, 2013.

[54] J. V. Paatero and P. D. Lund. A model for generating household electricity load profiles. *International Journal of Energy Research*, 30(5):273–290, 2006. ISSN 1099-114X. doi: 10.1002/er.1136. URL `http://dx.doi.org/10.1002/er.1136`.

[55] J. Page, D. Robinson, N. Morel, and J.-L. Scartezzini. A generalised stochastic model for the simulation of occupant presence. *Energy and Buildings*, 40(2):83 – 98, 2008. ISSN 0378-7788. doi: http://dx.doi.org/10.1016/j.enbuild.2007.01.018. URL `http://www.sciencedirect.com/science/article/pii/S037877880700031X`.

[56] P. Palensky, G. Zucker, F. Judex, R. Braun, F. Kupzog, T. Gamauf, and J. Haase. Demand response with functional buildings using simplified process models. In *IECON 2011 - 37th Annual Conference on IEEE Industrial Electronics Society*, pages 3230–3235, Nov 2011. doi: 10.1109/IECON.2011.6119828.

[57] D. Papadaskalopoulos, G. Strbac, P. Mancarella, M. Aunedi, and V. Stanojevic. Decentralized participation of flexible demand in electricity markets part ii application with electric vehicles and heat pump systems. *Power Systems, IEEE Transactions on*, 28(4):3667–3674, 2013.

[58] Passive House Institute US. `http://www.phius.org/what-is-passive-building-/the-principles`, January, 2016.

[59] L. Paull, H. Li, and L. Chang. A novel domestic electric water heater model for a multi-objective demand side management program. *Electric Power Systems Research*, 80(12):1446 – 1451, 2010. ISSN 0378-7796. doi: http://dx.doi.org/10.1016/j.epsr.2010.06.013. URL `http://www.sciencedirect.com/science/article/pii/S0378779610001434`.

[60] E. Persson and et al. Pilotstudie i vallentuna reflektioner rörande affärsmodeller fÃ¶r örbrukarflexibilitet och självlärande prognosstyrning fÃ¶r kundanpassad effektreglering. Technical report, Elforsk, 2012.

[61] S. Privara, J. Cigler, Z. Vana, F. Oldewurtel, C. Sagerschnig, and E. Zacekova. Building modeling as a crucial part for building predictive control. *Energy and Buildings*, 56:8 – 22, 2013. ISSN 0378-7788. doi: http://dx.doi.org/10.1016/j.enbuild.2012.10.024. URL `http://www.sciencedirect.com/science/article/pii/S0378778812005336`.

[62] I. Richardson, M. Thomson, D. Infield, and C. Clifford. Domestic electricity use: A high-resolution energy demand model. *Energy and Buildings*, 42(10):1878 – 1887, 2010. ISSN 0378-7788. doi: http://dx.doi.org/10.1016/j.enbuild.2010.05.023. URL `http://www.sciencedirect.com/science/article/pii/S0378778810001854`.

[63] K. S and N. Lu. Evaluation of residential hvac control strategies for demand response programs (symposium papers - ch-06-7 demand response strategies for building systems). *ASHRAE Transactions*, (112(1):535):1–12, 2006.

[64] J. Schachter and P. Mancarella. A short-term load forecasting model for demand response applications. In *European Energy Market (EEM), 2014 11th International Conference on the*, pages 1–5, May 2014. doi: 10.1109/EEM.2014.6861220.

[65] Science Partner (SP). `http://www.sp.se/en/Sidor/default.aspx`, September, 2015.

[66] S. Shao, M. Pipattanasomporn, and S. Rahman. Development of physical-based demand response-enabled residential load models. *Power Systems, IEEE Transactions on*, 28(2):607–614, 2013. ISSN 0885-8950. doi: 10.1109/TPWRS.2012.2208232.

[67] Y. Shimoda, T. Fujii, T. Morikawa, and M. Mizuno. Residential end-use energy simulation at city scale. *Building and Environment*, 39(8):959 – 967, 2004. ISSN 0360-1323. doi: http://dx.doi.org/10.1016/j.buildenv.2004.01.020. URL `http://www.sciencedirect.com/science/article/pii/S0360132304000319`. Building Simulation for Better Building Design.

[68] P. Siano. Demand response and smart grids a survey. *Renewable and Sustainable Energy Reviews*, 30:461 – 478, 2014. ISSN 1364-0321. doi: http://dx.doi.org/10.1016/j.rser.2013.10.022. URL `http://www.sciencedirect.com/science/article/pii/S1364032113007211`.

[69] Siemens. `http://w3.usa.siemens.com/smartgrid/us/en/transmission-grid/products/grid-analysis-tools/transmission-system-planning/pages/transmission-system-planning.aspx`, January, 2016.

[70] Smart Grid Gotland. `http://www.smartgridgotland.com/eng/about.pab`, October, 2015.

[71] Statistics Sweden. `https://www.scb.se`, December, 2015.

[72] D. Steen. *Modelling of Demand Response in Distribution Systems*. PhD thesis, Chalmers University, 2015.

[73] D. Steen, L. Tuan, and O. Carlson. Effects of network tariffs on residential distribution systems and price-responsive customers under hourly electricity pricing. *Smart Grid, IEEE Transactions on*, PP(99):1–1, 2015. ISSN 1949-3053. doi: 10.1109/TSG.2015.2464789.

[74] C. H. Stignor and et al. Nästa generations värmepumpssystem i bostader och lokaler. Technical report, SP Sveriges Tekniska Forskningsinstitut, 2009.

[75] P. Stoll, N. Brandt, and L. Nordstrom. Including dynamic {CO2} intensity with demand response. *Energy Policy*, 65:490 – 500, 2014. ISSN 0301-4215. doi: http://dx.doi.org/10.1016/j.enpol.2013.10.044. URL `http://www.sciencedirect.com/science/article/pii/S0301421513010677`.

[76] G. Strbac. Demand side management: Benefits and challenges. *Energy Policy*, 36(12):4419 – 4426, 2008. ISSN 0301-4215. doi: http://dx.doi.org/10.1016/j.enpol.2008.09.030. URL `http://www.sciencedirect.com/science/article/pii/S0301421508004606`. Foresight Sustainable Energy Management and the Built Environment Project.

[77] Sveriges Riksbank. `http://www.riksbank.se/sv/Press-och-publicerat/Tal/1997/The-Swedish-Experience/`, October, 2015.

[78] L. Swan, V. Ugursal, and I. Morrison. Occupant related household energy consumption in canada estimation using a bottom up neural network technique. *Energy and Buildings*, 43, 2011.

[79] L. G. Swan and V. I. Ugursal. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. *Renewable and Sustainable Energy Reviews*, 13(8):1819 – 1835, 2009. ISSN 1364-0321. doi: http://dx.doi.org/10.1016/j.rser.2008.09.033. URL `http://www.sciencedirect.com/science/article/pii/S1364032108001949`.

[80] Swedish Energy Agency. `https://www.energimyndigheten.se/nyhetsarkiv/2014/minskad-utbyggnadstakt-for-vindkraften/`, December, 2015.

[81] A. Thavlov. *Power System Integration of Flexible Demand in the Low Voltage Network*. PhD thesis, 2015.

[82] The Guardian. `http://www.theguardian.com/environment/2014/jan/29/norway-electric-cars-sale`, October, 2015.

[83] The Guardian. `http://www.theguardian.com/environment/2014/oct/13/wind-power-is-cheapest-energy-unpublished-eu-analysis-finds`, September, 2015.

[84] The National Board of Housing, Building and Planning. Sa mar vara hus. Technical report, The National Board of Housing, Building and Planning, 2009.

[85] The National Board of Housing, Building and Planning. Optimala kostnader för energieffektivisering. Technical report, The National Board of Housing, Building and Planning, 2013.

[86] The Swedish Energy Agency. Forbattrad energistatistik for lokaler. Technical report, The Swedish Energy Agency, 2007.

[87] The Swedish Energy Agency. Sverige ledande på värmepumpar heta värmepumpar. Technical report, The Swedish Energy Agency, 2009.

[88] The Swedish Energy Agency. Energy statistics for non-residential premises 2012. Technical report, The Swedish Energy Agency, 2013.

[89] The Swedish Energy Agency. Energy statistics for one- and two-dwelling buildings in 2012. Technical report, The Swedish Energy Agency, 2013.

[90] The Swedish Energy Agency. Energiläget 2013. Technical report, The Swedish Energy Agency, 2013.

[91] The Swedish Energy Agency. `https://www.energimyndigheten.se/Hushall/Din-uppvarmning/Varmepump/Luftvarme/`, September, 2015.

[92] The Swedish Meteorological and Hydrological Institute. `http://www.smhi.se/en/about-smhi`, September, 2015.

[93] TRNSYS. `http://www.trnsys.com/`, January, 2016.

[94] K. Tsuji, F. Sano, T. Ueno, O. Saeki, and T. Matsuoka. Bottom-up simulation model for estimating end-use energy demand profiles in residential houses. In *ACEEE Summer Study on Energy Efficiency in Buildings*, 2004.

[95] UK Electricity Association Load Research. `http://ukedc.rl.ac.uk/cgi-bin/edc_search.pl?GoButton=Detail&WantComp=42&WantResult=&WantText=EDC0000041`, November, 2015.

[96] US Energy Information Administration. `http://www.eia.gov/consumption/commercial/`, October, 2015.

[97] A. Vaccaro, G. Velotto, and A. Zobaa. A decentralized and cooperative architecture for optimal voltage regulation in smart grids. *Industrial Electronics, IEEE Transactions on*, 58(10):4593–4602, Oct 2011. ISSN 0278-0046. doi: 10.1109/TIE.2011.2143374.

[98] Vattenfall AB. `http://corporate.vattenfall.se/`, September, 2015.

[99] S. Voima, H. Laaksonen, and K. Kauhaniemi. Adaptive protection scheme for smart grids. In *Developments in Power System Protection (DPSP 2014), 12th IET International Conference on*, pages 1–6, March 2014. doi: 10.1049/cp.2014.0139.

[100] D. Volk. Electricity networks: Infrastructure and operations. Technical report, The International Energy Agency (IEA), 2013.

[101] A. Von Meier. *Electric Power Systems A Conceptual Introduction*. Wiley Interscience, 2006.

[102] D. Wang, C. C. Federspiel, and F. Rubinstein. Modeling occupancy in single person offices. *Energy and Buildings*, 37(2):121 – 126, 2005. ISSN 0378-7788. doi: http://dx.doi.org/10.1016/j.enbuild.2004.06.015. URL `http://www.sciencedirect.com/science/article/pii/S0378778804001951`.

[103] J. Widen and E. Wackelgard. A high-resolution stochastic model of domestic activity patterns and electricity demand. *Applied Energy*, 87(6):1880 – 1892, 2010. ISSN 0306-2619. doi: 10.1016/j.apenergy.2009.11.006. URL `http://www.sciencedirect.com/science/article/pii/S0306261909004930`.

[104] J. Widen, M. Lundh, I. Vassileva, E. Dahlquist, K. Ellegard, and E. Wackelgard. Constructing load profiles for household electricity and hot water from time-use data modelling approach and validation. *Energy and Buildings*, 41(7):753 – 768, 2009. ISSN 0378-7788. doi: 10.1016/j.enbuild.2009.02.013. URL `http://www.sciencedirect.com/science/article/pii/S0378778809000413`.

[105] J. Widen, A. M. Nilsson, and E. Wackelgard. A combined markov-chain and bottom-up approach to modelling of domestic lighting demand. *Energy and Buildings*, 41 (10):1001 – 1012, 2009. ISSN 0378-7788. doi: 10.1016/j.enbuild.2009.05.002. URL `http://www.sciencedirect.com/science/article/pii/S0378778809000978`.

[106] L. Wiginton, H. Nguyen, and J. Pearce. Quantifying rooftop solar photovoltaic potential for regional renewable energy policy. *Computers, Environment and Urban Systems*, 34(4):345 – 357, 2010. ISSN 0198-9715. doi: http://dx.doi.org/10.1016/j.compenvurbsys.2010.01.001. URL `http://www.sciencedirect.com/science/article/pii/S0198971510000025`. Geospatial Cyberinfrastructure.

[107] U. Wilke, F. Haldi, J.-L. Scartezzini, and D. Robinson. A bottom-up stochastic model to predict building occupants' time-dependent activities. *Building and Environment*, 60:254 – 264, 2013. ISSN 0360-1323. doi: http://dx.doi.org/10.1016/j.buildenv.2012.10.021. URL `http://www.sciencedirect.com/science/article/pii/S0360132312002867`.

[108] Y. Yamaguchi and Y. Shimoda. District scale simulation for multi purpose evaluation of urban energy systems. *Journal of Building Performance Simulation*, 3(4):289–305, 2010.

[109] R. Yao and K. Steemers. A method of formulating energy load profile for domestic buildings in the {UK}. *Energy and Buildings*, 37(6):663 – 671, 2005. ISSN 0378-7788. doi: http://dx.doi.org/10.1016/j.enbuild.2004.09.007. URL `http://www.sciencedirect.com/science/article/pii/S037877880400307X`.

[110] R. Yao, N. Baker, and M. McEvoy. A simplified thermal resistance network model for building thermal simulation. In *Sim2002 in: Proceedings of the eSim*, 2002.

[111] G. Y. Yun, P. Tuohy, and K. Steemers. Thermal performance of a naturally ventilated building using a combined algorithm of probabilistic occupant behaviour and deterministic heat and mass balance models. *Energy and Buildings*, 41(5):489 – 499, 2009. ISSN 0378-7788. doi: http://dx.doi.org/10.1016/j.enbuild.2008.11.013. URL `http://www.sciencedirect.com/science/article/pii/S0378778808002594`.

[112] T. Zhang, P.-O. Siebers, and U. Aickelin. Modelling electricity consumption in office buildings: An agent based approach. *Energy and Buildings*, 43(10):2882 – 2892, 2011. ISSN 0378-7788. doi: http://dx.doi.org/10.1016/j.enbuild.2011.07.007. URL `http://www.sciencedirect.com/science/article/pii/S0378778811003094`.

[113] F. Zhao, J. Wang, V. Koritarov, and G. Augenbroe. Agent-based modeling of interaction between commercial building stocks and power grid. In *Innovative Technologies for an Efficient and Reliable Electricity Supply (CITRES), 2010 IEEE Conference on*, pages 225–232, Sept 2010. doi: 10.1109/CITRES.2010.5619806.

[114] Z. Zhou, F. Zhao, and J. Wang. Agent-based electricity market simulation with demand response from commercial buildings. *Smart Grid, IEEE Transactions on*, 2 (4):580–588, Dec 2011. ISSN 1949-3053. doi: 10.1109/TSG.2011.2168244.

[115] J. Zimmermann. End-use metering campaign in 400 households in sweden assessment of the potential electricity savings. Technical report, Dept. Syst. Anal., Enertech, 2009.

Part II

Papers 1 to 5

Paper 1

Forecasting household consumer electricity load profiles with a combined physical and behavioral approach

Paper 2

Day-ahead predictions of electricity consumption in a Swedish office building from weather, occupancy, and temporal data

Paper 3

Simulating Occupancy in Office Buildings with Non-Homogeneous Markov Chains for Demand Response Analysis

Paper 4

Modeling Office Building Consumer Load with a Combined Physical and Behavioral Approach: Simulation and Validation

Paper 5

Assessment of congestion management potential in distribution networks using demand-response and battery energy storage