ARTICLE TEMPLATE

Modeling Aggregation of Multi-Family Building loads for Demand Response Analysis

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ABSTRACT
Demand Response (DR) could potentially solve issues related to mismatch of supply and demand in power systems. Multi-family buildings are a suitable customer category for DR as these stands for a large share of the heating demand on a national scale. This paper presents a bottom-up simulation model that can generate multifamily building load profiles representative for Northern Europe. The model connects behavioral aspects of residential end-users with energy usage from appliances and heating of buildings.

Two cases are simulated to validate and demonstrate the model. The validation data set is collected from a multi-family building complex in Sweden. The data includes hourly measurements for heating demand and indoor temperature for one year. The validation shows that the simulated load captures the general trend of the data well, although the peak loads are generally underestimated. Furthermore, the model capabilities to simulate loads from aggregations of buildings are demonstrated by using building stock statistics from national databases. The demonstration shows that the model can output load diverse load profiles from different building types and heating installations. The model can be used for analyzing large-scale DR scenarios in the power systems.

Multi-family building, Aggregations, HVAC system, Markov-chains, Lumped capacitance, Demand Response.

1. Introduction

The electric power systems are being transformed through integration of intermittent renewable energy resources and new types of electric loads. These developments will introduce imbalances between electricity supply and demand, along with voltage and congestion management issues. A promising solution to overcome these challenges is Demand Response (DR), where customers are flexible in their electricity consumption with respect to external price signals Siano (2014). DR is facilitated by ongoing advancements in the digital economy OECD (2015), deregulation of energy markets Albadi and El-Saadany (2007), and increased electrification of the residential sector with heat pumps The Swedish Energy Agency (2009) and electric vehicles IEA (April, 2013).

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Multi-family buildings have a DR high potential as they stand for a significant share of the national energy-use, e.g. 30 % of the space heating and Domestic Hot Water (DHW) demand in Sweden. For now however, only around 10% of the Swedish multi-family buildings are primarily heated by electricity through Heat Pumps (HP) or electric radiators The Swedish Energy Agency (2013). Installing HPs at the building site may get more popular in the future because of technology developments, reduced investment and operational costs, together with growing fees for using District Heating (DH) systems. Today, a majority of the Swedish multi-family buildings have DH as their primary heating source. It is believed that DH networks could support the electric power grids with balancing power from, e.g. heat pump units Averfalk et al. (2017). Multi-family buildings have an interesting role to play in these contexts.

It is yet uncertain how flexible multi-family buildings can be in their consumption. To estimate this potential, improved knowledge and modeling techniques on the load characteristics are required. Fundamentally, the consumption can be modeled as a stochastic process, influenced by multiple factors: (i) the building properties, (ii) the available appliances, (iii) the load parameters of the appliances, and (iv) the usage of appliances. By far, factor (iv) is the most complicated factor to estimate, as it is connected to weather dynamics and the behavior of the occupants Widén and Wäckelgård (2010). For example, presence is a necessary condition for some energy use, such as computers and lighting Page et al. (2008). This usage, along with occupancy, generates internal gains, which together with the weather affect the indoor temperature. The space heating system will output the required heating or cooling energy to maintain a reference indoor temperature. These types of load characteristics are highly dynamic, and will vary between hours, days and seasons. Consequently, this will put prerequisites on the flexibility potential. In future energy systems where DR may be required, it will be important to understand these connections for the building stock.

Bottom-up simulation models are needed to capture consumption processes on load-level Swan and Ugursal (2009). As opposed to top-down models, bottom-up models start from the lowest level of components (e.g., an appliance), and the aggregates the loads from a building, district or city level. 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 accurately predict the heating dynamics and temperature variation for a specific point in a building, complex heating models need to be formulated with detailed building based software, e.g. EnergyPlus EnergyPlus (n.d.) or DOE-2 DOE-2s (n.d.). However, these software require extensive knowledge about the building parameters, and the resulting models tend to be computationally cumbersome and difficult to scale Prívara et al. (2013). Secondly, as individual buildings only can contribute with a small volume of flexibility, a larger group of buildings is required. Every building is unique with respect to building design, used materials, landscape orientation, 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. Therefore, it is necessary to use building models which makes it possible to aggregate the consumption of several buildings, meanwhile being able to reflect unique consumption patterns of individual buildings. Preferably, such models are simplified and standardized to minimize the demand for input data, parameter value estimations, and model assumptions. Such models will simply and enable modeling activities of DR scenarios in future electricity systems.

1.1. *Related Work*

Several models for simulating end-user load profiles in buildings that can be used for DR applications are proposed in literature. These are bottom-up models that are constrained by specific conditions of a country or region. Other modeling techniques, e.g. time series and econometric models are not appropriate as these generally produce data on an aggregated scale, i.e. no electricity use information on appliance level is derived.

In Sandels, Widen, and Nordström (2014) and Sandels et al. (2016), bottom-up load models for detached houses and office buildings are presented. The model combines activities of occupants and their interaction with appliances based on time-use data (TUD), along with physical properties of the building envelope. By validating the simulation results on real load measurements, it is concluded that the models produces representative load profiles. Similar models in residential settings are presented in Widen, Molin, and Ellegard (2012), Richardson et al. (2010) and Fischer, Härtl, and Wille-Haussmann (2015).

Multi-family building loads are modeled by in Fischer et al. (2014). In this paper, the authors introduce and evaluate a range of cost minimization operational strategies for capacity controlled HP:s with thermal storage. The heating operation is modeled with model predictive control together with simplified models of the heating demand in buildings, thermal storage, HP operation and its controller. The simulation results show that HP operation that accounts for variable day-ahead prices leads to decreased operation efficiency but improved economy. A similar study can be found in Verhelst et al. (2012), where the controller aims to minimize the weighted sum of electricity cost and thermal discomfort of the occupants. Note, in these papers physical models of the HVAC systems are prioritized, thus, no behavioral attributes of the end-users are considered.

A dynamic pricing framework for DR in low voltage networks is described by McKenna and Keane (2016). The model simulates occupancy and appliance usage through non-homogenous Markov chains with TUD from Ireland IRI (2013). Data from an Irish residential distribution feeder with 85 buildings is then simulated for a typical winter day. The simulation results of DR scenarios 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. Steen, Tuan, and Carlson (2016) presents a comparable study, which models 100 detached houses in a low voltage grid in Sweden to investigate the impact of dynamic tariffs on the grid operation.

Yao and Steemers (2005) presents a simplified load model which simulates the daily household load for four different dwelling types in the UK. The model accounts national statistics on appliance ownership, energy-use characteristics of these, and household types. 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. By combining appliance statistics and occupancy profiles with a random uniform probability distribution function, daily load profiles can be simulated for an individual household. Similar high level building stock load models based on national statistics are found in Shao, Pipattanasomporn, and Rahman (2013) and Zhou, Zhao, and Wang (2011).

Moreover, Baetens et al. (2012) studies how Zero-Energy Buildings (ZEB) with PV impact the voltage quality in low voltage distribution network. 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 processes in the buildings, with models for PV production, occupancy behavior based on Markov chains, and general appliance consumption is mainly based on Belgian statistics. Four different dwelling types which are representative of the Belgian building stock are proposed. A neighborhood of 33 Belgian ZEBs is simulated with respect to energy consumption features.

1.2. *Scope of the paper*

The scope of this paper is to present a bottom-up simulation load model for multi-family buildings. The consumption includes appliances (e.g. lighting and TV), DHW, and space heating. The main goal with the model is to be able to simulate load profiles from an aggregation of buildings with reasonable accuracy that can be suitable for DR scenario analysis.

To verify that the model can output reasonable load profiles, a data set has been collected for model validation. The data set includes detailed background information about a real multi-family building in Sweden, together with energy-use measurements at an hourly time resolution. Another case is to demonstrate the model capabilities to simulate loads from multiple buildings by input parameter values collected from national statistics.

As opposed to the models described in the related work, the simulation model proposed in this paper focuses on occupant activities and their interactions with appliances and indoor comfort in the loads from aggregations of multi-family buildings. McKenna and Keane McKenna and Keane (2016) model such behavior as well, but only for end-users in detached houses. Multi-family building loads are modeled by Fisher et al Fischer et al. (2014), but it excludes end-user behavior. In addition, systematic validation of simulation results against real energy measurements from a case study is included in this paper, which is lacking in the related work studies.

The model is implemented in MATLAB Mathworks (October, 2018a), where the built-in Statistics Toolbox package is used Mathworks (October, 2018b).

1.3. *Outline*

The paper is structured as follows. In Section 2, the proposed multi-family building simulation model is presented. The data sets that are used for model validation and demonstration are introduced in Section 3. It is followed in Section 4 by simulation results and analysis of the data sets. Section 5 contains a discussion of the results, and some concluding remarks are given in Section 6.

2. Model description

In this section, the methodology of the multi-family building load model is described. The model has three modules that reflect important energy-use related processes in buildings: (i) the behavior of end-users, (ii) the usage of appliances and DHW which

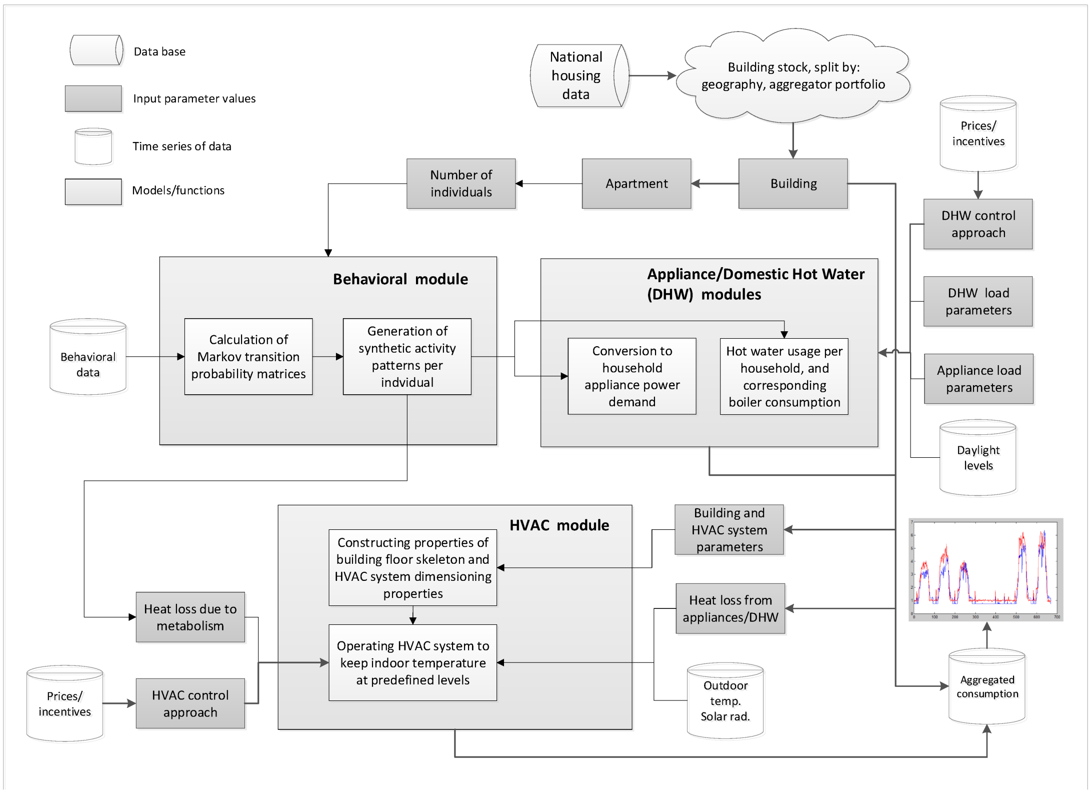

Figure 1.: The diagram shows the functioning, dependencies, and the data inputs of the simulation modules. The containers are input data to the functions (gray boxes) within the modules. Each function is producing various outputs that are shown by the arrows from each gray box.

are connected to behavior, and (iii) the use of HVAC systems to supply an indoor comfort and DHW demand. Module (iii) is influenced by the ambient weather situation, the properties of the building, the space heating system itself, and the output from modules (i) and (ii). The main goal with the model structure is to keep it as simple as possible, meanwhile making it representative for the real consumption processes in multi-family buildings. A diagram depicting the basic functions and relationships between the modules can be seen in Figure 1. Below, each module is described in more detail.

2.1. *Initial model assumptions, parameters, and sets*

The model can simulate load profiles for an individual building or a group of buildings $\mathrm{N_{building}}$. Every building is populated by a total number of apartment household members $\mathrm{N_{persons}}$. Each household member has an average heated living space $\mathrm{A_{person}}$. Thus, the total heated living space per building is:

$$\mathrm{A_{building}} = \mathrm{N_{persons}} \cdot \mathrm{A_{per,\ person}} \quad [\mathrm{m}^2]. \tag{1}$$

Moreover, the model is discretized in time, thus reflecting household member behavior and building load dynamics in predefined time slots t, with a time step of Δt.

The simulation period is N_{sim} time steps, where $\Delta t = t_{k+1} - t_k$.

2.2. *Behavior module*

The behavior of individual household members is simulated with a non-homogeneous Markov chain methodology. Unlike the Markov chain model in our previous study (Sandels, Widen, and Nordström 2014), which consisted of two separate Markov chains for electric appliance activities and DHW activities, the model used here contains all activities in the same Markov chain. This yields more realistic profiles, as it makes sure that incompatible activities, e.g., showering and watching TV, are not performed at the same time by the same person.

The Markov chain has 11 states (denoted as the set Ω), where states 1-2 are 'away' and 'sleeping', states 3-8 are related to appliance use ('cooking', 'dish washing', 'washing', 'TV', 'computer', 'audio'), states 9 and 10 are 'bathing' and 'showering', and state 11 is 'other' (all other unspecified activities). All states except the two hot-water related states are thus the same as in the original Markov-chain model proposed by Widén and Wäckelgård (2010).

Transition probabilities $p_{ij}(t)$ define the likelihood for transitions from state i to state j between time steps $t-1$ and t. Note that $\Sigma_{j=1}^{i\in\Omega} p_{ij} = 1$ because one of the possible transitions from state i must take place. An activity profile is generated by randomly sampling a number between 0 and 1 in each time step and comparing it to the transition probabilities. The transition probabilities are allowed to change over time to reflect that some activities are more likely to occur during certain times of day, e.g., sleeping at night and being away during working hours.

The transition probabilities are estimated with TUD collected by the Statistics Sweden (SCB) in 1996 Ellegård and Cooper (2004). These data are more than 20 years old, but they are the most detailed ones available, and it has been shown that the crucial activities related to energy use still yielded valid load profiles 13 years later Widén and Wäckelgård (2010), and most likely today. In total, this data set covers the activities of 463 individuals aged 10 to 97 years in 179 households, both in apartments and detached buildings. For this study, only data for the 69 households living in apartments are used. The activities were recorded by the participants with a time resolution of down to 1 minute, on one weekday and one weekend day. More details about the TUD, estimation of transitions probabilities and the properties of the Markov-chain model can be found in Widén and Wäckelgård (2010) and Widen, Nilsson, and Wackelgard (2009).

2.3. *Appliance and DHW module*

The activity profiles generated by the Markov chain are converted to electricity and DHW profiles through three basic conversion functions: (1) constant power (or flow rate) during the whole activity, with possible standby power between activities, e.g., use of TV or computer, (2) load cycle that starts with the activity and continues until it or the activity ends, e.g., filling up a bath in the beginning of a bathing activity, and (3) load cycle that starts when the activity ends and continues until it ends or the activity starts again, e.g., dish washing after the activity 'fill the dishwasher'. The exception to these simple load schemes is the indoor lighting model, which is also dependent on total occupancy and daylight level Widen, Nilsson, and Wackelgard (2009).

The conversion functions for electric appliances are the same as for apartments in Widén and Wäckelgård (2010). For the DHW use, both showering and bathing are modeled with conversion function (2) above. In addition to these, a simple model was implemented for miscellaneous hot water tapping. These additional tapping are randomly added with a constant probability for each household member during times when the person is at home and active (not sleeping). For showering a flow rate of 10 l/min during 4 minutes is assumed, and for bathing a flow rate of 16 l/min during 6 minutes. Additional tapping are assumed to occur at a given minute with a probability of 1 %, with a flow rate of 4 l/min during 2 minutes. All these flow rates and times are chosen to comply with the DHW profiles developed within the IEA SHC Task 44 (Haller et al. 2013).

The DHW usage is converted to heat use (Q_{drain}) that is discharged from, e.g., a hot water tank. Q_{drain} is defined as:

$$Q_{\text{drain}}(t) = V^a_{flow}(t) \cdot C_{p,water} \cdot (T_{outlet} - T_{inlet}) \quad [W]. \tag{2}$$

$C_{p,water}$ is the specific heat capacity of water. T_{outlet} and T_{inlet} are the inlet and outlet water temperatures, respectively. V^a_{flow} is the total hot water flow to serve the current DHW activity of the household member.

2.4. *HVAC module*

The HVAC module includes the thermodynamic processes in buildings and the usage of heating systems to serve an indoor comfort and DHW demand. Three types of dynamics are included in this module: (a) the heat demand of the building and DWH usage, (b) the installation characteristics of the HVAC system, and (c) the possible HVAC control approaches.

2.4.1. Building heat demand

A simplified lumped capacitance methodology is applied to model the building's heating demand. The indoor temperature (T) will deviate from a reference temperature set point (T_{ref}) due to the following disturbances: (i) outdoor temperature (T_{out}), (ii) DHW use, (iii) solar radiation (P_{sun}), and (iv) internal heat gains from occupants and appliances (Q_{int}). Ambient leakage together with DHW usage are the factors that drain energy from the building. The other disturbances are energy suppliers to the building. The ambient leakage that are transferred between the indoor and outdoor environments is determined by the conduction properties of the building envelope (transmission losses), along with an amount of indoor air that is released from the building (leakage/ventilation losses). Potential ventilation activities from end-users by opening windows are excluded. The total losses Λ are given by:

$$\Lambda = \sum_j \mathrm{U}_j \cdot \mathrm{A}_j + \mathrm{V_b} \cdot \bar{N}_{\text{vent}} \cdot C_p \cdot (1 - \alpha_{rc}), \quad \left[\frac{\mathrm{W}}{^\circ\mathrm{C}}\right], \tag{3}$$

where, U_j is the transmission coefficient of each building component j, and A_j is the total area of that component. V_b is the total volume of the building, $\bar{N}_{\text{vent}}$ 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 losses Q_{loss} from the building to the outside environment at time t are quantified by:

$$Q_{loss}(t) = \Lambda \cdot (T(t) - T_{out}(t)), \quad [\text{W}]. \tag{4}$$

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 horizontal area SMHI (January, 2015) (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 Q_{sun} is:

$$Q_{sun}(t) = \alpha_{red} \cdot A^{side}_{window} \cdot G_{sun}(t), \quad [\text{W}]. \tag{5}$$

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

$$Q_{int}(t) = P_{met} \cdot N_{occ}(t) + \gamma_{app} \cdot P_{app}(t) + \gamma_{DHW} \cdot P_{DHW}(t) \quad [W], \tag{6}$$

where N_{occ} is the number of occupants, P_{met} is the heat loss constant 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. The heating imbalance $Q_{imbalance}$ for the building at time t is the following due to the aforementioned disturbances:

$$Q_{imbalance}(t) = Q_{int}(t) + Q_{sun}(t) - Q_{loss}(t) \quad [W]. \tag{7}$$

Evidently, as all of these energy flows will not be in balance to provide a stable indoor temperature, a space heating solution is installed to compensate the energy imbalances over time.

2.4.2. HVAC installation

The main objective of the HVAC system is to supply heating to the building to maintain a predefined indoor temperature (T_{ref}) and to serve the DHW demand. In the model, three parameters are considered when it comes to the physical design of the HVAC solution: (i) the heat supply concept, (ii) the dimensioned heating capacity, and (iii) the Coefficient of Performance (COP) of the installation.

For parameter (i), three options of heating supplies are available: monovalent, mono-energetic or bivalent systems. A monovalent heating supply means that only one type of heating technology is used, such as a stand-alone HP that serves the whole space heating and DHW demand. Mono-energetic supplies refer to systems with combined heating technologies in a building, but which uses the same energy carrier (e.g., electricity) to produce the heat. An example of this is a heating system with heat pumps that serve the base heating load, and an electric heater that covers the peak load. The last supply type is a bivalent system, which works in the same way as the mono-energetic solution, but, here, at least two different energy carriers are used for supplying the heat, e.g. a combined system with HP and district heating. The total heating power can be represented by a base heating load (P_{base}) and a peak heating load (P_{peak}).

Further, the installed heating capacity of the HVAC system is set by the temperature data from the geographic area, the thermal inertia of the building (τ), and the COP value of the system during cold temperatures. These values will give the dimensioning outdoor temperature (T_{DWT}), and, thus, the peak heating demand during very cold days. In addition, the dimensioning of the heating solutions could also consider the building's expected DHW demand ($\bar{P}_{DHW}$), introduced in the previous subsection. Due to these arguments, the installed space heating capacity ($\hat{P}_{HVAC}$) can be given by:

$$\hat{P}_{HVAC} = \hat{P}_{base} + \hat{P}_{peak} = \frac{\Lambda \cdot (T_{ref} - T_{DWT}) + \bar{P}_{DHW}}{COP(T_{DWT})} \quad [W]. \tag{8}$$

Due to the aforementioned discussion about heat supply concepts, $\hat{P}_{HVAC}$ can be added up by different heating technologies. If the system is monovalent, one heating solution covers the whole heating demand of the building, i.e., $\hat{P}_{peak} = 0$. If the HP cannot cover the peak demand, a secondary heating is required ($\hat{P}_{peak} > 0$). If the secondary heating system is bio fueled heater the system is a bivalent system, and if it is an electric heater the system is mono-energetic. Further, the HP is dimensioned according to the heating it can be provide during cold days. For example, if it is an air source heat pump, the COP will decrease during cold temperature, and, will reach zero when it is sufficiently cold. At these times, electric or district heating are required. For a ground source heat pump the COP will be better at low ambient temperatures compared to an air source, as the bore hole temperature is higher and more stable than the ambient temperature.

The heating capacity of a ground source HP unit co-operating with a electric heating as function of outdoor temperature are shown in Figure 2. As can be seen, the ground source has a less steep heating supply line, which means it can supply more heating energy per input of electric heating. However, the HP can only cover the demand to a certain outdoor temperature, and thus the electric heater kicks in when the temperature drops, with a steeper electricity use as a result. The electric heater gives the total installed electric capacity to provide heating energy during the peak demand. Such diagrams can be sketched for other combinations of heating solutions as well, e.g. standalone air source heat pumps, combined ground source heat pump and district heating, etc.

In the model, a constant COP for the space heating system is assumed over the possible range of outdoor temperatures.

2.4.3. HVAC system control - ruled based outdoor temperature control

The controller can either be rule based or predictive. The rule based controller makes decisions based on real time conditions, whereas the predictive controller accounts future possible disturbances. The heating can be controlled based on various input

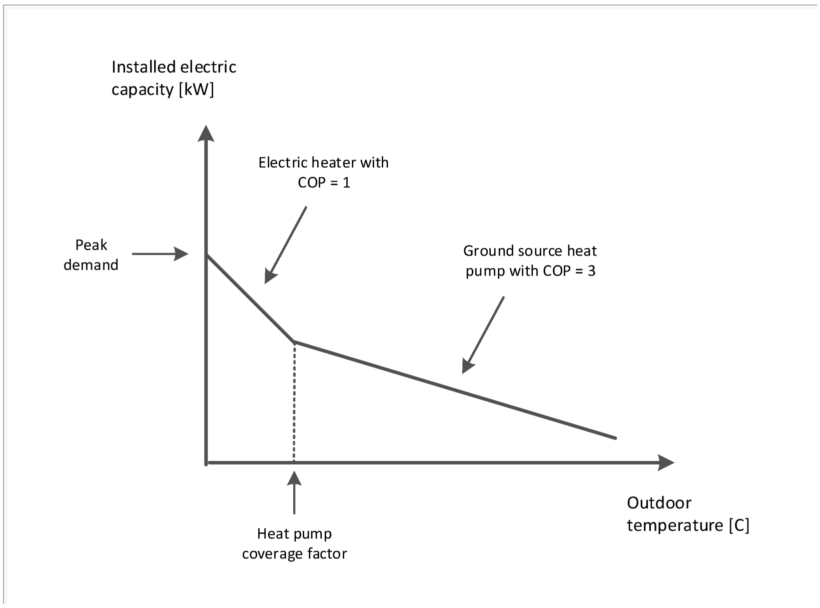

Figure 2.: The dimensioning of heat pumps in relation to: (i) building peak demand, (ii) COP factor, (iii) the installed power of the primary heating system, and (iv) the COP of the secondary heating system.

signals, e.g. outdoor temperature, indoor temperature, prices etc. In this paper, only reactive controllers based on outdoor or indoor temperature are considered.

In today's buildings, a common heating control scheme is to regulate the supply heating temperature based on predefined heating curves. The heating curve is a function of (i) the moving average of the outdoor temperature, (ii) the building's thermal characteristics, and (iii) expected internal heat gains. The supply temperature is then controlled with an integral method which allows the measured supply temperature to be slightly over or under the set point value. This method will decrease the number of on/off cycles of the HP and will improve its life expectancy. Note, if the outdoor temperature is above a certain heating balancing temperature, no space heating is required at all. However, there will be a DHW demand during these occasions.

Hence, an outdoor temperature controller estimates the heating demand based on the moving average outdoor temperature $\bar{T}_{out}$. The supplied heating energy Q_{reg} by the space heating system at time t is determined by:

$$Q_{reg}(t) = \begin{cases} COP \cdot P_{HVAC}(\bar{T}_{out}), & \text{if} \quad \sum \xi(t) \leq \xi_{max} \\ 0, & \text{if} \quad \sum \xi(t) > \xi_{min} \\ Q_{reg}(t-1) & \text{else} \end{cases} \tag{9}$$

where P_{HVAC} is the total installed heating capacity, e.g. heat pump plus direct electric heating. The outdoor temperature will determine which heating systems that are used, and, thus, the COP factor. ξ is the degree minute function mentioned earlier, and ξ_{min} and ξ_{max} are the threshold values of this control. The degree minute function is updated at every time step according to the following equations:

$$Q_{drop} = \alpha_{comp} \cdot \Lambda \cdot (T_{ref} - \bar{T}_{out}) \tag{10}$$

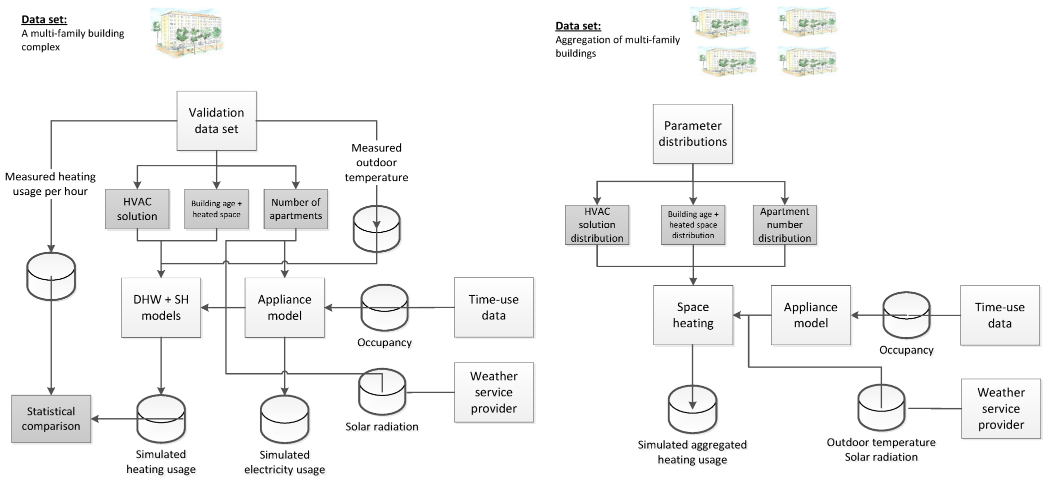

Figure 3.: The diagram shows the setup for the two data sets, e.g., background info about the buildings, used input data, and comparisons between measurements and simulated data.

$$\Delta T = \begin{cases} \frac{Q_{reg} - \hat{Q}_{drop}}{C_b}, & \text{if} \quad \text{duty cycle} = \text{on} \\ \frac{-\hat{Q}_{drop}}{C_b}, & \text{if} \quad \text{duty cycle} = \text{off} \end{cases} \tag{11}$$

$$\xi(t) = \xi(t-1) + \Delta T. \tag{12}$$

The controller approximates the energy loss Q_{loss} with the heating curve. This value depends on a compensation factor α_{comp} (accounts for expected internal gains), the transmission losses, and a temperature difference between the reference temperature and the averaged outdoor temperature. This energy loss can be translated into a temperature difference per minute that is governed by the building's thermal mass C_b. The temperature will increase or decrease whether the heating system is on or off. In reality, if the distribution system is radiators, then the degree minute will be calculated based on the difference between the measured supply water temperature and the set point. The hydronic circuit is however not modeled in this paper. So, here we assume that the distribution system and the indoor environment is in balance - meaning that the heating imbalance in the indoor climate will be seen directly by the heating system. In reality, this occurs with some time lag, but using this assumption will simplify the model. The temperature difference is then accumulated in the degree minute function. Depending on whether the heating system is in an on or off state, the process will continue until the function values exceeds or falls below the threshold values ξ_{max} or ξ_{min}, respectively.

3. Data collection

The data sets that are used for simulation are presented in this section. The first data set is for a building complex and is used for model validation. The second data set is for model demonstration and involves an aggregation of buildings. Real measurement data is available for the first case, but not for the second case. See Figure 3 for more information on the setup.

3.1. *Data set 1: Model validation*

The first data set is collected from a multi-family building complex located in the Swedish city of Jönköping (latitude: 57.78145, longitude: 14.15618). The building has 150 apartments, with a total heated floor space of 9,500 m^2. The complex is built in the 1960s and consists of four separate buildings. The building complex has a bivalent heating system, where two local HP:s serve the base heating load, and district heating is used during peak demand. The HP:s are controlled on the outdoor temperature, and district heating is used when it is colder than 7 °C outside. The heat is distributed to the apartments through water based radiator systems.

To validate the simulation model, the following hourly measured data has been collected for almost a whole year: (i) the heating use from the HP:s and district heating, (ii) outdoor temperature at the premises, and (iii) indoor temperature measurements from four apartments. Unfortunately, the national weather service provider does not measure solar radiation for the concerned city, and is not measured at the building site. Therefore, hourly solar radiation data has been collected from a weather station located 100 km south of the premises. The time period for the measurement campaign is between 2016-09-30 and 2017-09-18. Furthermore, the required building parameters are assigned according to a multi-family building from the 1970s specified by The Swedish National Board of Housing, Building and Planning (2013). Note, the parameter setting is listed in Table 1. This validation will give a justification that the heating modeling approach of one multi-family building is sound, as detailed data about the heating and DHW energy use, along with comfort data from different apartments are available.

3.2. *Data set 2: Model demonstration*

Input for the model parameters have been collected from national statistics on multi-family buildings and HVAC system installations, in order to demonstrate the outputs that can be produced at an aggregated scale with the simulation model. The statistics come from Statistics Sweden SCB (n.d.) and The Swedish National Board of Housing, Building and Planning (2013). The case includes data on thermodynamic properties and HVAC system installations for 30 buildings. The buildings are located in the geographic area of Stockholm, Sweden so that the same climate data can be used for all buildings.

In the right-hand side Table 1 the parameter setting of this data set is shown. As noted here, the parameter values have various ranges, and is randomly selected from statistical distributions so that unique building compositions can be constructed. The simulation time period is two winter days with a time resolution of one hour. Note, it is only the space heating consumption that is demonstrated in this simulation.

Table 1.: The parameters and their assigned values for the simulations of the two respective cases.

Parameter	Description	Validation case	Demonstration case
Age	The construction year of the building	1960s	N(1965, 25)
$N_{buildings}$	The number of buildings	Four	30
$A_{per,person}$	The heated living space per person	30 m^2	30 m^2
$N_{persons}$	The total number of end-users	300	Two in average per apartment
$N_{households}$	The number of apartments	150	The building area from / $(N_{persons} \cdot A_{per,person})$
Λ	The isolation factor of the building	13.1 kW/°C	Depends on building age and $N_{households}$
α_{rc}	The heating recovery factor of the ventilation system	0.0	0.0
N_{vent}	The ventilation rate of the building	0.2 h^{-1}	0.2 h^{-1}
τ	The thermal inertia of the building	100 hours	100 hours
A_{window}^{side}	The total exposed window area per building side	1000 m^2	Depends on building
α_{red}	The shadowing effect of the windows and surroundings	0.20	0.20
T_{ref}^{SH}	The reference indoor temperature	21 °C	21 °C
COP	The COP factor of the heat pump	2.5	Bivalent: 3.8, Mono-energetic: 3.7 at 0 °C
T_{DUT}	The dimensioning outdoor temperature	-14.0 °C	-14.4 °C
Supply concept	The heating supply concept	Bivalent	70 % is bivalent, 30 % is monovalent
Controller	The control approach of the heating system	Outdoor temperature	Outdoor temperature
HP type	The type of HP used in the building	Ground source HP	33 % air source HP, 66 % ground source HP
Controller	The control approach of the heating system	Outdoor temperature	Indoor temperature
$\xi_{max,min}$	The threshold values of the integral control method	± 1.0 °C	± 1.0 °C

4. Simulation Results and Analysis

In this section, the simulation results from the two cases are presented. For the validation, the results are displayed together with the empirical measurements to facilitate

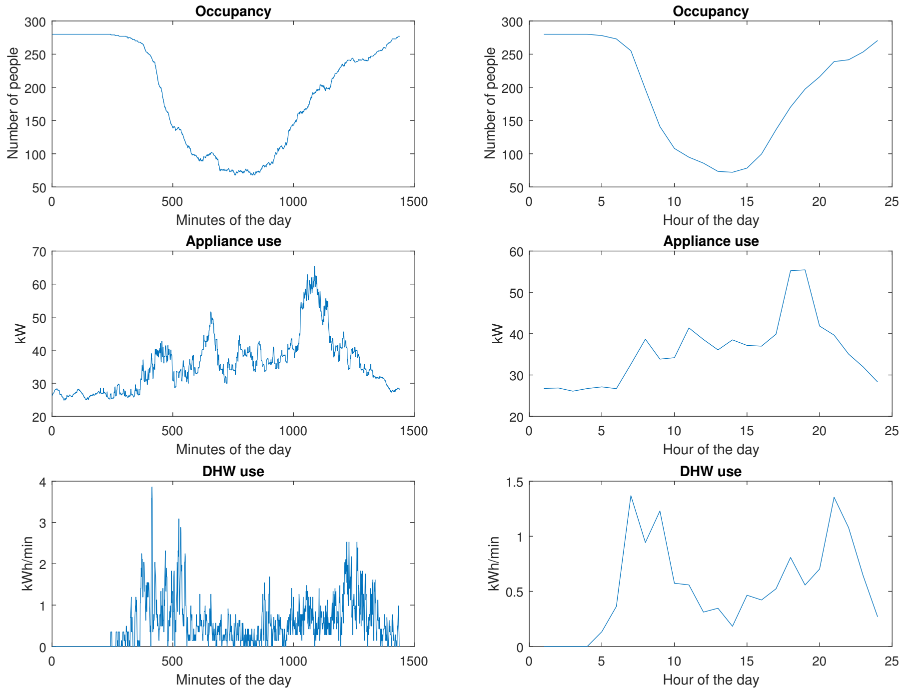

Figure 4.: Examples of output data at a minute and hourly resolution for occupancy, appliance use, and DHW use for the whole building. The subplots to the left are minutely, and the plots to the right are hourly.

statistical comparisons. The validation results will be presented with respect to seasonal and daily variation. In addition, detailed simulation results are also shown, e.g. high resolution time series of appliance, DHW, SH usage, in order to exemplify what kind of data that can be emulated with the simulation model. Secondly, the simulation results for data set 2 is presented in section 4.2.

4.1. *Data set 1 results*

Firstly, we present high resolution plots for occupancy, appliance, and DHW use for the data set 1 building in Figure 4. This plot is shown to give an idea of the complexity of the output data that can be generated with the model, and to argue that the profiles are realistic. Hourly averaged profiles (right plots) for the aforementioned variables are shown next to the minute profiles (left plots), to indicate how much information that is removed when averaging the data, e.g., peaks values that are smoothed out.

As seen in the upper left plots, the aggregated number of occupant people is the highest during night. The occupancy decreases during the morning when people start to get off to work and school, and then drops to its minimum at midday, when it finally starts to increase again in the afternoon. For the appliance use, a steady base load can be seen during night which is composed by stand by consumption from mainly the freezers and refrigerators due to the fact that end-users are sleeping. During the morning hours a number of different peaks can be seen. This is linked to unique morning behaviors of the end-users, i.e. when they get up, how they use their appliances, and

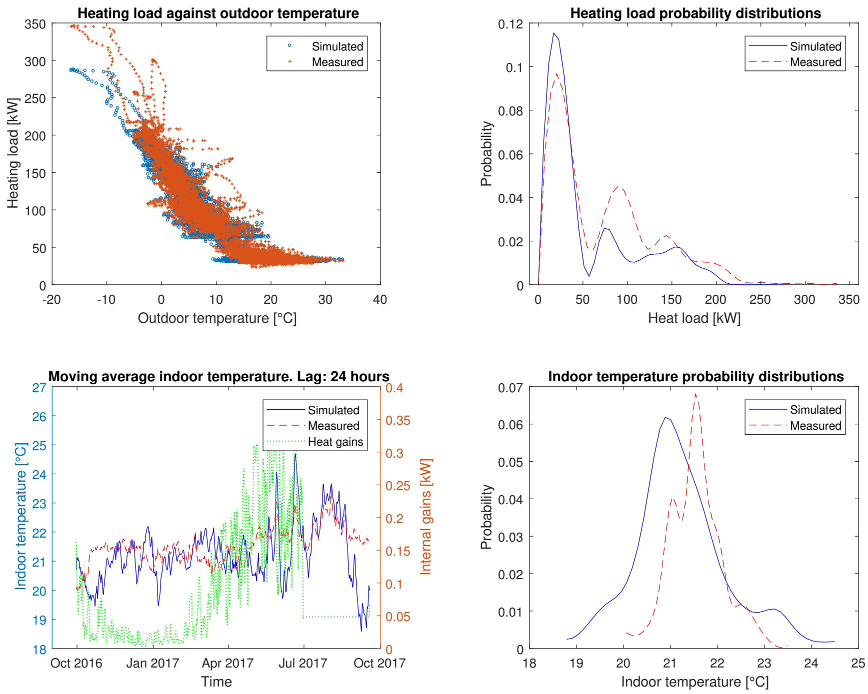

Figure 5.: Statistical comparisons between the simulated and measured DHW and SH load for data set 1.

leave for work. Note, the behavior model is based on averaged data, and these unique behaviors are created through randomness in the MATLAB program. A larger peak in the evening can be observed, which depends on coinciding behavior effects between the households.

In the lower left subplot the minute wise DHW consumption can be studied. Here, the morning peaks are higher than the evening peaks, i.e., opposite to the appliance use. This is most likely linked to the DHW needs before work. When looking at the hourly DHW use data, the morning and evening peaks look equal in amplitude. The end-users may take more baths in the evening, which smooths out the DHW consumption over longer time frames.

Moreover, simulations are performed for a full year with the parameter values specified in Table 1 and the collected weather data. The simulated and measured heating load is plotted against the outdoor temperature in the top left plot of Figure 5 for the whole time period. As seen, the simulated load follows the general trend of the measured data. However, the peak loads are underestimated by the simulation model. This could be due to higher distribution system losses in the real system which is not included in the model. These losses can be higher during cold temperatures and will drive the heating demand. Other explanations can be higher ventilation losses or over-supply of heating to guarantee the indoor comfort. Moreover, in the top right subplot the load probability distribution for both quantities are displayed. The two distribution have similar shapes, but the measured load has higher frequency of mid load values (e.g. 100 kW), and peak load values (over 200 kW).

In the bottom left plot, the time series of the simulated and measured indoor temperatures are shown. As seen, the variation of the measured indoor temperature is captured to some extent by the model. For example, the higher indoor temperature during the summer period is due to higher heat gains from solar radiation. However, the model overestimates the temperature peaks in June because it assumes the same type of end-user behavior and appliance use during summer which can be lower due to vacation times. Additionally, in reality, the end-users air their apartments when it is warm outside. This will reduce the indoor temperature even further. The model does not account weathering by the occupants. The inaccuracies could also be because due too gross control, where only outdoor temperature is the input. Mosty likely the control of the heating system is also dependent on radiator settings in the apartments which are not included in the model. In the right bottom subplot it can be seen that the simulated temperature data has a higher spread in the distribution than the measured temperature. When applying a linear model fit between the simulated and measured values for the two quantities, a R^2 of 93.3 % for the heating load, and 38.0 % for the temperature are obtained. In other words, the indoor climate is more difficult to replicate than the heating demand.

4.2. *Data set 2 results*

By inserting the parameter values for the demonstration case into model, the space heating loads of 30 multi-family buildings are simulated for two winter days at an hourly time resolution. The average outdoor temperature for these two days are 0 °C. In Figure 6, the heat pump load and the indoor temperature for the respective building, along with aggregated HP load and total heating load for the two days are shown for one, ten and 30 buildings at each row of plots. As seen in the left subplots, the heat pump load for the different building have different amplitudes and operation times. The heat pumps are of on/off type, which means that they will operate at 100 % when heating is required. The different sizes of the building, along with various isolation factors based on age of building, the HP installation capacities will be different. Thus, the model reflects varying building and HVAC system characteristics.

Moreover, the individual indoor temperature for each building can be seen in the middle plot of the same figure. The temperature is fluctuating between ± 1 °C, which is the bandwidth of the indoor temperature controller. Each building has its own temperature profile, meaning that it varies between the maximum and minimum values for different times of the day. The initial indoor temperature is chosen at random within the allowed temperature range, thus, it will vary uniquely for each building. Finally, the total aggregated heating load for the buildings is shown in the bottom-right plot. A significant share of the total load is composed by HP:s in this data set. The peak load is by covered by DH in some buildings, which typically occurs when the outdoor temperature is under a certain level (as for the building in the validation data set). Another observation is that the total load smooths out when the number of buildings in the aggregation increases. This demonstration shows that it is possible to construct various building objects with different characteristics, and, then, study aggregation effects of multiple buildings.

5. Discussion

In this section, a discussion regarding the advantages and potential applications of the simulation model is presented. Also, limitations of the model, along with the

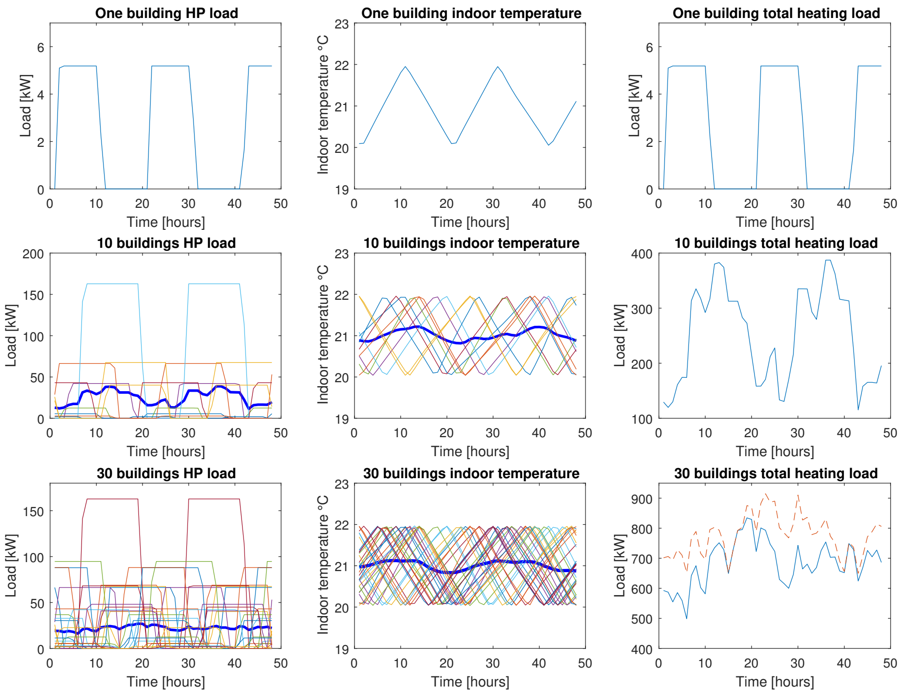

Figure 6.: Left plots: Individual HP load (thin lines) and average heat pump load for all HP:s (thick line). Center plots: Indoor temperature in every building (thin lines), and average temperature in all buildings (thick line). Right plots: The aggregated HP load and total load. The number of buildings that are simulated are increased per row of plots. First row: one building. Second row: 10 buildings. Third row: 30 buildings. The bottom-right plot includes two time series: the dashed curve is the total heating load, and the solid curve is the HP load.

possibility to use it to simulate multi-family building load profiles in other countries, are discussed.

5.1. *Advantages and potential applications of the model*

There are a number of advantages with the proposed simulation model, in comparison with other modeling approaches, such as detailed building simulation models and time series models. Firstly, the model includes behavioral aspects of the occupants in a straightforward way through the Markov chain module. This opens up for additional degrees of freedom in the load modeling, where normally only weather and temporal data are taken into account Hong et al. (2010). Further, the model includes multiple end-uses, where the occupancy is linked to a wide range of appliance categories, and not just the HVAC system which is common in related work. Due to the fact that occupancy and appliance usage affect the indoor climate and the operation of the HVAC system, it is important to incorporate these factors in the analysis.

Another benefit is the simplicity of the modeling approach, since requirements on input data and collection of parameter values are limited. Retrieving specific building data can be costly with respect to time and money, which makes it challenging to simulate aggregations of buildings with traditional building based modeling software. In the presented simulation model, it is assumed that differences in characteristics between the building objects will cancel each other out when larger populations are analyzed. In other words, if an average building type is instantiated in the model, the properties of the aggregation of buildings will be reproduced. Lastly, the statistical comparisons between the simulated and the empirical measurements provide confidence that the model can simulate load profiles that are representative for multi-family buildings. However, validation on other data sets would be beneficial to increase this confidence.

The model outputs the operation status of the loads in the building for all time steps. As this is given, the potential of increasing/reducing the consumption of these appliances can be quantified. For instance, based on a certain day type (e.g., a cold winter weekday), the model can calculate how much power is consumed by the space heating load to keep a reference indoor temperature. If the heating load is not operated at full capacity, it is technically feasible to increase the consumption, and consequently increase the temperature. If explicit indoor temperature constraints are set to satisfy the comfort, it is possible to estimate for how long time a certain control strategy can be sustained, e.g. increasing the heating load at an outdoor temperature of 5 °C and quantify how long it takes until the indoor temperature drops 1 °C. Conversely, it is feasible to decrease the heating load, and thereby decrease the temperature.

Since it is possible to assess the availability of flexibility for various scenarios and conditions (weekdays vs weekends, summer vs winter days, etc.) when comfort constraints are introduced, it can be simulated in parallel with the business logic of an electricity market actor. Practically, the market actor can utilize the consumers' flexibility to maximize its business goal subject to the constraints. For example, a DSO can curtail the heating loads for a number of his multi-family building customers to decrease peak load in the distribution grid, meanwhile assuring that the curtailed consumption does not introduce a new peak later.

Moreover, with the presented multi-family building simulation model, any aggregation size of buildings can be considered. Also, the user can change parameter settings to capture the dynamics of various building types, e.g. older and newer multi-family buildings with less or better insulation, etc. This means that a wide range of scenarios can be instantiated and simulated.

5.2. *Model limitations and sources of errors*

The model consists of multiple assumptions and parameter estimations. Evidently, the assumptions can be inaccurate for the studied multi-family buildings. One of the biggest uncertainties with the simplification assumptions is the one related to the space heating and indoor climate. A multi-family building tends to be large with many apartments and household behaviors. In the model, one temperature node is assumed for the whole building. This can of course be too inaccurate for the real indoor climate dynamics in such a complex. For example, the apartments will have different orientations in the landscape, e.g. south vs north directions. Depending on direction, the apartment will have varying influx of solar radiation, and, therefore, heat gain in the indoor environment. Further, the model does not include dynamics of the ventilation system, potential airing activities of occupants, and the distribution system. These model design decisions will affect the accuracy of the flexibility potential. However, there are a number of advantages of using a simplified approach: (i) the model generally becomes less complex, (ii) fewer assumptions need to be made regarding the design and construction of the multi-family building, and (iii) the requirements on collection of input data and parameter estimations are reduced.

5.3. *Generalization issues*

The model is primarily developed for the conditions in climates similar to Northern Europe. However, it can be used for other countries if the appropriate adaptions are applied. Four model factors need to be respected: (i) weather dynamics, (ii) household member behavior, (iii) multi-family building heading demand, and (iv) properties of the HVAC system. (i) is easy to adapt to other countries and regions, as only the adequate time series for outdoor temperature, and solar radiation need to be extracted. The TUD used for simulating the behavior of the household members might be applicable for other countries. Yet these countries must have comparable socioeconomic, behavioral and cultural characteristics as Northern Europe, e.g., Western European and North American countries. If these requirements are not met, it may be necessary to collect complementary TUD from these countries.

For factor (iii), statistics of the countries' building stock need to be analyzed. According to the statistics, an appropriate reconfiguration/alteration of the multi-family building parameter setting is required for, e.g., solar heating gains, isolation characteristics, etc. The actual parameters that define the office building architecture in the HVAC system module is considered to be generic. The last factor (iv) is dependent on multiple sub-parameters, e.g., HVAC system design, weather dynamics, and the energy production mix of the country. For example, historic data on outdoor temperatures partially sets the capacity of the HVAC system, and the usage of these. If the relevant region has cheap gas prices, it is possible that the HVAC system is powered by another primary energy source/carrier than electricity or district heating. Such factors will influence the conditions for the simulations, and must be adjusted accordingly.

6. Conclusion

A simulation model that could generate load profiles in multi-family buildings in climates similar to Northern Europe was presented in this paper. The simulation model considered both behavioral attributes of the household members and the physical indoor environment of the building. A data set from a real multi-family building with 150 apartments was used to validate the model. Hourly heating energy use and indoor temperature measurements from the building were available for almost a full year. The results from the simulations showed that model could reproduce heating demand and indoor temperature similar to the measurements. However, the model underestimated heating load peaks during low outdoor temperatures. In addition, an aggregation of 30 buildings was simulated for two winter days to demonstrate the model capabilities to emulate load curves from different multi-family buildings with respect to, e.g., building age and HVAC system installation. It was concluded that simplifications in the modeling approach introduced inaccuracies in results. However, the model requires less input data and estimation of parameter values. This provided a significant advantage if larger scale scenarios of DR from a population of different multi-family buildings in power systems and markets would be simulated.

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