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

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HIGHLIGHTS

- A model is developed that can forecast electricity profiles for detached houses.
- The model is validated on consumption data for a neighborhood of houses in Sweden.
- It is shown that the model can produce realistic electricity profiles.
- Larger deviations appear for some periods in the heating season.
- The deviations arise due to not having enough background data for the neighborhood.

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ABSTRACT

In this paper, a simulation model that forecasts electricity load profiles for a population of Swedish households living in detached houses is presented. The model is constructed of three separate modules, namely appliance usage, Domestic Hot Water (DHW) consumption and space heating. The appliance and DHW modules are based on non-homogenous Markov chains, where household members move between different states with certain probabilities over the days. The behavior of individuals is linked to various energy demanding activities at home. The space heating module is built on thermodynamical aspects of the buildings, weather dynamics, and the heat loss output from the aforementioned modules. Subsequently, a use case for a neighborhood of detached houses in Sweden is simulated using a Monte Carlo approach. For the use case, a number of justified assumptions and parameter estimations are made. The simulations results for the Swedish use case show that the model can produce realistic power demand profiles. The simulated profile coincides especially well with the measured consumption during the summer time, which confirms that the appliance and DHW modules are reliable. The deviations increase for some periods in the winter period due to, e.g. unforeseen end-user behavior during occasions of extreme electricity prices.

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1. Introduction

Governments all over the world are applying regulations to improve the environment. In the European Union the following objectives have been manifested for the year 2020: the renewable energy supply is 20% of the total production mix, the overall energy consumption is decreased by 20% with respect to the forecast levels of 2020, and the greenhouse gas emission levels is reduced by 20% (in comparison to 1990) [1]. There are even more ambitious goals for the year 2050. The electric power systems will be the key-enabler to obtain these goals; as an increasing share of the energy is produced by wind turbines and solar panels, and the transportation sector relies more on electrical energy to reduce its dependence on petroleum. However, there are inherent problems with these renewable energy production resources. The availability of the energy is variable, and might therefore not coincide with the demand. For instance, there can be windless days while the demand for electricity is high from the end-users. In essence, this mismatch affects the power systems negatively in two ways: (i) short term energy imbalances causes operational parameters, e.g. voltage and frequency to deviate from their reference values (which may lead to power outages) and (ii) more long-term and substantial mismatches can lead to power flow levels that cannot be sustained by the power grid. This can lead to failure of individual components,

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Nomenclature

$Q_{drain}(t)$	the power demand of the tap water tank at time t [W]
$Q_{sun}(t)$	heat gain from solar radiation at time t [W]
$Q_{occ}(t)$	heat gain from occupancy at time t [W]
$Q_{app}(t)$	heat gain from appliance usage at time t [W]
$Q_{loss}(t)$	total heating power loss due to the outdoor temperature at time t [W]
$Q_{heat}(t)$	the heating power from the electric heating system at time t [W]
$T_{tank}(t)$	the water temperature in the tap water tank at time t [°C]
$T(t)$	the indoor temperature at time t [°C]
Λ_{tank}	the insulation coefficient of the tap water tank [W/°C]
Λ_{trans}	the transmission coefficient of the building envelope [W/°C]
Λ_{vent}	the heating loss coefficient due to ventilation in the building [W/°C]

e.g. the collapse of distribution lines due to thermal stress [2]. A significant fraction of the renewable energy production is established directly in the distribution networks today, i.e., geographically close to the end-consumers. A smaller share of production (as a ratio of the local demand) can have a mitigating effect on the distribution system, as the general load level is decreased. But when the levels are increased beyond the hosting capacity level, problems related to voltages and power flows are introduced [3]. This fact, combined with an increasing demand for electricity from the end-users (e.g., charging of electric vehicles), it is likely that distribution system operators will encounter problems of (i) and (ii).

A promising solution to deal with these set of issues is Demand Response (DR). In short, DR involves end-users (industries, households, etc.) that have the possibility to adapt their energy consumption with respect to external signals, e.g., a price. These signals are submitted by an energy market actor who wants to solve a predefined market or power system related problem. The potential tasks that can be performed are numerous, e.g., day-ahead spot market optimization by a retailer (market related), or load shifting operation to decrease peak load in an ageing distribution network (power system related) [4]. While the tasks can be very different from one another, the underlying process and functions constituting the energy consumption of the end-user are driven by separate factors. For example, a steel-plant uses their electric-arc furnaces based on a predefined schedule to meet the expected demand for their steel goods [5], and household individuals use their kitchens based on food intake needs. In the future power networks, it will be important to have a good understanding of what drives the consumption of these end-users in a reference situation (i.e., when the end-users are not flexible). If the market actor has a good picture of this consumption with respect to temporal and spatial variation, and appreciates the implications of controlling the appliances, it can be used to solve the aforementioned problems (e.g., level out mismatches between local production and demand).

From a pure DR volume potential perspective, residents who live in detached houses is an interesting consumer type to model. First of all, this set of consumers constitutes a significant share of the total electricity consumption (e.g., 15.2% of the total annual Swedish demand, in comparison to apartment buildings which have 3.8% of the demand [6]). Secondly, the domestic sector is thought to have noteworthy DR potential, especially from their space heating/cooling and tap water systems [7] (60% of the Swedish detached houses are primarily heated by electricity from, e.g. heat pumps and electric radiators [8]). Thirdly, these end-users are situated in the low voltage part of the grid.

1.1. Related work

Several models for simulating detached houses load profiles have been proposed by literature. These models have been deployed for various applications, and take respect to specific boundary conditions of a country. The common denominator of the models is their representation of end-user behavior, and their interaction with, among other things, electric appliances, hot water demand and space heating/cooling equipment, to satisfy their needs and comfort within a building.

In [9], a simulation tool for analyzing how a neighborhood of domestic Net-Zero Energy Buildings (ZEB) (houses that supply as much energy on site as they use on an annual basis) impacts the dynamical electric features of the local electric distribution feeder, is described. The tool allows for simulations of both thermal and electrical processes in the buildings. The model combines detailed bottom up statistical approaches for usage of electric loads (comparable to the work in, e.g. [10,11]), and engineering modeling approaches to capture the behavior of the occupants, and a thermal building model which is based on the finite volume method. The tool also has mathematical formulations of various energy technologies (e.g., air–air heat pumps), and energy-efficiency measures (e.g., insulation and heat recovery systems in the ventilation). The tool is holistic as it covers electric and thermal consumption for appliance usage, tap water demand, and space heating. A Belgian use case is subsequently simulated for a neighborhood of 33 houses. Another model focusing on holistic electricity consumption models, but for Swedish ZEBs can be found in [12]. Here, a deterministic model is developed which can simulate the indoor temperature for a passive house to determine how various behaviors of the household individuals affect the perceived climate comfort. A drawback with these papers is the absence of validation of the simulation results against real energy measurements from ZEBs.

The authors of [13] have developed stochastic physical-based bottom up models for the previous mentioned loads (along with space cooling) for conventional detached houses. DR functionality is directly built into the respective models. Simulations are conducted for a population of houses based on residential data from various parts of the US (e.g., typical house sizes, boiler capacities for water tanks, etc.). The results are statistically compared to real load data for the different load categories. This model did not go into behavioral characteristics of the inhabitants.

Models mainly focusing on behavioral aspects can be seen in [14,15]. These models apply non-homogenous Markov-chains to simulate how occupants move between different zones within office buildings. Subsequently, it is shown how they manipulate the building's indoor climate by radiating heat, turning on/off thermal loads, opening windows, using shading devices, etc. The simulation results show that the inhabitants behavior and decisions have a significant effect on the energy consumption levels (up to a factor of two [15]). However, these papers take no consideration to behavioral attributes of residents living in detached houses.

Moreover, a domestic electricity demand model based on Time-Use Data (TUD) for UK conditions is defined in [16]. The model can synthetically generate consumption profiles with a one-minute resolution for individuals/households/neighborhoods, where detailed analysis of how the consumption coincide/diverse between the households can be done. The model takes into account changed behavior of the inhabitants during seasons, e.g. an increased home occupancy during winter time. Further, the model is also statistically compared to typical mean daily consumption profiles of UK, and shows good agreement to real data. The mismatches are apparently biggest during night time because the model does not take respect to lighting used during night and use of timers for some appliances. In addition, no consideration is taken to thermal loads, such as heat pumps. Therefore, the model cannot predict consumption pattern that is related to the building's physical indoor environment. A similar approach to simulate occupant behavior can be found in [17,18], where deterministic and stochastic models based on Swedish TUD are presented. These papers are mainly focused on electric appliance usage.

1.2. Scope of the paper

The main purpose of this paper is to develop a quantitative simulation model that can generate realistic electricity consumption profiles. The profiles are characterized by Swedish residents living in detached houses with electric heating systems. The model is aimed to generate detailed reference energy profiles (i.e., active power demand with no flexibility or price sensitivity) for a population of houses. The study also includes a validation of the model results. The validation aims to statistically check whether the model can reproduce load curves that have a resemblance with empirical load measurements from a detached house neighborhood in Sweden.

The model is intended to produce data that are of high detail when it comes to temporal and spatial attributes of the energy usage (info regarding what appliances consume energy when and where). This is done so that DR functionality can easily be incorporated to the model afterwards. For example, indoor temperatures are tracked through the simulations so that flexibility schemes can be implemented based on the operation of the heating systems. As opposed to the models described in the previous section, this simulation model will couple advanced behavioral models of inhabitants, with detailed models capturing thermodynamical aspects of conventional buildings. In addition, as this model has the potential to simulate various DR schemes, it adds value to whomever actor interested to use such schemes to solve power system related problems. The model is implemented in MATLAB [19], where their built in Statistics Toolbox package is used [20].

1.3. Outline

The remainder of this paper is structured as follows. In Section 2, the proposed detached house consumer model is presented. Information about the simulation use case is found in Section 3. It is followed in Section 4 by simulation results, and a corresponding statistical analysis. Section 5 contains a discussion of the results, and some concluding remarks are given in Section 6.

2. Model description

In this section, the basic functioning and properties of the quantitative simulation model is defined. The model is built on the assumption that the electricity consumption is composed of three separate modules: (i) the usage of electric appliances (e.g., lighting, cooking, computers, etc.), (ii) DHW consumption (e.g., taking showers, etc.), and (iii) Space Heating (SH). (i) and (ii) are operated individually, and are primarily driven by behavioral factors of the occupants, and a predefined appliance setup of each household. Module (iii) is dependent of weather dynamics, the properties of the building, and the output from the other two modules. A diagram depicting the basic functions and interrelationship of the modules can be seen in Fig. 1. Below, each module is described in detail.

2.1. Initial model parameters and sets

As a starting point detached houses need to be instantiated (denoted N_{det}). Each house is populated by a household i (i.e., $i \in \{1, 2, \ldots, N_{det}\}$), with a family size β_{family} (which is an integer value larger than zero). β_{family} is the realization of the uniform random variable X_{family} which assign reasonable family sizes over the N_{det} house objects. Note, β_{family} does not specify any additional information about the household member, such as, age, profession, hobbies, etc. Furthermore, the model is discretized in time, thus reflecting occupants behavior and building dynamics in predefined time slots t, with a time step of Δt. The simulation period is given by N_{sim} time steps (i.e., $t \in \{1, ., k, ., N_{sim}\}$), where $\Delta t = t_{k+1} - t_k$. NB: the applied time steps for the different modules are different (see Table A1).

2.2. Electric appliance module

The appliance module is based on the model introduced and described in [18]. The main idea of the model is to develop a high resolution stochastic model of electricity usage profiles derived from behavioral patterns of Swedish domestic occupants. The model uses a discrete time non-homogenous Markov chain methodology where individuals move between different predefined activity states over time with certain transition probabilities. These behavioral patterns are based on TUD collected by the Swedish Statistical Bureau (SCB) in 1996 [21]. The SCB study is encompassed by 463 individuals in the age span of 10–97 years from 179 households. The participants registered information regarding the activities that are performed every 5 min. The information includes the activity type, where it is taking place, and if the activity is done collectively [17]. All participants recorded their activities on one weekday and one weekend day. Further, the TUD are complemented with a set of background variables, making it possible to distinguish between, e.g. detached houses and apartments.

Subsequently, the activity data is converted to energy load profiles by linking each activity that is done at home with an end use category. Three main activity-to-power conversion schemes are implemented in the model: (A) power demand which is constant during the activity (e.g., freezers), (B) a variable load-cycle demand which starts directly after the activity (e.g., starting a filled dishwashing machine), and (C) a power demand which is constant during the activity, with a standby level during non-use (e.g., TV watching). Lighting (which is a time dependent power demand activity) is assigned a separate model. This model is dependent on occupancy data and daylight levels [22]. Moreover, by assigning reasonable power ratings and run times for the appliances, synthetic electricity consumption profiles can be produced for an arbitrary number of individuals and time series. The models are validated against real measurement data (the measurements are done for a subset of the households in the TUD study) and showed that it can produce realistic energy profiles [18]. All the states and their corresponding conversion models, along with the appliance power ratings and run times are listed in Tables A2 and A6.

2.3. Domestic Hot Water module

The DHW module comprises a simplified water tank model, where the aim is to keep a reference temperature in the tank (T_{tank}^{ref}). The tank temperature T_{tank} decreases in either two ways: (i) by hot water usage of the occupants or (ii) through heat loss from the insulated tank to the surroundings. For (i) only two hot

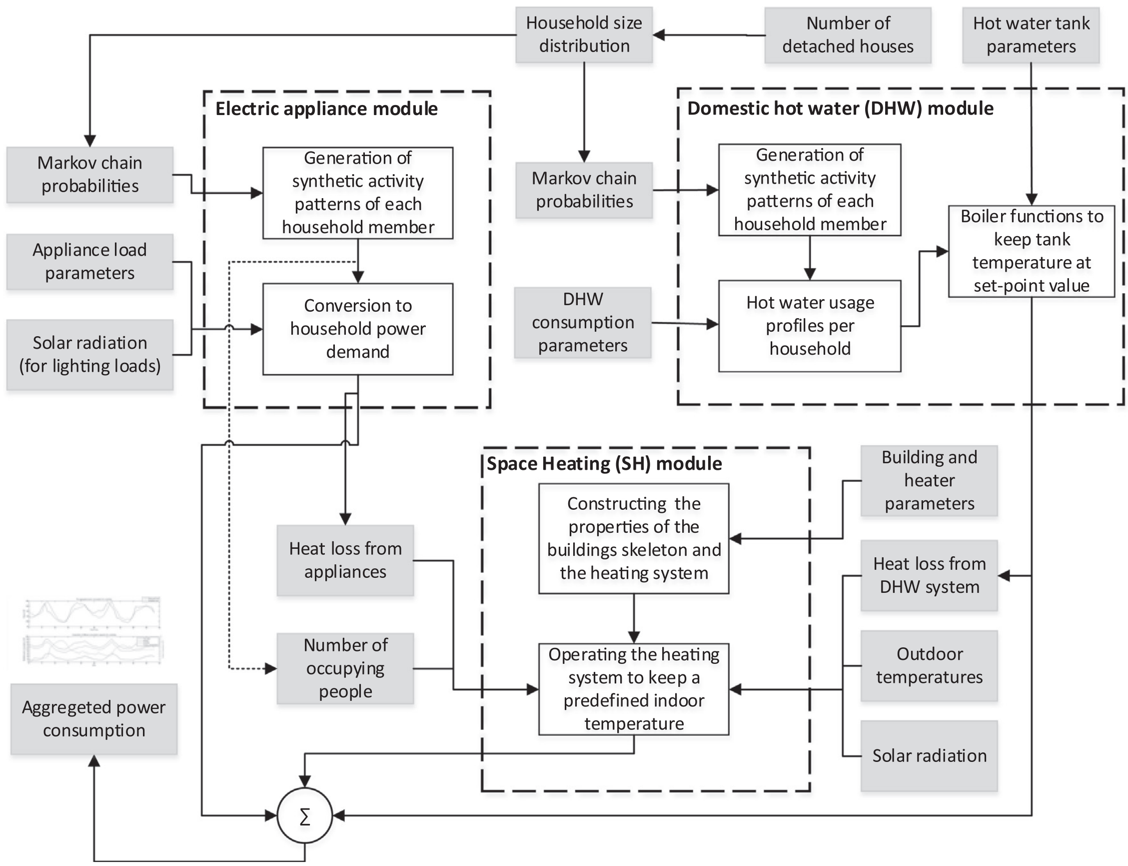

Fig. 1. Model overview showing the functioning, interrelationship, and the data requirements of the simulation modules. The gray boxes are input data to the function (white boxes) within the modules. Each functions is producing various parameters shown by the output arrows from each white box.

water activities exist which can extract energy content from the water tank, and that is taking showers or baths. Evidently, other activities at home will cause hot water consumption, e.g. hand wash and perform manual dishes. However, shower and bath activities are the large consumer of hot water in comparison to other possible activities [17]. So, in order to keep the complexity level at its minimum, meanwhile making it representative, it is decided to only consider these activities. The timing and duration of the occupants' DHW activities are determined by a separate Markov chain which is derived from the original SCB data [21]. This Markov chain is run in parallel with the appliance module Markov chain (listed in Table A6). This means that an individual can perform two separate energy demanding activities at the same time, e.g., taking a shower and watching TV. However, the small loss of accuracy of the activity model that can be expected is outweighed by the avoided complexity and simulation time that would be the result of including the additional activities in the existing Markov model. In addition, as the consumption curves for each individual are aggregated to a population's consumption, it is expected that these small errors will tend to cancel themselves out. Moreover, it is assumed that the boiler of the hot water tank has no intelligence. As soon as T_{tank} deviates from T^{ref}_{tank} (due to activities of the household members) the boiler will produce energy at full capacity (P_{boil}) to take the temperature back to its set-point value. The equation that yields the power demand (Q^{drain}) of the hot water at time t for household and water tank i, and activity type a is determined by:

$$Q^{drain}_i(t) = V^{flow}_{i,a}(t)Cp_{water}(T_{outlet} - T_{inlet}), [W]. \tag{1}$$

where Cp_{water} is the specific heat capacity of water. T_{outlet}, and T_{inlet} is the respective temperatures of the inlet and outlet water. $V^{flow}_{i,a}(t)$ is the total hot water flow to serve the current DHW activity of the household member. In addition, the heat losses are given by: $Q^{loss}_i(t) = \Lambda_{tank}(T_{tank}(t) - T_{amb}(t))$, where Λ_{tank} is the insulation coefficient of the water tank, and $T_{amb}(t)$ is the temperature of the ambient air at time step t. In the end, the hot water tank is a battery where discharge of energy is a result of usage and losses, and the recharge is performed by the boiler. The maximum energy that can be stored in the tank is given by: $Cp_{water}V_{tank}(T_{max} - T_{inlet})$, where T_{max} is the boiling temperature of water, and V_{tank} is the volume of the water tank.

2.4. Space heating module

The main function of the SH module is to keep a predefined reference indoor temperature T_{ref} by controlling the heat output of an electric heating system (assumed to be controlled by a thermostat). The indoor temperature T will deviate from T_{ref} due to the following disturbance signals: (i) the outdoor temperature T_{out}, (ii) the solar radiation Q_{sun}, (iii) the presence of occupants Q_{occ}, and (iv) the use of appliances and hot water Q_{app}. The building is considered to be a container with stored energy, where the aforementioned factors can interact with the energy level. The only factor which can drain energy from the house is factor (i). If the outdoor temperature is below the reference temperature, power will flow through the building envelope (walls, windows, etc.) to the external surroundings. This is called the transmission losses of heat and is captured by the insulation coefficient Λ_{trans}. Λ_{trans} is defined by: $\sum_j U_jA_j$, where U_j is the transmission factor of each building component j, and A_j is the total area of that component. In addition to the transmission losses, there will be power losses when the heated air is exchanged with fresh outside air, i.e. ventilation losses (labeled as Λ_{vent}). This parameter is given by: $V_bN_{vent}Cp_{air}(1 - \alpha_{rc})$, where V_b is the total internal volume of the building, Cp_{air} is the heat capacity factor of air, N_{vent} is the exchange rate of the air, and α_{rc} is the heat recycle factor of the ventilation system. The total heating power loss Q_{loss} at time t is determined by:

$$Q_{loss}(t) = (T(t) - T_{out}(t))(\Lambda_{trans} + \Lambda_{vent}),\ [W]. \tag{2}$$

Moreover, factors (ii)–(iv) are considered to be power deliverers to the building (besides the actual heating system), and can therefore increase the indoor temperature for "free". Energy provision from solar radiation is a result of sunlight transmitted through the windows of the building, which subsequently heats the space inside. Calculating the heat contribution from solar radiation is a complex procedure. This paper is using a simplified model where three parameters are taken into account (inspired by the model presented in [23]): (i) the solar radiation against a vertical object for time slot t ($P_{sun}(t)$), (ii) the total window area per building side (A^{side}_{window}), and (iii) the reduction factor α_{red}. Further, α_{red} depends on the following sub-factors: the solar heat gain coefficient of the window (g), the characteristics of the window curtains ($F_{curtain}$), the reflecting affect of the window frames (F_{frame}), and the shadowing effects of the adjacent terrain (F_{shahow}). The instantaneous heat contribution from solar radiation for time t becomes:

$$Q_{sun}(t) = \alpha_{red} A^{side}_{window} P_{sun}(t), \quad [W]. \tag{3}$$

Heat is provided by metabolism of the occupants (Q_{occ}), and heat losses from usage of electric appliances and hot water (Q_{app}). P_{met} is simply determined by how many persons that are occupying the house, times the average power that a human being radiates due to metabolism. It is assumed that all the radiated heat from the individuals can be utilized by the building. However, for appliances and hot water the utilization factor varies (see Tables A2 and A3 for more info).

One important property of the heating system is its sizing. Here, the dimensioning winter temperature (T_{DWT}) is a key concept. This parameter dimensions the heating unit based on two sub-factors; (i) the thermal inertia of the building τ (the heat energy that can be stored in the interior and therefore work as a buffer) and (ii) the coldest annual registered outdoor temperature for the geographical area. Consequently, the heater size is calculated based on how many days the building can sustain a reasonable indoor temperature (typically above 18 °C) at the coldest outdoor temperature. It is considered too expansive to have a heater that can sustain a specific indoor temperature for all weather conditions. The resulting heater capacity P_{heat} is: $(\Lambda_{trans} + \Lambda_{vent})(T_{ref} - T_{DWT})$. Plainly, P_{heat} will determine the upper limit to produce Q_{heat} for the building. Ultimately, due to all the aforementioned processes, there will be a net flow of energy from the house that will affect the indoor temperature between time t and $t + 1$. This procedure is governed by:

$$T(t+1) = T(t) + \frac{Q_{heat}(t) + Q_{sun}(t) + Q_{occ}(t) + Q_{app}(t) - Q_{loss}(t)}{\tau(\Lambda_{trans} + \Lambda_{vent})}\Delta t \tag{4}$$

In other words, the indoor temperature for the next time slot is dependent on the temperature value for the prior time slot, the net flow of energy, and the thermal resistance of the system (captured by the factor $\tau(\Lambda_{trans} + \Lambda_{vent})$). Subsequently, the task of the thermostat is to keep $T(t+1)$ close to T_{ref} by controlling the provision of heat from the radiators (i.e., adjusting Q_{heat}). During summer time, the indoor temperature will inexorably exceed T_{ref} as the outdoor temperature will increase and the solar radiation will be more intense. Here, we assume that the buildings do not have an air conditioning system (this is a common condition for the Swedish building stock [8]) which can reduce the indoor temperature.

3. Use case description

The input data and parameter estimations which define the scenario for the model validation are presented and justified in this section.

3.1. Use case parameter values

The simulation setup is based on a low voltage substation in the Stockholm area of Sweden. The only information available for the use case is: (i) the consumer segment (defined as households living in detached houses), (ii) the number of houses, (iii) the geographical area, (iv) the heating system used, and (v) the time period and resolution of the aggregated consumption measurements. Other data, e.g. family composition, the routines of the household members, exact properties of the buildings (e.g., dimensions and components, and electric appliance setup), are not available. Evidently, these prerequisites will make it impossible to produce modeled consumption curves that perfectly coincides with the measured consumption. However, what we can do is to assign reasonable parameter values, and see whether the output of the simulations statistically correlates with the empirical data.

The most challenging part of the parameter setting is by far the one for the buildings (i.e., the SH module). To define a building architecture that is representable for the Swedish conditions, the actual building stock of the country needs to be analyzed. A majority of the single family houses are constructed before the year 1970, and generally have a higher heating demand per m^2 [8]. Due to the fact that our aim is to describe the energy usage of a population, it is reasonable to choose a building architecture that can resemble the mean features of the Swedish building stock. So by assigning one building class for the whole neighborhood, there is an increased probability that we capture the mean aggregated behavior. Therefore, it is assumed that the type of buildings in the neighborhood is normally distributed. A building architecture that is characterized by the construction standard before year 1970 is defined in [24]. The exact parameter setting of this building, along with the parameter settings of the other modules (and a corresponding justification of these) can be found in Tables A2, A3, and A4.

Lastly, the orientation of the individual buildings in the landscape is unknown. So, here it assumed that the buildings are located randomly and independently from one another in the landscape. This implies that the neighborhood as a whole is exposed to solar radiation independently on the building's side and direction. The assumption reduces the complexity level of the model, which is beneficial in itself.

3.2. Input data for the exogenous variables

In Fig. 2, a conceptual diagram showing the interrelation between the validation data and the required input data is shown. The validation data (i.e., the measurements from the substation) works as a foundation for the other input data. First of all, the number of detached houses with their corresponding heating systems is required. In this neighborhood there are 41 houses, which all are heated by electric radiators. The geographical area and given time period for the measurements allows us to extract the adequate time series for outdoor temperatures, solar radiation and electricity prices. NB: electricity prices are not an input to the model, as it is assumed that the consumers are not price sensitive. However, this exogenous variable is used in the statistical analysis of the model validation (see Section 4.1). Furthermore, the data for the Markov chains which gives the consumer behavior are also required. As mentioned in Section 2.2, this data is taken from a Swedish TUD study. Additional information regarding the used data sets for the exogenous variables are listed in Table A5.

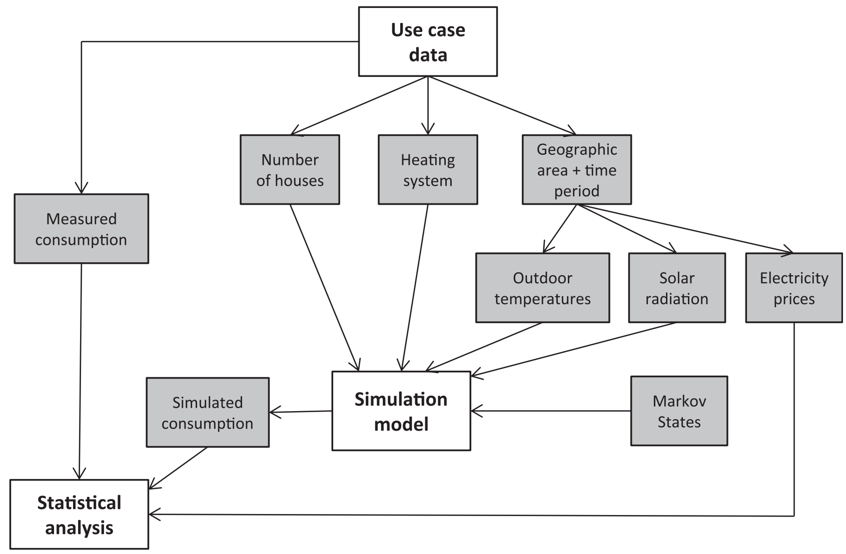

Fig. 2. A conceptual diagram visualizing the interrelationship between the validation data, the exogenous variables, and the simulation model.

4. Results and analysis

In this section, results from the use case simulations are presented. The results are depicted on a seasonal and daily time scale, separately. A statistical analysis that compares the simulation data and the empirical measurement data is performed, trying to deduce whether the model is a proper representation of reality. As the appliance and DHW modules are probabilistic, a Monte Carlo approach is applied for capturing the mean behavior of the population. The simulations are repeated 20 times, and then presented as the average of these samples.

4.1. Simulation results: seasonal trends and daily variations

By inserting the aforementioned data into the model, the electricity consumption can be simulated for the given time period. In the upper subplot of Fig. 3, the simulated and measured daily mean energy consumption for the whole period is shown. The lower subplots show the outdoor temperatures, solar radiation, and the electricity prices for the same period. As seen, the simulated curve follows the empirical data well, where both seasonal variations in magnitude and phase are captured. However, there are two time periods that are significantly inaccurate, i.e. the

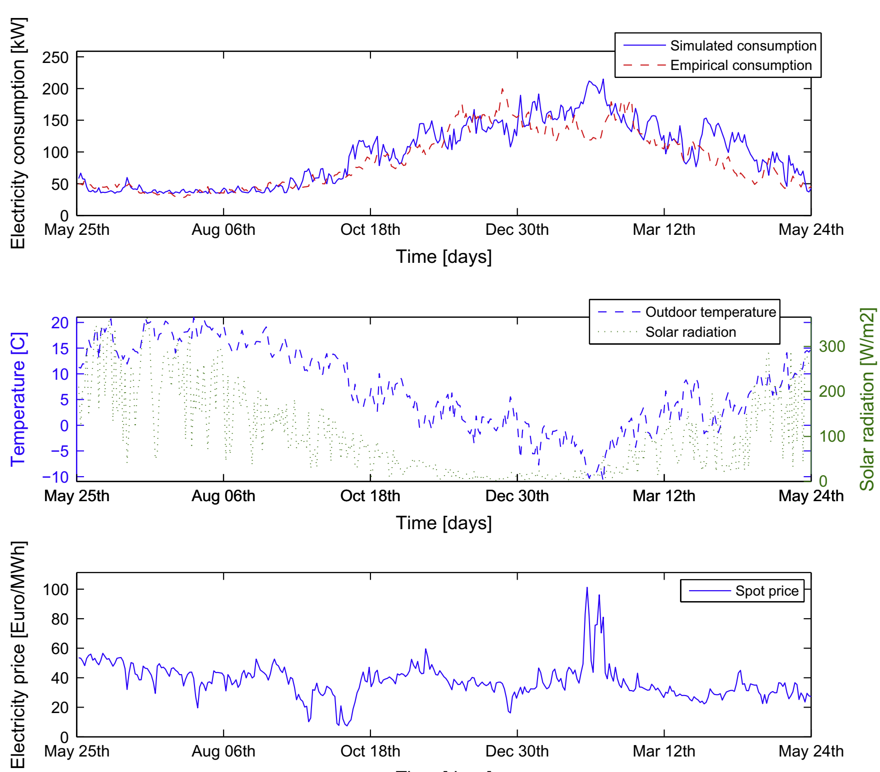

Fig. 3. The upper plot shows the simulated and measured daily mean load for one year (May 25th 2011 to May 24th 2012). The middle plot depicts the outdoor temperature and solar radiation for the same period. The lower plot shows the electricity prices.

consumption profiles in the first weeks of February and April, respectively. The first mismatch is due to extreme price peaks (depicted in the lowest subplot of the same figure). These price peaks are so severe that media cover the events [25]. Obviously, the residents responded to the extreme price signals, and reduced their consumption. The model does not take these kinds of situations into account as it reflects non-flexible consumers. Instead it is the outdoor temperature that sets the consumption level (the prices coincides with low temperatures).

The second mismatch is more difficult to argue for. One possible explanation is that the model underestimates the heating effect of solar radiation, as the radiation is quite intense while outdoor temperatures are low. On the other hand, the simulated data shows a good resemblance with the empirical data during summer time (May 25th to the beginning of September). This implies that the electric appliance and DHW module provide realistic predictions of the consumption (as the electric heating in the SH module is inactive most of the time).

The upper subplot of Fig. 4 shows a scatter diagram of the simulated and the empirical consumption with an hourly resolution (i.e., 8760 pairwise data points). By applying a least square method on the data, a linear model describing the relationship between the two quantities is calculated (the line in the same graph). Subsequently, the correlation of the data is given by the equation: $Y = \alpha_{obs} + \beta_{obs}X$, where Y is the empirical load variable, and X is the simulated load variable. In this case, α_{obs} becomes 16.2 kW, and β_{obs} yields 0.73. In other words, when the consumption in the model increases by 1 kW, the empirical load tends to increase by 0.73 kW. The error rate between the simulated and the observed hourly data is 18% in average.

Furthermore, the lower subplot of the same figure shows the probability density function of the two data sets. As seen, the overall shape of the two curves is similar. However, the model tends to underestimate smaller consumption segments (under 100 kW), and overestimate larger consumption (above 150 kW) in comparison to the measured data.

Fig. 5 shows the correlation between the exogenous variables and the empirical and the simulated load data, respectively. Two clear trends can be observed from the plots: (i) the empirical consumption is much more spread with respect to outdoor temperatures than the simulated consumption and (ii) electricity prices over 60 €/MW h result in a lower empirical energy consumption. The reason behind observation (i) is due to model simplifications, and insufficient background data for the neighborhood (e.g., preferred indoor temperatures, operation logic of the heating system, absence of the actual building skeleton parameter values, etc.). For example, no consideration is given to potential secondary heating systems (e.g., stoves, fireplaces, etc.) in the model. If the temperatures are low, it may be reasonable to believe that the residents light their fireplace to get extra heat if such a system exists (i.e., decreasing the consumption and making it more unpredictable). The dynamic behavior of the heating environment in a building is very complex and it is challenging to produce a model in perfect detail. The analysis of the data confirms these difficulties.

4.2. Simulation results: intra-day variation

The previous section handled seasonal trends of the simulations. Here, we will zoom in the simulation results on an hourly resolution and show how well the results coincide with the empirical data. To make the results easier to interpret, it is presented according to different day types. A day type is defined as a time period where certain preconditions are fulfilled. The preconditions are specific value intervals for daily average values outdoor temperatures and solar radiation levels, for weekdays and weekend days, respectively. Also, the electricity prices are kept under 60 €/MW h so that potential consumer reaction on peak prices are filtered out. Three day types are generated, which are denoted as a typical winter day, fall/spring day, and summer day. Below, each day type is described more elaborate:

- *Winter day* – The mean daily outdoor temperature is below 5 °C. The solar radiation is practically non-existing at these high latitudes during winter ($P_{sun} \leqslant 50\ \mathrm{W/m^2}$). 105 days meet these requirements.
- *Spring/Fall day* – The mean daily outdoor temperature is between 5 and 15 °C. The solar radiation is quite significant ($100 < P_{sun} < 200\ \mathrm{W/m^2}$). 40 days meet these requirements.

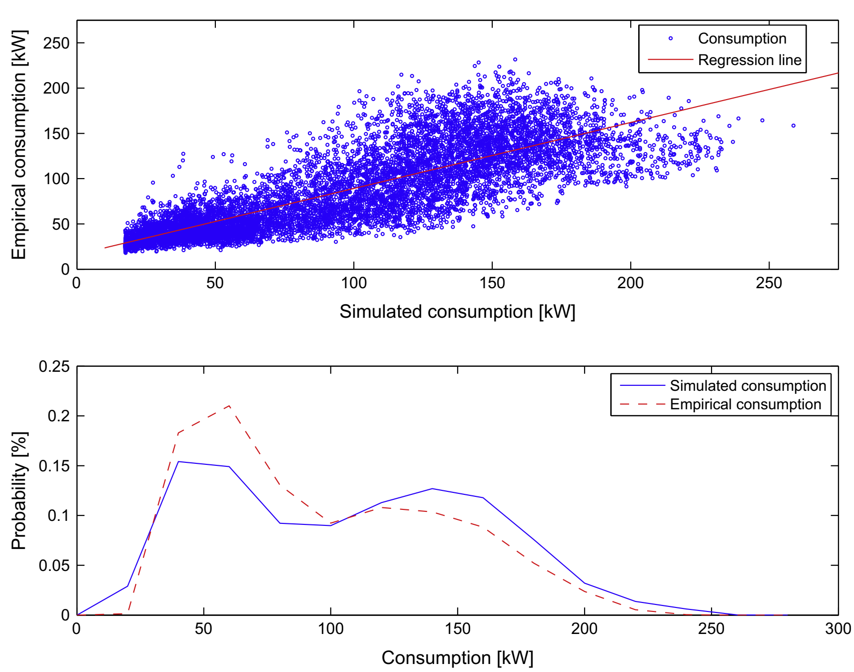

Fig. 4. The upper subplot shows the scatter diagram of the simulated load data (x-axis) and the empirical load data (y-axis) for an hourly resolution. The lower subplot depicts the probability distributions of the consumption level for the two respective data sets.

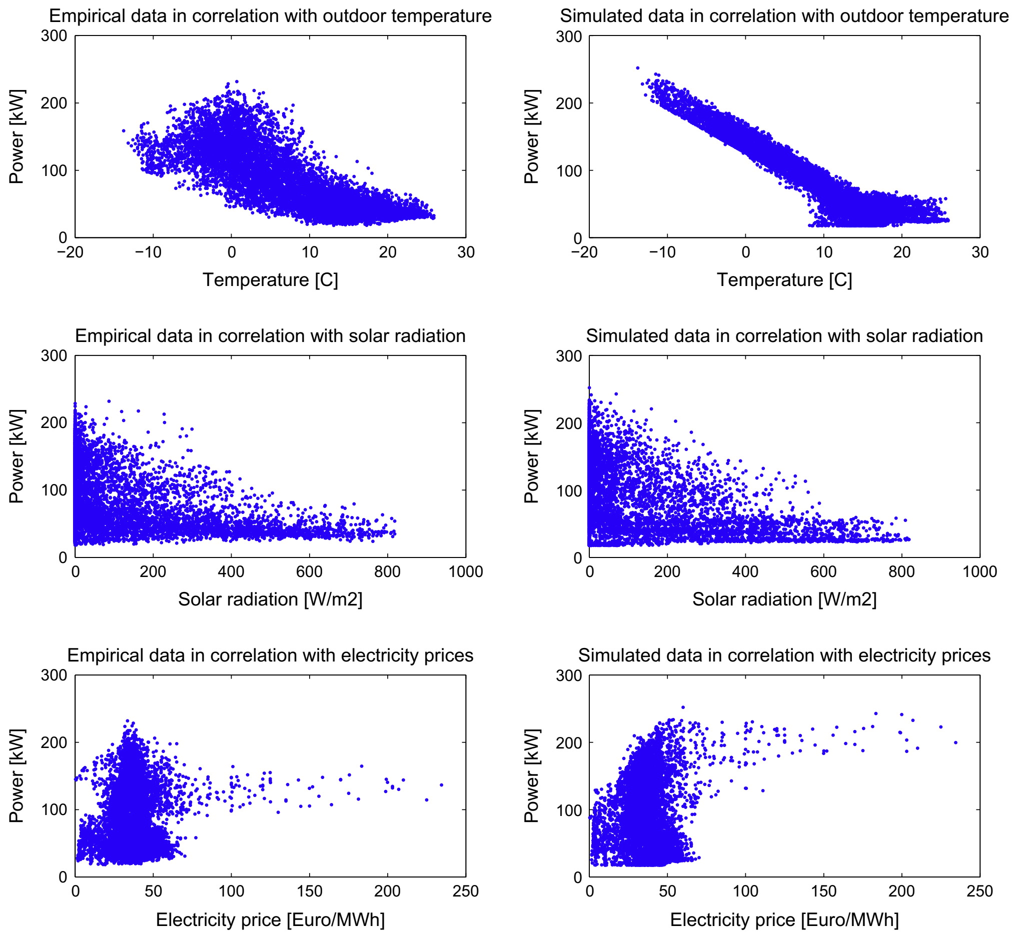

Fig. 5. The subplots to left are the correlation between empirical load data and the exogenous variables. The subplots to the right are identical but for the simulated data. The above subplots are outdoor temperatures, the middle are solar radiation, and the lower are electricity prices.

- *Summer day* – The mean daily outdoor temperature is above 15 °C. The solar radiation is high ($P_{sun} \geqslant 200\ \mathrm{W/m^2}$). 30 days meet these requirements.

In Fig. A1, averaged 24 h consumption profiles for the day types are plotted. The analysis on how well the simulated and empirical load match is based on three separate criteria. The criteria are: (i) the overall mismatch in daily electricity consumption, (ii) the variance in morning and evening peak load levels, and (iii) the timing difference for the respective peak loads. In Table 1 the figures of this analysis can be found for each day type.

The overall trend for criterion 1 is that the model overestimates the energy consumption in comparison to the empirical load. However, this overestimation tends to be more severe for weekends, higher outdoor temperatures and more intense solar radiation (with the exception of summer weekdays where the lowest mismatch is observed). The difference in peak magnitude (criterion 2) also has a tendency to be overemphasized. Here the results are more accurate for weekend days than weekdays, and less accurate for summer days. As the model assumes a constant behavior of the individuals over the seasons, and that the heating is not active during the summer, an error of reproducing the actual behavior of the individuals will results in a higher relative deviation of the real consumption. Lastly, for criterion 3, the model data shows a minor domination of lagging evening peaks in comparison to the empirical load (especially valid for colder days). A reasonable explanation to this can be the modeled operation logic of the heating system. As the heating system is functioned accordingly to the actual outdoor temperature, 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.

Table 1
The criteria analysis of the day types. The results on each row are relative comparisons between the simulated and the empirical data for each respective day type (the empirical load works as the reference). Each column is the corresponding criteria. Further, criterion 1 is the daily average mismatch in electricity consumption (in percentage). Criterion 2 is the deviation in morning and evening peak load levels (in percentage), and criterion 3 is the timing difference in these peak loads (in hours).

	Criterion 1 (%)	Criterion 2 (%)	Criterion 3 (h)
Winter			
Weekday	5.8	14.5/0.0	0/−2
Weekend	9.6	8.9/2.5	−2/−1
Spring/Fall			
Weekday	8.5	31.9/11.4	0/−2
Weekend	18.2	10.0/27.2	+2/−2
Summer			
Weekday	2.2	55.8/26.9	+2/−1
Weekend	24.2	50.8/44.0	+2/0

5. Discussion

In this section we will discuss potential applications of the model, and the plausibility to use it to forecast demand profiles for detached houses in other countries. Further, a discussion of why the simulated and empirical load data deviate from each other is made.

5.1. Potential applications of the model

The operation status of all the loads in the population of houses are given for all the simulated time slots. As this is known, we can appreciate the potential of increasing/reducing the consumption of these loads. For example, based on a certain day type, the model can calculate how much power that is consumed by the heater for maintaining a reference indoor temperature. If the heater is not operated at full capacity, it is technically feasible to increase the consumption, and thus rise the indoor temperature (see Eq. 4). Conversely, it is possible to reduce the heating and decrease the temperature.

Furthermore, if explicit indoor temperature constraints are introduced (to satisfy comfort requirements), we can estimate for how long certain a certain heating operation can be sustained, e.g. turning of the heater at an outdoor temperature of $-10\,^{\circ}\mathrm{C}$ and assess the time until the temperature drops $3\,^{\circ}\mathrm{C}$. So, instead of keeping the indoor temperature constant, it can fluctuate freely within the predefined boundaries. This analogy is valid for the DHW tank system as well. There is also some flexibility available in the starting time of the dish and washing machines (as it can be postponed).

As the model can technically assess the availability of flexibility for various scenarios, 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 objective function subject to the constraints. For example, a DSO can curtail the heating loads for a number of his detached house clients to decrease peak load in the network (see Section 1). By conducting these kind of co-simulations, the following questions can be addressed: (i) What can the end users provide in terms of demand flexibility? (ii) What are the technical and economic benefits/disadvantages for the market actor to utilize this flexibility? In future work the authors will perform such simulations.

5.2. Generalization aspects

The model is primarily developed for the conditions in Sweden. However, it can be used for other countries if the appropriate adaptations are applied. Four different model aspects need to be taken into consideration: (i) weather dynamics, (ii) behavior of the household members, (iii) detached house architectures, and (iv) properties of the heating systems. (i) is easy to adapt for 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 individuals' behavior (ii) might be applicable for other countries. Yet these countries must have comparable socioeconomic, behavioral and cultural characteristics as Sweden (e.g., Western European and North American countries). If these requirements are not met, it may be necessary to collect TUD for the specific nation.

For factor (iii), statistics of the countries' building stock need to analyzed. According to the statistics, an appropriate reconfiguration/alternation of the detached house parameter settings is required, e.g. for solar heating gains, shading and natural ventilation dynamics. NB, the actual parameters that define the detached house architecture in the SH module are generic. The last factor (iv) is dependent on multiple sub-parameters, e.g., weather dynamics,

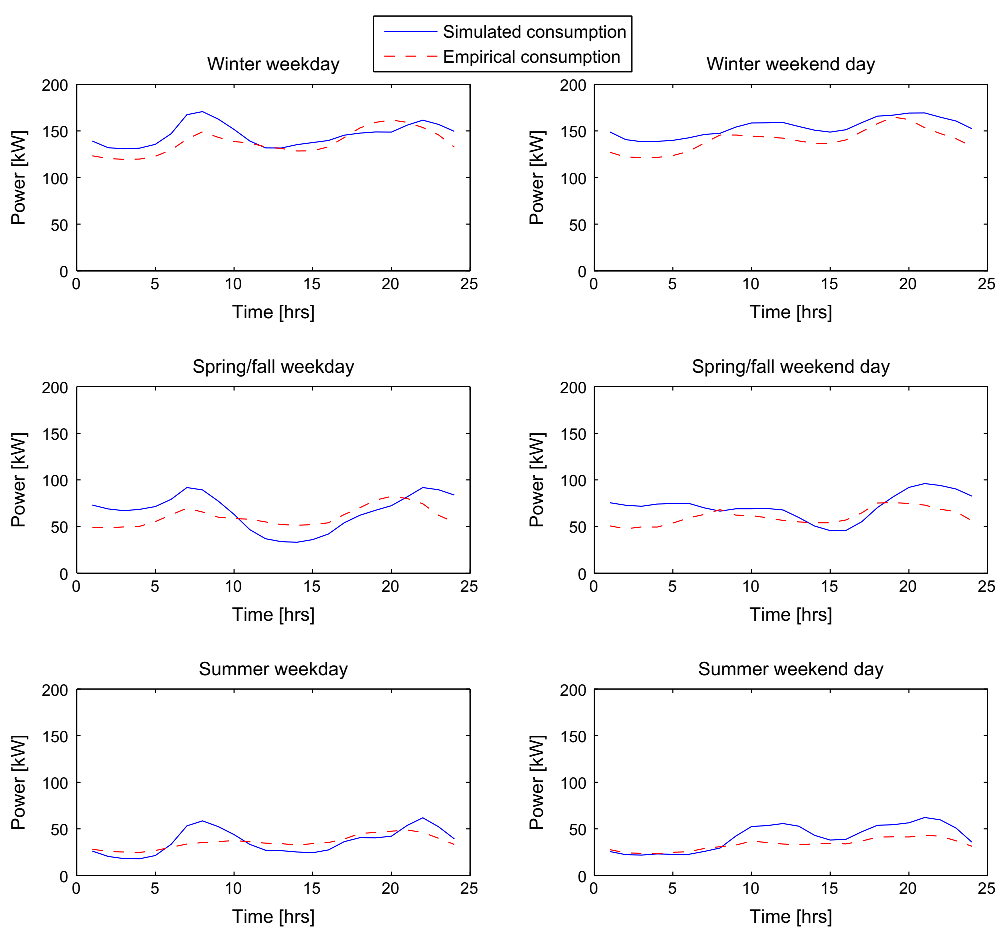

Fig. A1. The 24 h average consumption profiles for the three type days. The subplots to the left are weekdays, and the subplots to the right are weekend days.

and the energy production mix of the country. For example, historic data on outdoor temperatures partially sets the capacity of the space heating system. In addition, if the country/region in question has a warmer climate, it is reasonable that domestic air condition systems are used. Therefore, such loads must be added to the model. Furthermore, if the detached houses are widely heated by gas or/and remotely heated, the SH module must be deactivated.

5.3. Sources of deviations in simulation results

The simulation model presented in this paper consists of multiple assumptions and parameter estimations (both regarding their relevance/justification and numerical value assignment). Firstly, these assumptions can be irrelevant for the neighborhood in question. For instance, no information about architectural and construction aspects of the buildings are available (precise values on house dimensions, insulation factors of building components, etc.). As this information is missing, reasonable assumptions and estimation are applied. This is an apparent source of defection in the simulation results. Secondly, the model assumes a constant behavior of the household members. The only separation is between weekdays and weekend days. In real life, behavior is not constant, but rather affected by factors such as weather, holidays (e.g., national holidays, vacations), and potential sickness in the family. As an example, consider differences in behavior during warm sunny weekend days, and cold, rainy and dark weekdays. As occupancy is a prerequisite for energy consumption at home, an incomplete representation of the variation in the behavior of the individuals will impact the results. Thus, it can be anticipated that the explanation factor of the model can be increased if more specific data for the neighborhood in question is collected and inputted to the simulation model (both when it comes to the building and its occupants). However, this approach can introduce the risk of making the model too calibrated for the conditions in the specific use case neighborhood, and not reflect the generic properties of the consumer cluster population.

6. Conclusion

In this paper we have developed a simulation model which could forecast active power profiles for a population of Swedish

Table A1
Simulation parameters and initial data.

Parameter	Numerical value	Description
Δt_{app}	1 min	The simulation time step for the electricity appliance module. This is believed to be sufficient to reflect the variation in appliance usage by the occupants [16]
Δt_{DHW}	1 min	The simulation time step for the DHW module. Set according to Δt_{app}
Δt_{SH}	1 h	The simulation time step for the SH module. The data for outdoor temperatures and solar radiation are only available for an hourly time resolution. In addition, it is appreciated that the static variation of the building's heating system is slow [27]
N_{det}	41 houses	Obtained from the use case data (see Section 3)
β_{family}	1,...,7 members	The number of possible household members per detached house [18]
X_{family}	X_{family} is a stochastic variable	The following probabilities are given for the different household sizes β_{family} (starting from 1 member, and continuing to 7 members): 0.068, 0.38, 0.25, 0.22, 0.058, 0.012, 0.012 [18]

Table A2
The parameters and their assigned values for the appliance module. The applied conversion schemes for each appliance are also listed. NB: all of these are taken from [18,22].

Parameter	Numerical value	Description
$P_{fridge,ON}$	50 W	Power consumption of the fridge when operating. Operated according to a cyclic fashion. Conversion scheme A used
$P_{freezer,ON}$	80 W	Power consumption of the freezer when operating. Operated according to a cyclic fashion. Conversion scheme A used
$P_{cooking,ON}$	1500 W	Power consumption when cooking. To model the actual power need is very complex and would require assumptions regarding sub-activities (e.g., use of micro ovens, stoves, etc.). Assumed to be constant instead. Conversion scheme C used
$P_{dishwasher,1}$	1944 W	Dishwasher power consumption during cycle 1. Conversion scheme B used
$P_{dishwasher,2}$	120 W	Dishwasher power consumption during cycle 2
$P_{dishwasher,3}$	1920 W	Dishwasher power consumption during cycle 3
$k_{dishwasher,1}$	17 min	Dishwasher time duration of cycle 1
$k_{dishwasher,2}$	57 min	Dishwasher time duration of cycle 2
$k_{dishwasher,3}$	73 min	Dishwasher time duration of cycle 3
$P_{washer,1}$	1800 W	Washer power consumption during cycle 1 Conversion scheme B used
$P_{washer,2}$	150 W	Washer power consumption during cycle 2
$k_{washer,1}$	20 min	Washer time duration of cycle 1
$k_{washer,2}$	110 min	Washer time duration of cycle 2
$P_{TV,ON}$	100 W	Power consumption of TV when on. Conversion scheme C used
$P_{TV,STANDBY}$	20 W	Power consumption of TV in standby.
$P_{computer,ON}$	100 W	Power consumption of computer when on. Conversion scheme C used
$P_{computer,STANDBY}$	40 W	Power consumption of computer in standby
$P_{stereo,ON}$	30 W	Power consumption of stereo when on. Conversion scheme C used
$P_{stereo,STANDBY}$	6 W	Power consumption of stereo in standby
P_{add}	53 W/person	Additional power consumption per person (derived from activities not included in the Markov state list (see Table A6). Conversion scheme A used
L_{lim}	1000 lux	Limiting daylight level
P_{away}	40 W	Minimum lighting demand when there is no occupancy
P_{min}	80 W	Minimum lighting demand in an occupant state (depends on the actual sun light level)
P_{max}	200 W	Maximum lighting demand in an occupant state (depends on the actual sun light level)
Q_{adj}	0.1	The probability that the lighting level will be adapted with an incremental change (ΔP) when the solar light level is increased/ reduced
ΔP	40 W	The incremental power change
P_{sleep}	40 W	Lighting demand when the occupants are in a sleeping state

Table A3
The parameters and their assigned values for the base case for the DHW module.

Parameter	Numerical value	Description
T_{tank}^{ref}	80 °C	To avoid bacterial growth, it is recommended to maintain a high temperature [28]. Numerical value taken from a manufacturer [29]
T_{inlet}	10 °C	Is equal to the soil temperature [13], which varies between seasons. The value is assumed to be constant for simplicity, and taken from [17]
T_{outlet}	40 °C	Assumed to be a preferred water temperature for baths and showers
T_{max}	100 °C	[29]
P_{boil}	3.0 kW	Common boiler capacity for larger DHW tanks [29]
Cp_{water}	1.17 W h/kg °C	For a water temperature of 80 °C [9]
V_{tank}	300 l	Ordinary size for a household with four members [29]
$V_{i,a=shower}^{flow}$	10 l/min	Hot water flow for shower activities [17]
$V_{i,a=bath}^{flow}$	140 l	Hot water requirement for a bath [17]
Λ_{tank}	1 W/°C	The tank is assumed to be medium insulated [28]

Table A4
The parameters and their assigned values for the base case for the SH module.

Parameter	Numerical value	Description
d_{hight}	2.5 m	Height of the building. Assumed to be a one floor building
A_{floor}	100 m^2	Total floor area (assumed to be quadratic). Value taken from [8]
U_{floor}	0.4 W/m^2 °C	Transmission factor of the floor [24]
A_{roof}	100 m^2	Total roof area. Assumed to be flat and equal to A_{floor}
U_{roof}	0.25 W/m^2 °C	Transmission factor of the roof [24]
A_{window}	20% of A_{floor}	Total window area [24]
A_{window}^{side}	$A_{window}/4$	Assumed to be equally distributed over the building sides
U_{window}	3 W/m^2 °C	Transmission factor of two-layer windows [8]
A_{door}	4 m^2	Total door area. The house has one front and one back door
U_{door}	1.5 W/m^2 °C	Transmission factor of the doors [24]
A_{wall}	79 m^2	Total wall area (given by: $(4d_{hight}\sqrt{A_{floor}}) - A_{window} - A_{door}$)
U_{wall}	0.3 W/m^2 °C	Transmission factor of the walls [24]
Cp_{air}	0.33 W h/m^3 °C	At room temperature [30]
ρ_{air}	1.20 kg/m^3	Air density at room temperature [31]
N_{vent}	0.20 h^{-1}	The building has natural ventilation [24]
V_b	250 m^3	Given by: $d_{hight}A_{floor}$
α_{rc}	0.0	No heat is recycled
g	0.75	The value is given for two-layer windows [23]
$F_{curtain}$	0.70	All windows have garish curtains [23]
F_{frame}	0.85	Standard value for windows with the dimension of 1.7 × 1.0 m [23]
F_{shadow}	0.80	Only some shadowing effects caused by adjacent pine trees
P_{met}	90 W	Average heat radiation from a household member due to metabolism [30]. The individuals' occupancy patterns are taken from the electric appliance module in Section 2.2
γ_{app}	0.75	Assumed value for the utilization factor of heat losses from appliance usage.
γ_{dhw}	0.25	Assumed value for the utilization factor of heat losses from DHW usage.
T_{ref}	20 °C	Recommended indoor temperature for Swedish conditions [32]
τ	100 h	The buildings are assumed to be medium-heavy [24]
T_{DWT}	−15.0 °C	The value is given for the Stockholm region with a τ-value of four days [27]

Table A5
The data sets used for the exogenous variables.

Variable	Description	Geographical area	Time period	Resolution
$P_{measured}$	Measured consumption data from the substation. Data is provided by Vattenfall AB (a Swedish utility company) [kW]	Suburb to Stockholm	2011-05-25 to 2012-05-24	Hourly
T_{out}	Outdoor temperatures [°C]. Data provided by Vattenfall AB.	Stockholm	2011-05-25 to 2012-05-24	Hourly
P_{sun}	Solar radiation against a vertical area [W/m^2]. Data provided by Vattenfall AB.	Stockholm	2011-05-25 to 2012-05-24	Hourly
p_{spot}	Day-ahead electricity prices [€/MWh] [33]	SE3 price area [34]	2011-05-25 to 2012-05-24	Hourly
States	The data sets for the construction of Markov activity patterns for electric appliance and DHW usage, respectively [17]. NB: the size of each data set is 10x10x1440	Numerous geographical areas in Sweden	Autumn 1996	1 min

households living in detached houses. The simulations results for a Swedish use case showed that the model could produce realistic power demand profiles. The simulated profiles coincided especially well with the measured consumption during the summer time, which confirmed that the appliance and DHW modules were representative. However, for some periods during the winter period

Table A6
The Markov states for the electricity appliance module and DHW module, respectively [17,18].

State	Appliance module	DHW module
1	Away	Away
2	Sleeping	Sleeping
3	Cooking	Bathing
4	Dish washing	Showering
5	Washing	Other
6	TV	
7	Computer	
8	Audio	
9	Other	

(i.e., when the space heating module was active), there were significant deviations between the simulated and the measured data. For example, the real consumers reduced their energy consumption during a period of extreme electricity prices. As these aspects were not covered by the model, mismatches could be observed. Moreover, it is concluded that several potential sources caused the deviation in the results: (i) model simplifications and assumptions, (ii) insufficient background data of the neighborhood in question, and (iii) an incomplete representation of how the household members change their behavior due to different situations.

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Appendix A

The appendix include Fig. A1, and Tables A1–A6.

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