Energy 144 (2018) 1080–1091

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

A stochastic modelling and simulation approach to heating and cooling electricity consumption in the residential sector

E.J. Palacios-Garcia*, A. Moreno-Munoz, I. Santiago, J.M. Flores-Arias, F.J. Bellido-Outeirino, I.M. Moreno-Garcia

Universidad de Córdoba, Departamento A.C., Electrónica y T.E., Escuela Politécnica Superior, Campus de Rabanales, E-14071, Córdoba, Spain

ARTICLE INFO

Article history:
Received 25 July 2017
Received in revised form
23 November 2017
Accepted 16 December 2017
Available online 19 December 2017

Keywords:
Stochastic models
Heating consumption
Cooling consumption
Residential electricity demand
Occupancy
Smart grid

ABSTRACT

Heating and cooling consumption is one of the most significant terms in the total supply, which may come to represent half of the total demand in European countries. These appliances are supplied by a wide range of sources, being electrical devices of special interest in the Smart Grid. Current tools allow the assessment of the consumption with a high accuracy, nevertheless, they lack the temporal resolution or low-level details to study advanced control techniques. In this context, bottom-up stochastic models are a main tool to simulate high-resolution demand profiles. This paper presents a 1-min resolution model for electricity demand of heating and cooling appliances. The system is based on the simulation of individual households considering variables such as the number of residents, location, type of day (weekday or weekend) and date. It was used to simulate daily profiles which showed two main demand peaks, one during mornings and another during dinner time, for heating, and a high demand during midday for cooling consumption. Moreover, annual simulations depicted the importance of cooling appliances, which despite having a lower annual demand, can overcharge the grid with their concurrent utilisation, highlighting the usefulness of this tool for studying the impact of these devices.

1. Introduction

Based on the total energy demand, the residential sector represents on average 30% of the total energy consumption in the worldwide supply [1]. In the case of Spain, this figure is around 17% of the total energy consumption and 25% of the total electricity demand [2]. Moreover, this consumption is increasing in recent years due to the higher level of comfort required by the standards of modern society and by the widespread installation of new domestic appliances. These devices mainly comprise of electronic loads, whose supply quality specifications must also be accomplished [3].

Inside the global domestic electricity demand, different types of consumption can be distinguished such as those from lighting, general appliances, and heating and cooling electrical devices. From all of these sources, the energy demand due to heating and cooling appliances is probably the most significant and variable term [4]. The maximum heating demand in some European countries may come to represent more than half of the total energy consumed in the residential sector [5]. On the other hand, the cooling energy term is significantly lower, but with an upward trend [6]. Specifically in Spain, heating and cooling appliances represent between 15% and 18% of the total electricity consumption for a household, and usually, the heating systems have a higher energy demand than the cooling appliances [7].

Information about heating and cooling demand in the residential sector, as well as daily load profiles for various appliances, already exist for some European countries, specifically inside the REMODECE (Residential Monitoring to Decrease Energy Use and Carbon Emission in Europe) project [8]. However, Spain was not included in this study, and the different schedules of this country [9], as well as the major use of electrical appliances for heating, in contrast with other European countries, reinforce the importance of this analysis. This fact is especially significant in the context of the future Smart Grid. General domestic appliances are supplied with electricity, whereas a wide range of technologies and different energy sources such as natural gas, propane, fuel oil, and hot water (district heating) can be used for the heating systems, making the modelling process more complex than for other energy end uses

* Corresponding author.
E-mail addresses: p92pagae@uco.es (E.J. Palacios-Garcia), amoreno@uco.es (A. Moreno-Munoz), el1sachi@uco.es (I. Santiago), jmflores@uco.es (J.M. Flores-Arias), fjbellido@uco.es (F.J. Bellido-Outeirino), p92mogai@uco.es (I.M. Moreno-Garcia).

https://doi.org/10.1016/j.energy.2017.12.082
0360-5442/

[10].

In addition, not only do these devices have a heterogeneous distribution and a high demand, but the interdependence between their consumption and the weather conditions is even more significant. What is more, this relationship has been found to be more sensitive in the case of residential buildings due to the higher ratio of building envelope surfaces [11]. These external factors also influence the renewable resources integrated into the grid such as solar or wind power. Hence, to reduce the electricity consumption and provide a better understanding of this type of demand, it is essential to have a high level of resolution in the consumption profiles and a separate treatment of each specific energy end use [12,13], instead of merely knowing the aggregate figures [14]. This higher resolution of the results is also justified since most demand response (DR) strategies require a level of granularity between 5 and 30 min [15].

Previous works have studied the interdependence of electricity consumption and temperature mainly by means of so-called temperature response functions. A review of these models can be found in Fazeli et al. [16]. Pardo et al. [17] and Valor et al. [18] studied the seasonality of the electricity demand in Spain due to the influence of the temperature using linear symmetric models. Likewise, in the work of Moral-Carcedo and Vicéns-Otero [19], the influence of temperature on consumption was studied, emphasising the existence of a nonlinear relationship and proposing different regression strategies. In addition, some other works can be found in the context of Europe [20]. However, these functions can only estimate the daily trends, but not the actual daily behaviour of each heating or cooling load.

In parallel, a wide range of modelling systems based on information regarding the building structure and/or historical consumption records can also be found in the literature. These models are usually classified as white, black or grey-box. The white-box models or physical driven models require a detailed knowledge of the building structure and parameters. As opposed to, the black-box models or data-driven models establish a relationship between the source and the consumption by means of statistical techniques. Finally, the grey-box models lie somewhere in between, making use of both building parameters and statistical approaches [21].

Currently, many calculation tools that implement some of these models are available on the market and are widely applied such as EnergyPlus, TRNSYS, DOE-2, BLAST or ESP-r among others [22,23]. However, in the context of electricity consumption and grid impact simulation, they present some problems such as the necessity of a large amount of information regarding the constructions, low temporal resolutions (usually the minimum available time step is an hour), and high computational load. Consequently, if the heating and cooling electrical consumptions of a whole community composed of 500 or 1000 households are to be simulated, considering the heterogeneity and the residents' behaviour, their use is limited [24].

In this field, bottom-up modelling techniques have shown to be the solution to generate high-resolution energy profiles, while keeping the individual dispersion of the parameters, since they use data corresponding to entities below the global heating and cooling demand. Thus, by using occupancy variations of households, appliances consumption data, and temperature profiles, for instance, the daily electricity demand can be modelled [25].

Different models were previously developed using a bottom-up approach and stochastic techniques. Richardson et al. developed a model grounded in the usage of daily occupancy profiles [26], which were subsequently employed as the base data for the estimation of lighting [27] and appliances [28] consumption. Nevertheless, in this paper, only the space heating consumption was considered, relating its use with the occupancy and temperature seasonality. Later, a thermal-electrical model was developed by the same authors, but the heating appliances were supplied with hot water [29]. Likewise, Widén et al. also studied the different electricity and hot water profiles for Swedish households, but without specifically focusing on the energy consumed by heating devices [30]. Moreover, none of them considered the air conditioner consumption, due to the different climate characteristics of the locations.

Therefore, based on these considerations, the main objective and the novelty of this work is the development of a model to simulate not only the heating, but also the cooling electricity consumption in the residential sector, with a high temporal resolution, and enough flexibility so it can be adapted to different geographical locations. This model not only takes into account the temperature seasonality, but also some other parameters such as the type of day (weekday or weekend), the number of residents per household and the operation of the actual appliances. The methodology for developing the model, its application to the case of Spain and its capabilities for assessing the impact of cooling and heating appliances on the grid are presented.

The following structure will be used in the paper. Section 2 addresses the different data required, the methodology, and the simulation process. Next, Section 3 presents and discusses the results obtained using the proposed model, while in Section 4 a comparison with other previous studies and an error analysis is performed. Finally, Section 5 gives some conclusions of this work and future lines.

2. Methodology

The model follows a bottom-up approach and uses a stochastic algorithm to obtain the consumption profiles of the electricity demanded in the residential sector by the use of heating and cooling devices. Moreover, it is not very complex and computationally efficient. However, it previously requires some information related to the cooling and heating electricity consumptions, the appliances, the external weather conditions, and the consumers' behaviour. The following subsections describe the required datasets and the calculation procedure in detail.

2.1. Parameters and data

The input parameters comprise a collection of datasets that aims to assist in the energy modelling process. Five main groups of data can be distinguished which are the active occupancy of the dwellings, the external weather conditions, the relationship between external temperature and energy consumption, the type, technology, penetration rate and modelling techniques for the heating and cooling appliances and the household thermal losses. Each of these datasets mainly depends on the region to be studied. The following subsections explain the methodology employed to obtain and use these data.

2.1.1. Active occupancy in households

The occupancy profile is the cornerstone of the model since energy consumption in the residential sector is strongly related to people's activity at home. This occupancy is considered as an active household occupancy, meaning the number of residents at home and not sleeping. The residential daily occupancy profile was generated by simulating a stochastic model based on Markov-Chains theory and Monte-Carlo techniques. This modelling technique was previously implemented and validated by Richardson et al. for UK [26], Lopez et al. for Spain [9], and Widén et al. for

Sweden [31]. In addition, the model developed by Lopez et al. was already used in a previous work to simulate the lighting consumption in the residential sector showing accurate results [32].

The transition matrices for the Markov-Chain model were obtained from the Time Use Survey (TUS), conducted in Spain during the year 2010 covering 19,295 people living in 9541 homes [33]. However, similar surveys have been carried out in most of the European countries and their information is periodically collected by the harmonised European time use surveys (HETUS) [15]. In this study, each interviewee wrote information in a diary, during a completed day and with a frequency of 10 min, about the daily activities they performed, where these activities took place, and whether someone accompanied them.

The occupancy profile throughout the day was calculated as a transitional procedure, where the next state of occupancy depends on the previous one. In Markov-Chains theory, this is ruled by the so-called transition matrices [34,35]. Since it is a non-homogeneous Markov process, these matrices were calculated for each of the 144 instances of time (intervals of 10 min for a whole day). Using these matrices and the Markov-Chains calculation procedure, the daily active occupancy profiles were obtained, being able to differentiate between different numbers of residents, locations and the types of days (weekday or weekend). Finally, the results are supplied to the main algorithm to estimate the heating and cooling consumption.

2.1.2. Nonlinear response between temperature and energy demand. Smooth transition regression (STR)

The use of heating and cooling appliances is directly related to temperatures. Nevertheless, this relationship is clearly nonlinear since both increases and decreases in temperature around a so-called comfort threshold produce a consumption increment. Some authors previously estimated this threshold around 20 °C (68 °F). Sailor et al. [36] considered 21 °C (70 °F) for Florida and Giannakopoulos and Psiloglou [37] 22 °C (72 °F) for Greece. However, other authors such as Sarak and Satman [38] obtained 15 °C (59 °F) for Turkey, or in the case of Spain, 18 °C (65 °F) by Valor et al. [18].

The Heating and Cooling Degree days, HDD and CDD respectively, daily defined as the difference between the average temperature and a given base temperature T^* [39], are widely-used tools to study this relationship. Nevertheless, as different previous studies depicted, the main problem is the lack of consensus over the comfort reference temperature T^*, which has led to the existence of various bases for the HDD and CDD calculations. Furthermore, the HDD and CDD methods do not take into account the progressive transition between the cooling and heating consumption [20]. Consequently, in this work, the relationship between temperature and energy consumption intensity was studied by means of smooth transition regression (STR) techniques as it was previously done by Moral-Carcedo et al. [19].

The STR is based on two linear regression models whose influence is weighted by means of a logistic function that depends on temperature T and limits the cooling and heating trends. The total demand intensity $D(T)$ is obtained as the sum of the linear heating trend of coefficients a_1, b_1 and the cooling regression with coefficients a_2, b_2. Its expression is indicated in (1).

$$D(T) = (a_1 + b_1 T)(1 - G(T)) + (a_2 + b_2 T)G(T) \tag{1}$$

In this equation, $G(T)$ is the logistic function which varies in the interval [0,1] and has two parameters as indicated in (2). The parameter γ controls the smoothness of the transition between the heating and the cooling area, whereas c determines the value of T for which the change of state occurs.

$$G(T) = \frac{1}{1 + e^{-\gamma(T-c)}} \tag{2}$$

To establish the relationship between the temperature T and the consumption D, both daily temperatures and consumption values were collected for the studied region. The values of the daily temperatures used in this work were specifically obtained from the State Meteorological Agency (AEMET) comprising of hourly values for the years 2014, 2015, and 2016 [40]. Seven representative climate zones were selected based on the cluster analysis performed by Moral-Carcedo et al. [19] taking a reference city for the daily temperature profiles. The location of each zone, as well as the referenced cities, are illustrated in Fig. 1.

As it can be observed each of these climate zones represent a different percentage of the whole population. Thus, a weight factor was assigned to each zone according to the 2015 population census of the country, so the total consumption of the country could be related to the weighted temperatures. The selected data are indicated in Table 1.

As regards the Electricity demand, it was obtained from the national network operator in Spain, Red Electrica Española (REE) [41]. These data include the total aggregate consumption of the country with a 10-min resolution for the same years as the temperature (2014, 2015, and 2016). Unfortunately, no disaggregate data for the residential sectors were available, so a preprocessing was carried out to eliminate the influence of holiday periods, as well as sectors which are insensitive to the temperature such as large industrial consumers. Therefore, the official holiday periods were eliminated and the daily average consumption of the industrial sector was subtracted from the aggregate figure.

Finally, the historical temperature data indicated above were employed as the input explanatory variable, whereas the consumption data represented the output response variable. The four coefficients of the linear functions for the heating a_1, b_1 and cooling regression a_2, b_2, as well as the two parameters of the logistic function γ and c, were obtained using the non-linear least squares method as proposed by Teräsvirta [42].

2.1.3. Cooling and heating appliances percentages

The active occupancy and temperature influence the heating and cooling consumption. Nevertheless, the number and

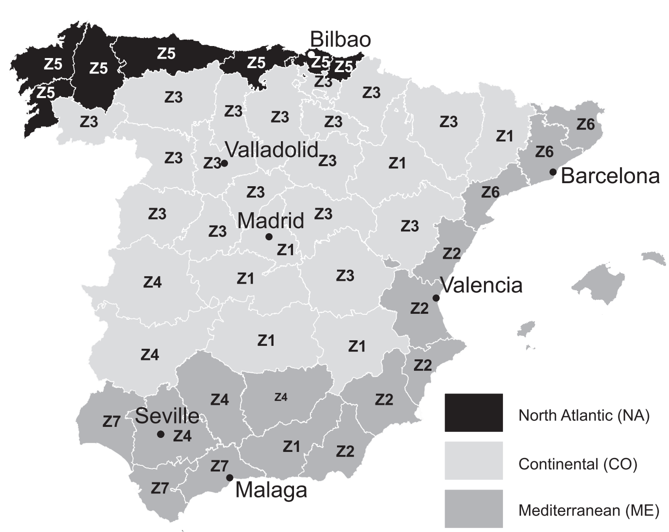

Fig. 1. Climate zones for the study of temperatures (Z) and for the appliance selection (coloured).

Table 1
Selected climate zones, reference cities and weight factor for the study.

Zone	Weight	Reference City
Z1	0.2391	Madrid
Z2	0.1647	Valencia
Z3	0.1073	Valladolid
Z4	0.1037	Seville
Z5	0.1451	Bilbao
Z6	0.1629	Barcelona
Z7	0.0773	Malaga

technology of the appliances installed in each household will eventually define the demand. Hence, information about the possession rate of these appliances, as well as their technology and distribution, is necessary for an accurate estimation. Furthermore, this information will be necessary for each one of the geographical locations in which the simulations will be implemented since the rates of possession might vary even within the same country.

The percentages of installed heating and cooling appliances in Spain were obtained from the report published by the Institute of Diversification and Saving of Energy (Instituto para la Diversificación y Ahorro de la Energía, IDAE) [7]. In this report, corresponding to the year 2011, an analysis of the energy consumption in Spain was carried out, distinguishing between the energy source, energy end use, and climate region. Three climate regions were defined: the North Atlantic (NA) area (black), the Continental (CO) region (light grey) and the Mediterranean (ME) region (dark grey). Each of them is represented in Fig. 1.

Three different figures were used for the simulation model. For simplification, the subscript H/C will be employed in all of the expressions meaning that the calculus is performed for both heating and cooling appliances. First, the probabilities of a household having at least one heating p_H and/or one cooling p_C appliance respectively were calculated for each region r. For that aim, from all the households N_h the total number of houses H with one or more heating or cooling appliance $a_{H/C}$ were divided between the total number of households in the studied region. The employed expression can be seen in (3).

$$p_{H/C}(r) = \frac{\sum_{h=1}^{N_h} H\left(h, r \middle| a_{H/C}(h) \geq 1\right)}{\sum_{h=1}^{N_h} H(h, r)} \quad (3)$$

Subsequently, the average number of appliances per each household with heating or cooling installation $\overline{A_H}$ and $\overline{A_C}$ was determined, by dividing the total number of devices between the number of houses with heating or cooling installation for each case as indicated in (4). This means that, whereas some households might not have cooling or heating appliances at all, the ones which possess these kinds of devices might have installed more than one for this purpose.

$$\overline{A_{H/C}}(r) = \frac{\sum_{h=1}^{N_h} a_{H/C}(h, r)}{\sum_{h=1}^{N_h} H\left(h, r \middle| a_{H/C}(h) \geq 1\right)} \quad (4)$$

The probability and the average number of appliances for each region can be observed in Table 2. The heating systems are installed in almost every house with an average number of devices per household greater than one. The lower percentage of possession is found in the Mediterranean region where winters are softer. Regarding the cooling appliances, the situation is completely different with almost no penetration in the NA region, while in the CO and the ME areas the percentages are significant but not as high as in the case of the heating equipment.

In addition to the installation rate and the number of appliances per household, the type of each one was studied. The probability of an appliance belonging to a certain technology or type $p_{d_{H/C}}$ was obtained by dividing the total number of each type of appliance d_H or d_C between the total number of appliances installed in each region as expressed in (5).

$$p_{d_{H/C}}\left(r, d_{H/C}\right) = \frac{\sum_{h=1}^{N_h} a_{H/C}\left(h, r, d_{H/C}\right)}{\sum_{h=1}^{N_h} a_{H/C}(h, r)} \quad (5)$$

Table 3 shows the obtained percentages for different types of appliances considered, differentiating between climatological regions. It can be observed that a significant variation is obtained between the values corresponding to the ME region and those corresponding to the others. Specifically, the heating appliances such as the conventional or the condensing boilers, which work mainly with natural gas, have a lower percentage of use in ME climate than in any of the other regions. However, the percentages of electric heating appliances are higher in the ME zone, highlighting the electrical heater and the electric radiator, along with non-reversible heat pumps.

Among all these devices, this paper only considers those appliances which are supplied with electricity, which are the non-reversible heat pumps, reversible heat pumps, electric radiators and electric heaters. That is a key point since, whereas in the NA region the use of heating devices is significantly higher than in the ME region, as it was observed in Table 2, the appliances in the NA region are not usually supplied with electricity, while the ones in the ME are, therefore, their impact on the grid is higher.

As regards cooling appliances, also shown in Table 3, the observed percentages within the Mediterranean region are higher too. The use of reversible pump systems for cooling achieves almost 83%, whereas fans and air conditioners represent a relatively small percentage. It should be also emphasised that reversible pump systems could be used for both cooling and heating, nevertheless, they have a marginal usage rate for heating. In this case, all cooling appliances are supplied with electricity, consequently, the three proposed, fans, air conditioners, and reversible pump systems, were considered in the model.

2.1.4. Model of an appliance and thermal behaviour

Each heating or cooling electrical device is modelled using a series of parameters that identify its behaviour. The definition combines the operation of the device and the influence of the insulation and external conditions. In this way, each appliance is assigned with an on power P_{on}, a coefficient of performance COP, an

Table 2
Percentage use of heating and cooling installation. Average number of appliances per household.

Region	Heating		Cooling	
	Households with Installation (p_H)	Appliances per Household ($\overline{A_H}$)	Households with Installation (p_C)	Appliances per Household ($\overline{A_C}$)
NA	0.9275	1.18	0.0112	0.98
CO	0.9505	1.23	0.3986	0.99
ME	0.8615	1.41	0.6765	0.99
Spain	0.9001	1.31	0.4959	0.99

Table 3
Percentage use of each heating and cooling technology.

Appliance	NA ($p_{d_{H/C}}$)	CO ($p_{d_{H/C}}$)	ME ($p_{d_{H/C}}$)	Spain ($p_{d_{H/C}}$)
Conventional Boiler	0.4972	0.6098	0.2062	0.3756
Condensing Boiler	0.0144	0.0162	0.0063	0.0106
Not Electric Heater	0.0432	0.0300	0.0375	0.0357
Solar Panels	0.0115	0.0101	0.0052	0.0076
Other Heating	0.0649	0.0572	0.0605	0.0599
Non-reversible Pump (Heating)	0.0025	0.0672	0.2459	0.1571
Reversible Pump (Heating)	0.0078	0.0045	0.0039	0.0046
Electric Radiator	0.2138	0.1152	0.1977	0.1722
Electric Heater	0.1447	0.0898	0.2368	0.1768
Fan	0.6683	0.0890	0.0495	0.0620
Air Conditioner	0.0485	0.2543	0.1215	0.1570
Reversible Pump (Cooling)	0.2832	0.6567	0.8293	0.7810

on time t_{on}, an off delay t_{off}, a power factor PF and a probability of having a thermostat control P_{Th}, which have associated an average threshold temperature T_{th} that varies with a given standard deviation δ whose value was obtained from Ref. [43].

The values for t_{on} and t_{off} were assigned by considering a one-thermal mass equivalent thermal parameter (ETP) model of a household as it was proposed by Smullin [44]. The thermal mass C is coupled with the outdoor temperature T_a by means of the equivalence transmittance radio of the house denoted as H. In addition, a coefficient Q_{loss} has been added to represent the internal gains. The expression of t_{off} in minutes for the cooling case is indicated in (6) where $T_{thL} = T_{Th} - \delta$ represents the thermostat low threshold and $T_{thH} = T_{Th} + \delta$ is the upper bound. This expression is only valid when $T_a + \frac{Q_{loss}}{H} > T_{thH}$ since, otherwise, the temperature will be between the comfort limits and no cooling will be necessary, meaning $t_{off} = \infty$. Practically, this value was considered as an hour for the study, a value long enough to allow for further switch-on events.

$$t_{off}(T_a) = \begin{cases} \dfrac{C}{H\cdot 60} \ln\left[\dfrac{T_a - T_{thL} + \dfrac{Q_{loss}}{H}}{T_a - T_{thH} + \dfrac{Q_{loss}}{H}}\right], & T_a + \dfrac{Q_{loss}}{H} > T_{thH} \\ 60\,, & T_a + \dfrac{Q_{loss}}{H} \le T_{thH} \end{cases} \quad (6)$$

In the same way, the t_{on} for the cooling is expressed in (7) where Q_c is the heat removed, considered positive for the cooling case and calculated as (8). As well as in the previous case, this expression is only valid when the removed heat can compensate the rest of the thermal losses, for the rest of the cases where the operating time will be equal to infinity, again a maximum period of operation of an hour was selected.

$$t_{on}(T_a) = \begin{cases} \dfrac{C}{H\cdot 60} \ln\left[\dfrac{T_{thH} - T_a + \dfrac{Q_C - Q_{loss}}{H}}{T_{thL} - T_a + \dfrac{Q_C - Q_{loss}}{H}}\right], & T_a + \dfrac{Q_{loss}}{H} - T_{thL} < Q_c \\ 60\,, & T_a + \dfrac{Q_{loss}}{H} - T_{thL} \ge Q_c \end{cases} \quad (7)$$

$$Q_c = COP \times P_{on} \quad (8)$$

The Equations (6)–(8) are also valid for the heating case, but the thresholds T_{thL} and T_{thH} are interchanged since the behaviour of the hysteresis band is the opposite and the heat Q_c from the heating appliances has to be considered negative.

In the case of non-thermostat controlled appliances, no t_{off} is assigned and the t_{on} is regulated by the users' behaviour and the external conditions with a continuous operation until the switch-off event. The mean power, COP value, as well as an average estimated power factor, were obtained after a study of the main available products from some heating and cooling manufacturers [45–48]. In addition, the t_{on} of each appliance for the non-controlled cases was selected based on [49], where the use patterns of the domestic appliances within Europe were studied. Table 4 lists the selected values.

Regarding the insulation parameters and the type of construction that allows for the calculation of the parameters C and H, the data collected in the European project ENTRANZE [50] were considered. The values are presented in Table 5.

2.2. Simulation methodology

The simulation process was implemented in two stages. First, each dwelling is assigned a group of heating and cooling devices, as well as thermal characteristics, depending on the climate zone. Furthermore, for the selected period and the number of residents the active occupancy profile is estimated. After this and using the daily temperature profile, the system determines the on/off events of each appliance with 1-min resolution, consequently, calculating the electrical consumption that they have associated. Fig. 2 depicts this process whose operation is described in the following subsections.

2.2.1. Initialisation process

The initialisation process is carried out for each of the N_h households that will be simulated. In this stage and after loading the probabilities for the selected region, the system defines the heating and cooling appliances, and the insulation characteristics. The appliances are selected using three stochastic processes. First, two random numbers r_H and r_C uniformly distributed between [0,1] are generated and used in an inverse sampling in the cumulative distribution function (CDF) of having heating P_H or cooling P_C devices installed, where $P_{H/C}$ are Bernoulli distributions with

Table 4
Parameters of the appliances considered in the model.

Appliance	P_{on} [W]	COP	PF	P_{Th} [%]	T_{th} [°C]	δ [°C]
Non-reversible Pump (Heating)	1142	4.05	0.9	86.46	24.5	4.52
Reversible Pump (Heating)	1151	4.02	0.9	86.46		
Electric Radiator	2200	1	1	75.72		
Electric Heater	1200	1	1	57.81		
Fan	70	1	0.9	0	25.3	5.87
Air Conditioner	1200	3.34	0.9	100		
Reversible Pump (Cooling)	1300	3.75	0.9	100		

Table 5
Distribution of dwelling stock for the studied region.

Year	Stock (%)	U Floor [W/m^{2}K]	U Walls [W/m^{2}K]	U Ceiling [W/m^{2}K]	U Windows [W/m^{2}K]	Area [m^2]
<1945	13	2.45	2.52	1.75	5.7	87
1945–1969	23	2.45	2.13	1.37	5.7	73
1970–1979	19	2.45	2.13	1.37	5.7	86
1980–1989	12	0.8	1.6	1	3.3	88
1990–1999	12	0.8	1.6	1	3.3	88
2000–2008	20	0.7	0.8	0.54	3.1	99

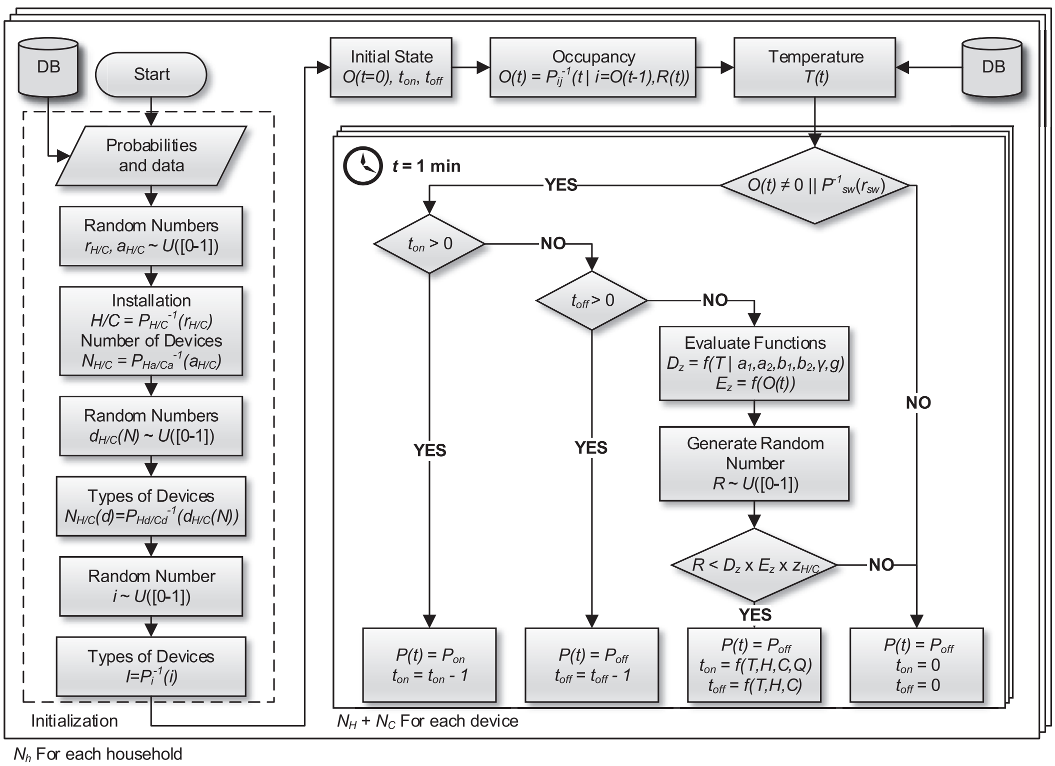

Fig. 2. Flowchart of the simulation algorithm.

$p = p_{H/C}$, calculated as indicated in (3).

If this operation equals 1 for the heating H and/or the cooling C installation, then the number of devices of each type is determined. In this process, two more random numbers are generated a_H and a_C, and then sampled inversely in the normal distributions P_{Ha}, P_{Ca} with $\mu_{H/C} = \overline{A_{H/C}}$, as in (4), and $\sigma_{H/C} = 1$. After this, the number of heating N_H and cooling N_C appliances is calculated.

Subsequently, each appliance is finally assigned to a given technology from the ones considered in Table 3. For that aim, a random number $d_{H/C}$ is generated for each of the $N_{H/C}$ appliances and used in an inverse sampling over the discrete CDF of an appliance belonging to a certain technology $P_{Hd/Cd}$, whose probability mass function (PMF) is defined by the columns corresponding to each region in Table 3. As it was indicated, the modelling process only considers those appliances supplied with electricity. Thus, in some cases, although the number of heating N_H and cooling N_C devices in the previous stage could be different to zero, if the selected technology in this step does not use electricity, the final number of devices will be zero.

Once the appliances are distributed, the insulation parameters of each house are assigned. This process is performed by means of a random number i uniformly distributed between [0,1], which is used to perform a random sampling over the discrete CDF of households' stock P_i. The PMF p_i in this case is defined in Table 5 as the stock of households of each year and insulation characteristics.

After the definition of the household, three steps are carried out before starting the simulation process for each minute. First, the initial conditions of the system are calculated, which means the initial occupancy $O(t=0)$ as well as the operation point of each appliance. The initial occupancy is assigned based on the discrete CDF of active occupants for the initial minute of the simulation, whereas t_{on} and t_{off} are calculated for each device using (6), (7), and (8), but multiplying the duty cycle by a random number between [0,1].

After that, the occupancy profile for the selected period is calculated with a 10-min resolution, using the number of residents in the household and the type of day. For each 10-min instance t_{10}, a random sampled number R_t uniformly distributed between 0 and 1 is generated. After this, the random number is employed to calculate the following state of occupancy $O_n(t_{10})$ by means of the inverse probability sampling of transition matrix P_{ij} for the step t_{10} and considering the previous occupancy state of the dwelling $O_n(t_{10}-1)$ as indicated in (9).

$$O_n(t_{10}) = P_{ij}^{-1}(t_{10}|O_n(t_{10}-1), R_t) \quad (9)$$

Since the occupancy profile has a lower resolution than the simulation algorithm, the occupancy is considered constant for each 10-min interval, an approximation that has no impact on the results since the occupancy changes have a much lower frequency than the appliances' activation and deactivation events.

Finally, before starting the simulation, the temperature profile which is contained in a database, was accessed depending on the date and selected region, and subsequently loaded. The profiles in the database are stored with 1-min resolution, but they were linearly interpolated from 1-h resolution data as indicated in Section 2.1.2. Nevertheless, the evolution of the temperature during the day is slow and hourly interpolated data were found to be enough to estimate accurate profiles. What is more, the structure of the system allows new data to be stored with more resolution when available.

2.2.2. 1-Minute consumption simulation

The simulation process after the initialisation of each household is performed for every minute of the simulation interval and for every appliance, evaluating the state of them and updating the t_{on}, t_{off}, and $P(t)$ accordingly. The whole process can be observed on the right side of Fig. 2.

In this way, first, the system checks the active occupancy of the dwelling, being a necessary condition for the activation of the heating and cooling appliances, but not sufficient. Nevertheless, since some appliances can be programmed to operate over periods of inactivity (absent or sleeping residents) an additional condition was added when no occupancy was detected. Thus, when no active occupants are in the dwelling a random number r_{sw} is generated and inversely sampled over the discrete CDF P_{sw} that follows a Bernoulli distribution with $p = 0.05$. This parameter is an average probability obtained from the survey on households and environment [43] where the interviewees indicated if they left the heating and cooling devices activated when they were either absent or sleeping. If the result of this comparison is false, the appliance is deactivated and its P_{off} is added to the 1-min total power profile $P(t)$.

In case there is active occupancy, the appliance can be in three different states: active $(t_{on} > 0)$, waiting $(t_{off} > 0)$ or deactivated $\left(t = 0,\ t_{off} = 0\right)$. If the appliance is in the active state, its operation cycle is decreased and its active power P_{on} is added to the total power profile. When the appliance is waiting, the off cycle, in this case, is decreased and the inactive power P_{off} is aggregated to the total load. Otherwise, if the appliance is completely deactivated the possibility of turning it on is evaluated based on the temperature profile, the active occupancy and the house insulation parameters. Two stages comprise this evaluation.

First, the relationship between the average daily temperature and the consumption intensity is evaluated by means of the STR function $D(T)$ previously described. This function was normalised (D_z) by dividing the generated values between the demand in the estimated equilibrium temperature (18.7 °C) and depends on the fitted parameters that will be presented in the results. Likewise, the active occupancy is considered but as an effective occupancy [12]. This relationship was obtained from the data provided by U. S. Energy Department in the so-called Residential Energy Consumption Survey [51]. This survey was carried out in 2009 in the United States and includes information about the end uses of each household and their characteristics (number of residents, appliances), allowing to relate the number of residents per household with the equivalent yearly consumption $E(O(t))$. As in the previous case, it was divided between the average consumption for 1-resident houses so it was normalised $E_z(O(t))$. This normalisation also allowed us to use U.S. consumption data although the model is being applied to Spain.

By means of these two indices D_z and E_z and a calibration scalar for each type of appliance, $z_{H/C}$, which is discussed in the following section, a probability is obtained and a comparison is performed with a randomly generated number R. In case this number is lower than the obtained probability the conditions of temperature and occupancy might require the use of heating or cooling appliances respectively. Otherwise, the appliance will remain inactive.

Finally, if the conditions determined that it is possible to use the appliance, the active t_{on} and waiting time t_{off} are assigned based on (6) and (7). These final equations take into account the household thermal characteristics and the high-resolution temperature profile. Therefore, depending on the values of these parameters the final assigned operation time could also be null, but they allowed for the simulation of the low-level behaviour of the appliances during the day, one of the main novelties of this model.

2.3. Calibration

Due to the random and stochastic techniques employed, the power and energy results are not scaled with the real values observed within the region where the simulation was accomplished. Therefore, an iterative process was implemented to calibrate both heating and cooling consumption by means of z_H and z_C variables, which previously appeared in Fig. 2. To obtain each of these scalars, 10 iterations over 1000 different households N_h were performed, considering the heating and the cooling appliances separately.

$$f_{H/C}(s) = \frac{E^*_{H/C}}{\left[\frac{1}{N}\sum_{h=1}^{N_h} E_{H/C}(h)\right]} \quad (10)$$

$$z_{H/C}(s) = z_{H/C}(s-1) \cdot f_{H/C}(s) \quad (11)$$

Before starting the calibration process, a value of 1 is given to $z_{H/C}$. In each of the 10 iterations (denoted by s) $f_{H/C}(s)$ and $z_{H/C}(s)$ are determined by means of (10) and (11). $f_{H/C}(s)$ is the quotient between the average value of the heating application consumption observed within the studied region $E^*_{H/C}$, taken as reference, and the average result of the 1000 simulated houses, being $E_{H/C}(h)$ the energy consumed during a year, and for a specific household h. The value of E^*_H was selected as 265.899 kWh and E^*_C equals to 139.311 kWh [2]. $z_{H/C}(s)$ is the updated scalar value obtained for each iteration s, which will be inserted in the next iteration using the Equation (11). This figure will be employed to update the value of the scalar for each iteration, where $z_{H/C}(s-1)$ is the value of the scalar obtained in the previous iteration (or 1 if it is the first iteration).

3. Results

3.1. Model implementation

The simulation process was implemented using JAVA programming language. This language and its object-oriented philosophy facilitated a flexible implementation with interoperability between operating systems, and other features required in this development such as database and network connectivity, concurrency and functional programming. The system was developed as a JAVA enterprise application and was provided with a RESTful

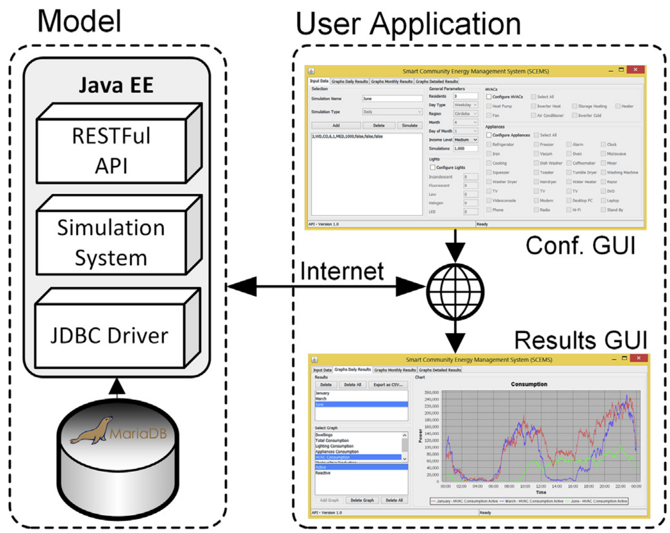

Fig. 3. Logical implementation of the simulation system and developed GUI.

application programming interface (API) and a database to store the required information as it is illustrated in Fig. 3. Using this API, the simulation parameters and the results can be sent to the system from any device that implements a network connection and the HTTP protocol which increases the usability and integrability of the system in other simulation platforms. In addition, a general user application (GUI) was developed to ease the use of the system, where the simulation parameters can be configured (Conf. GUI) and the results visualised (Results GUI). This GUI is integrated into the previous one developed in Ref. [32].

3.2. Temperature-energy STR function

The methodology described in Section 2.1.2 used the weighted temperature data by region and the filtered electricity consumption to estimate the STR model by means of the non-linear least squares method as proposed by Teräsvirta [42]. The scatter plot in Fig. 4 illustrates both the data point (black round symbols) and the fitted values (grey diamond symbols). As can be seen, the estimated trend clearly matched the observed values. An equilibrium temperature was observed with a value of 17.8 °C for which the electricity consumption is insensitive. This value was almost similar to the one previously found by Valor et al. [18]. Any value above or

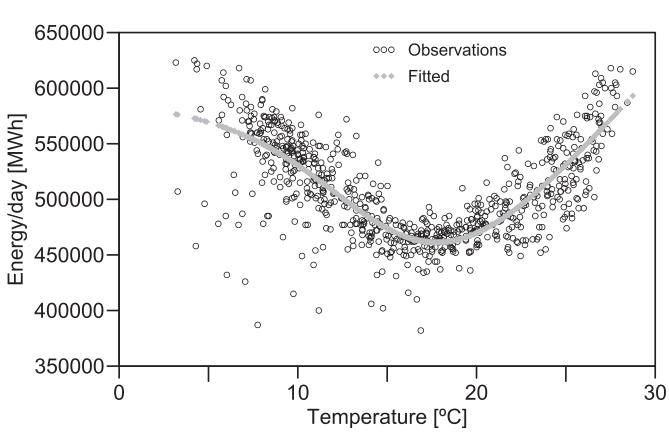

Fig. 4. Smooth Transition Regression (STR) model for temperature-demand relationship.

Table 6
Estimated values for the STR model using nonlinear least squares.

Parameter	Estimate	Std. Error
a_1	589,700	18,950
b_1	0	7236
a_2	90,370	90,190
b_2	17,500	3224
γ	0.2911	0.06241
c	15.16	1.798

below this threshold has associated a consumption increase.

The estimated parameters are listed in Table 6 together with their standard errors. It can be seen that the slope modelling the heating consumption b_1 was estimated as zero with no significance for the model. That is due to the deviation of the parameter c, which regulates the transition value for the logistic function, from the equilibrium temperature (17.8 °C). This is caused by the increase that the cooling consumption presents. In this way, whereas the heating demand reached a saturation point for lower temperature values, the cooling consumption increased even at high temperatures. This effect confirms the previous observations of Moral-Carcedo and Vicéns-Otero [19] for data from 1995 to 2003. In that study, a small upward trend in the cooling demand was observed throughout the study years. This trend is clearly visible in this study where data from 2014 to 2016 have been used, showing the higher penetration rate of cooling devices.

3.3. Daily aggregate trends

The results were obtained using the presented calculation algorithm and with the aid of the developed GUI. The individual daily profiles of an isolated house present a chaotic pattern as might be expected of a stochastic model. Therefore, in order to observe and detect aggregate trends, daily simulations were performed considering a group N_h houses located in different regions and for different dates. The daily consumption vectors of each household P_{1440} were aggregated according to (12):

$$P_{1440}^{N_h} = \sum_{h=1}^{N_h} (P_{1440})_h \tag{12}$$

Fig. 5 represents the daily consumption profiles for an aggregate of 10,000 households, simulated for a weekday in the locations of (a) Seville, (b) Madrid and (c) Bilbao and for 4 relevant dates in the year 2015.

As it can be appreciated in Fig. 5, the shapes and trends of the daily consumption profiles are highly related to the season and consequently with the type of appliances which are used in each case. During the months of January, February, March and part of April, heating appliances are responsible for the daily curve shape, so the highest consumption peaks are associated with the periods of high active occupancy and low temperature. As it can be observed for the 1st January (solid black line), these two peaks take place from 08:00 h to 12:00 h and from 20:00 h to 00:00 h.

Nevertheless, their amplitudes depend on the location. Thus, for (a) Seville, located in the south, the peaks are more pronounced due to the higher temperatures during midday, but the consumption is also larger since mainly electrical appliances are used. In the case of (b) Madrid the installation rate of electrical appliances is lower so the power demand is too. The same trend is observed in (c) Bilbao, which due to the lower temperatures, presents a higher consumption than (b) Madrid even though the installation rate of electrical heating devices is lower.

In the Summer scenario, the 28th June (solid grey line), the daily

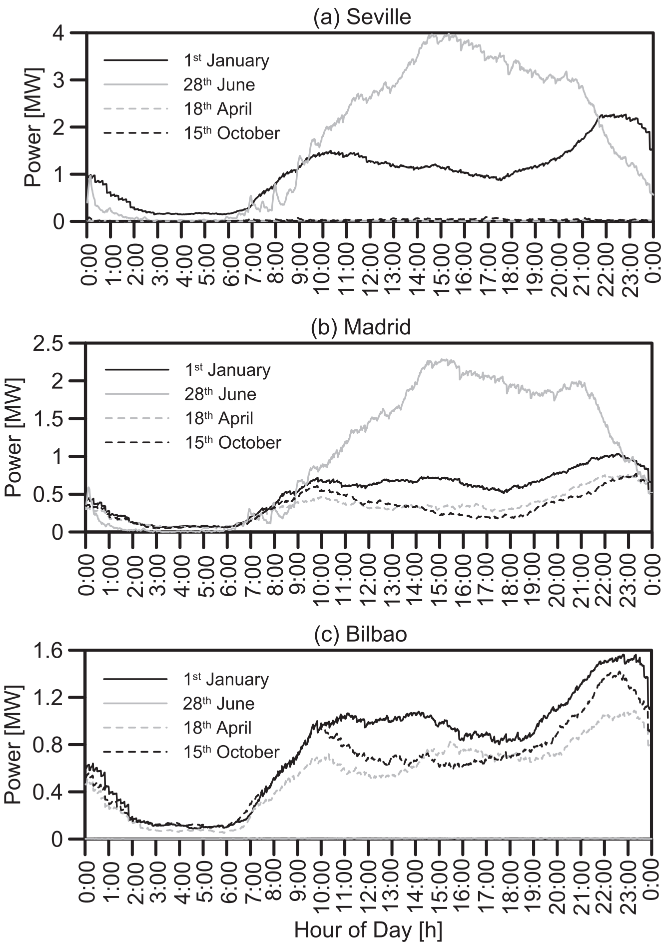

Fig. 5. Daily consumption profiles for heating and cooling appliances.

profile shows the main demand peak from 13:00 h to 18:00 h. This higher demand can only be observed in (a) Seville and (b) Madrid, whereas in (c) Bilbao almost no energy consumption takes place during the summer months as the percentage of cooling appliances is extremely low (around 1%) and the temperatures are moderate. It should also be pointed out that the cooling peak is almost twice the amplitude of the heating peaks. This higher figure is related to the hot and dry summers of the studied locations and the fact that only electrical appliances are employed for cooling purposes.

Finally, two other days, one in spring the 18th April (dashed grey line) and another in autumn the 15th October (dashed black line) were studied. They correspond to transition days between the heating and cooling consumption and vice versa. In the case of (a) Seville, no consumption is observed in these days as the city is located in the south and the temperatures are usually within the comfort limits in these dates. In contrast, both (b) Madrid and (c) Bilbao present consumption for the studied days, although the power demand is not as high as in the winter scenario.

For the 18th April, the consumption has a flat shape during the day once the active occupancy has started. In the case of the 15th October, the consumption figures are almost similar but the morning and night peaks are more pronounced since the thermal amplitude during this month is higher. To visualise this a broader time horizon was studied in the following section.

3.4. Annual demand

The daily estimation was extended to a year, although the model allows for simulating even a sequence of years, providing the temperature data are available in the system database. Using the three previous locations Seville, Madrid and Bilbao a cluster of 1000 households was evaluated for the year 2015. The results are illustrated in Fig. 6, where the daily energy demand for the whole year is represented. The results were obtained by calculating the daily energy of the aggregate power consumption P_i of each household h for the N_h houses selected for the simulation as expressed in (13).

$$E_{365}^{N_h} = \sum_{h=1}^{N_h} \left(\left[\sum_{i=1}^{1440} \frac{1}{60} [P_i] \right]_{365} \right)_h \tag{13}$$

The annual profiles show the peculiarities of each climate zone. In the case of Bilbao in the North (solid grey line), the consumption during the winter season is similar to the one found in Seville in the South (dashed black line). Nevertheless, although the temperatures in Seville are higher than in Bilbao the percentage of electrical appliances in Seville is almost twice as high as Bilbao. In the case of Madrid (solid black line), the use of electrical heating appliances is similar to the one in Bilbao but the temperatures are not so cold so the consumption is slightly lower.

Regarding the summer, the trend is completely opposite. Bilbao (solid grey line) shows no consumption at all during this period, whereas Seville (dashed black line) and Madrid (solid black line)

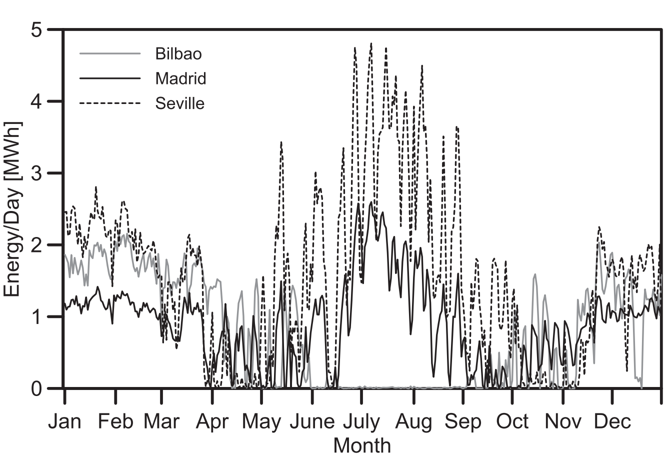

Fig. 6. Annual Demand Profiles for different locations.

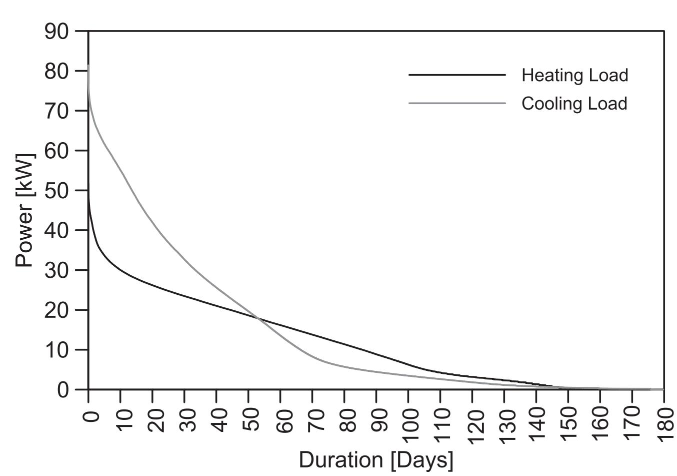

Fig. 7. Load duration curve for 200 households located in Seville during a year.

have a considerable high energy demand, being the highest consumptions of the year found during the months of July and August. Likewise, if the transition between the heating and cooling consumption is observed, Seville presents a very low or almost null consumption from April to the middle of May and from October to the middle of November, whereas Madrid and Bilbao have a low demand but still not zero.

3.5. Impact on the grid

The two previous simulation methodologies were combined to obtain a 1-min resolution annual power profile. Using this profile, the load duration curve for both heating and cooling demand was calculated. In this way, a simulation of 200 households located in Seville was performed for the year 2015. Fig. 7 represents the obtained results where the Y-Axis indicates the instantaneous power demand for the whole cluster of households and the X-Axis is the amount of time that this instantaneous power demand occurs during the studied year.

As it can be observed in Fig. 7, the cooling load presents higher instantaneous power demand than the heating curve for an equivalent time longer than 50 days a year. However, the heating load has a significant value for almost 110 days whereas the cooling load only presents a high consumption for 70 days. Hence, although the annual cooling energy demand is generally lower than the heating load, the concurrence of a high-power demand in a short period might cause the overcharge of the network. This is of special interest in the current context due to the integration of more renewable energy resources and the purchase of more cooling appliances to increase the comfort level.

4. Validation

The accuracy of the proposed model was evaluated by comparing the daily generated profiles with previous works. The main reference in the European context that includes high-resolution disaggregated data is the REMODECE project [52]. This research did not take into account Spain so a direct comparison cannot be performed. Nevertheless, other regions with similar climate characteristics were used in order to evaluate and validate the profiles. For this aim, the database of the REMODECE project was queried [8]. This database includes not only data from the REMODECE project (years 2006–2008) but also data from some other local projects such the Eureco project (years 2000–2001) in the case of Italy.

To allow the comparison of the profiles generated by the proposed model and the individual hourly energy records of the REMODECE project for each household, the model was used to estimate the average curves for one day of winter and one day of summer, calculated for 10,000 households, and weighted between the different studied location of Spain. Subsequently, the hourly energy consumption was calculated and compared with the average results of the REMODECE project for France and Portugal in the case of winter and Italy and Greece for the summer consumption. The results can be seen in Fig. 8 where the winter profiles are presented in the subfigure (a) and the summer consumption in the subfigure (b).

Table 7
Comparison between the developed model and REMODECE data for different countries and dates.

Country	Winter		Summer	
	France	Portugal	Italy	Greece
N Meas.	27	5	10	11
RMSE	849	102	222	172
NVF	0.7009	0.1601	3.5866	0.6905
E/day [kWh]	24.3	6.13	2.82	4.97
E/day [kWh] Model	4.61		5.63	

In the case of the winter profiles (a), a larger energy consumption is presented in the case of France with a consumption peak during the night, which might be justified due to the higher installation rate of storage heating systems and the colder winters. Nevertheless, the profile obtained for an average Portuguese household almost resembles the one estimated by the model. On the other hand, in the case of the summer profiles (b), the energy estimated by the model is larger than the one obtained for Greece or Italy in the REMODECE project. However, the different daily schedules, as well as the milder temperatures of these countries due to the sea influence, could lead to these different figures and profiles.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=0}^{n}\left(P_{Model}(t) - P_{Meas}(t)\right)^2} \tag{14}$$

$$\mathrm{NVF} = \frac{\mathrm{MSE}}{\overline{P_{Meas}}^{2}} = \frac{\sum_{t=0}^{n}\left(P_{Model}(t) - P_{Meas}(t)\right)^2}{n\left(\frac{1}{n}\sum_{t=0}^{n}P_{Meas}(t)\right)^2} \tag{15}$$

The profiles were numerically evaluated by means of two indicators, the root mean squared error (RMSE) expressed in (14), and the normalised variation factor (NVF), a pseudo-variance in which the mean squared error (MSE) between the generated profiles $P_{Model}(t)$ and the measured data from the REMODECE $P_{Meas}(t)$ is normalised using the squared mean of the reference measures as indicated in (15). The results are listed in Table 7 together with the number of measures (N Meas.) that were found in the REMODECE database for each country.

As can be seen, the highest RMSE was obtained between the model winter profiles and the ones found in France. Nevertheless,

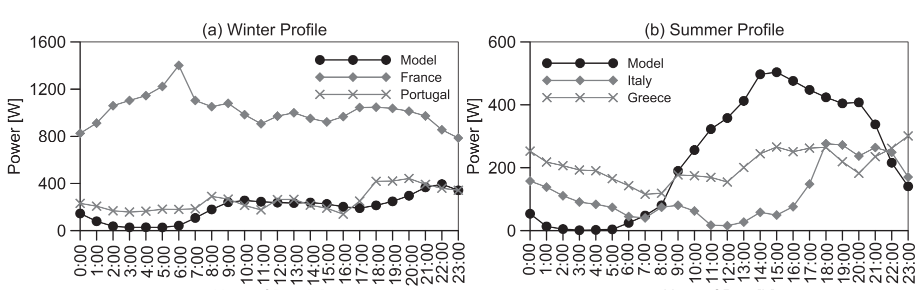

Fig. 8. REMODECE data for different locations vs Model.

the climate characteristics also vary significantly. In the rest of the cases, the RMSE and NVF have similar values indicating that although the model does not perfectly match the reference profiles, the estimated power figures are within the expected range. It should also be highlighted that, whereas the IDAE report used in this project [2] is composed of 6390 interviews and 600 details measurements of 22 appliances, the REMEDOCE database only includes a handful of households and offer a much lower temporal resolution (1-h) than the one proposed in this model (1-min).

Regarding how this accuracy compares with other simulation methodologies and previously published works in the field of load modelling [53], it should be considered that the main goal of the proposed model is to study the impact of low-level appliances such heating and cooling devices on the electrical grid for the residential sector. Thus, the chaotic behaviour of the residents and the heterogeneity of the buildings and installed appliances forced us to seek a compromise between precision and diversity.

In the context of energy forecasting, artificial neural network (ANN), autoregressive integrated moving average (ARIMA), and regression models are usually applied to hourly and sub-hourly predictions [54]. These models showed, in general, a higher accuracy than the proposed one [55,56], but they are limited to the context of a single building [57], mainly commercial ones with fixed schedules and patterns that also conferred them a good robustness [58,59]. Nevertheless, they lack the flexibility to be applied on a larger scale such as a district, a city or a region [60].

As opposed to, the bottom-up approach proposed in this article has a stochastic nature that provides a wide diversity of consumptions at the individual household level, but, as depicted by the figures, it presented a good accuracy in the aggregate trends as well as robust results due to the calibration process that is performed. Moreover, it provides a capability that none of the other methodologies has, which is the low-level simulation of the appliances. This feature makes the model especially suitable for studying the impact of the appliances in the grid in two ways. First, the operation of heating and cooling devices at an individual household level can be modified to simulate demand response programs and assess the benefits, both from the economic and the environmental point of view. Secondly, since the rate of possession of heating and cooling devices can be modified, future scenarios can be evaluated such as the increase in the number of cooling appliances and the possible overcharge of the network.

Finally, in terms of speed, the model is mainly designed to operate offline as an assessing tool. However, if the household parameters are known, the environmental variables are measured, and the occupancy patterns are established or given, an online simulation can be carried out, calculating the next consumption step based on the current state of the system.

5. Conclusions

This work has presented the development, implementation, along with the capabilities and potentialities, and followed by the validation process, of a stochastic model whose goal is the generation of synthetic high temporal resolution electricity consumption profiles for heating and cooling appliances that can be used to study the impact of these devices in the future Smart Grid. All the input data used in the simulations were obtained in the context of Spain. Nevertheless, the flexibility of the simulation procedure allows for the inclusion of new locations by providing the required input datasets as exposed in the Methods section.

The proposed algorithm was implemented using the high-level programming language JAVA and a server based philosophy so it can be easily integrated into other simulation tools. Likewise, a GUI was built in order to facilitate the selection of the input parameters for the model and the visualisation of the results, allowing the export of the data to CSV files and performing further processing with other software.

The daily profiles have shown the existence of two well-differentiated consumption intervals during the year. From November to the end of March, the energetic consumption can be attributed to the heating appliances, distinguishing two main peaks in the daily consumption profiles: one during the morning hours and another during the dinner time. In contrast, the demand during the middle hours of the day varies within the different regions. In opposition, during May, June, July, and August, cooling appliances account for the energy consumption. Therefore, the consumption was observed to be concentrated during the central hours of the day having a higher demand than the heating consumption in some locations.

That was confirmed by the yearly simulations which showed the ability of the model to simulate the climate characteristic of given locations. Thus, not only is the system able to simulate the daily and yearly variations, but also the peculiarities in the different zones, provided the system database contains the necessary input data.

Combining the 1-min resolution and the yearly simulations, the impact of the cooling and heating appliances on the grid was assessed by mean of the annual load duration curves. The results depicted the benefits of this tool that allowed the detection of the high instantaneous demand required by the cooling system. These devices, despite having a lower annual energy consumption can overcharge the electrical network due to their concurrent utilisation and their widespread use nowadays.

Finally, the results were validated against previously developed works focused on disaggregated consumption metering. The comparison between the REMODECE curves and the ones obtained by this model showed that the figures estimated by the model are concordant with the observed trends in other countries. Nevertheless, due to the differences in the climate characteristics between the studied region and those included in the REMODECE project the results are not directly comparable and do not perfectly match the reference data.

Therefore, this simulation model together with a previous one regarding lighting consumption simulation [32], are the first steps by the authors to build an assessment tool for the future Smart grid. The final aim is to develop an integrated platform for modelling the electricity consumption in the residential sector. Thus, a general appliances consumption model is being implemented, following the presented stochastic philosophy, and will be discussed in future papers. This will provide an overview of the global electrical consumption for the residential sector and it will also be the base from which to analyse the impact of different energy saving policies, focusing on both DR techniques and more efficient appliances.

Acknowledgements

This work is supported by the Spanish Ministry of Economy and Competitiveness under Research Project TEC2013-47316-C3-1-P; and TEC2016-77632-C3-2-R.

References

[1] Kavgic M, Mavrogianni A, Mumovic D, Summerfield A, Stevanovic Z, Djurovic-Petrovic M. A review of bottom-up building stock models for energy consumption in the residential sector. Build Environ 2010;45:1683–97. https://doi.org/10.1016/j.buildenv.2010.01.021.

[2] IDAE. Análisis del consumo energético del sector residencial en España INFORME FINAL. Spain. 2011. http://www.idae.es/uploads/documentos/documentos_Informe_SPAHOUSEC_ACC_f68291a3.pdf.

[3] de Almeida A, Fonseca P, Schlomann B, Feilberg N. Characterization of the household electricity consumption in the EU, potential energy savings and specific policy recommendations. Energy Build 2011;43:1884–94. https://

doi.org/10.1016/j.enbuild.2011.03.027.
[4] Connolly D. Heat Roadmap Europe: quantitative comparison between the electricity, heating, and cooling sectors for different European countries. Energy 2017. https://doi.org/10.1016/j.energy.2017.07.037.
[5] Isaac M, van Vuuren DP. Modeling global residential sector energy demand for heating and air conditioning in the context of climate change. Energy Pol 2009;37:507–21. https://doi.org/10.1016/j.enpol.2008.09.051.
[6] McNeil MA, Letschert V. Future air conditioning energy consumption in developing countries and what can be done about it: the potential of efficiency in the residential sector. Lawrence Berkeley Natl Lab; 2008.
[7] IDAE. Consumos del Sector Residencial en España Resumen de Información Básica. Spain. 2011.
[8] REMODECE project. Residential monitoring to decrease energy use and carbon emissions in Europe (REMODECE) database. 2015.
[9] Lopez MA, Santiago I, Trillo-Montero D, Torriti J, Moreno-Munoz A. Analysis and modeling of active occupancy of the residential sector in Spain: an indicator of residential electricity consumption. Energy Pol 2013;62:742–51. https://doi.org/10.1016/j.enpol.2013.07.095.
[10] Kipping A, Trømborg E. Hourly electricity consumption in Norwegian households – assessing the impacts of different heating systems. Energy 2015;93:655–71. https://doi.org/10.1016/j.energy.2015.09.013.
[11] Brown MA, Cox M, Staver B, Baer P. Modeling climate-driven changes in U.S. buildings energy demand. Climatic Change 2016;134:29–44. https://doi.org/10.1007/s10584-015-1527-7.
[12] Bladh M, Krantz H. Towards a bright future? Household use of electric light: a microlevel study. Energy Pol 2008;36:3521–30. https://doi.org/10.1016/j.enpol.2008.06.001.
[13] Martins JF, Oliveira-Lima JA, Delgado-Gomes V, Lopes R, Silva D, Vieira S, et al. Smart homes and smart buildings. Proc. Bienn. Balt. Electron. Conf. BEC 2012. https://doi.org/10.1109/BEC.2012.6376808.
[14] Arghira N, Hawarah L, Ploix S, Jacomino M. Prediction of appliances energy use in smart homes. Energy 2012;48:128–34. https://doi.org/10.1016/j.energy.2012.04.010.
[15] Torriti J. Demand side management for the european supergrid: occupancy variances of european single-person households. Energy Pol 2012;44:199–206. https://doi.org/10.1016/j.enpol.2012.01.039.
[16] Fazeli R, Ruth M, Davidsdottir B. Temperature response functions for residential energy demand – a review of models. Urban Chall 2016;15:45–59. https://doi.org/10.1016/j.uclim.2016.01.001.
[17] Pardo A, Meneu V, Valor E. Temperature and seasonality influences on Spanish electricity load. Energy Econ 2002;24:55–70. https://doi.org/10.1016/S0140-9883(01)00082-2.
[18] Valor E, Meneu V, Caselles V. Daily Air Temperature and Electricity Load in Spain. J Appl Meteorol 2001;40:1413–21. doi:10.1175/1520-0450(2001)040<1413:DATAEL>2.0.CO;2.
[19] Moral-Carcedo J, Vicéns-Otero J. Modelling the non-linear response of Spanish electricity demand to temperature variations. Energy Econ 2005;27:477–94. https://doi.org/10.1016/j.eneco.2005.01.003.
[20] Bessec M, Fouquau J. The non-linear link between electricity consumption and temperature in Europe: a threshold panel approach. Energy Econ 2008;30:2705–21. https://doi.org/10.1016/j.eneco.2008.02.003.
[21] Afram A, Janabi-Sharifi F. Review of modeling methods for HVAC systems. Appl Therm Eng 2014;67:507–19. https://doi.org/10.1016/j.applthermaleng.2014.03.055.
[22] Al-Homoud MS. Computer-aided building energy analysis techniques. Build Environ 2001;36:421–33. https://doi.org/10.1016/S0360-1323(00)00026-3.
[23] Crawley DB, Hand JW, Kummert M, Griffith BT. Contrasting the capabilities of building energy performance simulation programs. Build Environ 2008;43:661–73. https://doi.org/10.1016/j.buildenv.2006.10.027.
[24] Pettersen TD. Variation of energy consumption in dwellings due to climate, building and inhabitants. Energy Build 1994;21:209–18. https://doi.org/10.1016/0378-7788(94)90036-1.
[25] Swan L, Ugursal V. Modeling of end-use energy consumption in the residential sector: a review of modeling techniques. Renew Sustain Energy Rev 2009;13:1819–35. https://doi.org/10.1016/j.rser.2008.09.033.
[26] Richardson I, Thomson M, Infield D. A high-resolution domestic building occupancy model for energy demand simulations. Energy Build 2008;40:1560–6. https://doi.org/10.1016/j.enbuild.2008.02.006.
[27] Richardson I, Thomson M, Infield D, Delahunty A. Domestic lighting: a high-resolution energy demand model. Energy Build 2009;41:781–9. https://doi.org/10.1016/j.enbuild.2009.02.010.
[28] Richardson I, Thomson M, Infield D, Clifford C. Domestic electricity use: a high-resolution energy demand model. Energy Build 2010;42:1878–87. https://doi.org/10.1016/j.enbuild.2010.05.023.
[29] McKenna E, Thomson M. High-resolution stochastic integrated thermal-electrical domestic demand model. Appl Energy 2016;165:445–61. https://doi.org/10.1016/j.apenergy.2015.12.089.
[30] Widén J, Lundh M, Vassileva I, Dahlquist E, Ellegård K, Wäckelgård E. Constructing load profiles for household electricity and hot water from time-use data—modelling approach and validation. Energy Build 2009;41:753–68. https://doi.org/10.1016/j.enbuild.2009.02.013.
[31] Widén J, Wäckelgård E. A high-resolution stochastic model of domestic activity patterns and electricity demand. Appl Energy 2010;87:1880–92. https://doi.org/10.1016/j.apenergy.2009.11.006.
[32] Palacios-Garcia EJ, Chen A, Santiago I, Bellido-Outeiriño FJ, Flores-Arias JM, Moreno-Munoz A. Stochastic model for lighting's electricity consumption in the residential sector. Impact of energy saving actions. Energy Build 2015;89:245–59. https://doi.org/10.1016/j.enbuild.2014.12.028.
[33] National Statistics Institute of Spain. Ministry of Economy and competitiveness. Time use survey. Spain. 2010.
[34] Gilks WR, Richardson S, Spiegelhalter DJ. Markov chain Monte carlo in practice, vol. 39; 1996. https://doi.org/10.2307/1271145.
[35] Gamerman D. Markov chain Monte carlo: stochastic simulation for bayesian inference, vol. 1; 2006.
[36] Sailor DJ. Relating residential and commercial sector electricity loads to climate - evaluating state level sensitivities and vulnerabilities. Energy 2001;26:645–57. https://doi.org/10.1016/S0360-5442(01)00023-8.
[37] Giannakopoulos C, Psiloglou B. Trends in energy load demand for Athens, Greece: weather and non-weather related factors. Clim Res 2006;31:97–108. https://doi.org/10.3354/cr031097.
[38] Sarak H, Satman A. The degree-day method to estimate the residential heating natural gas consumption in Turkey: a case study. Energy 2003;28:929–39. https://doi.org/10.1016/S0360-5442(03)00035-5.
[39] Eto JH. On using degree-days to account for the effects of weather on annual energy use in office buildings. Energy Build 1988;12:113–27. https://doi.org/10.1016/0378-7788(88)90073-4.
[40] State Meteorological Agency (AEMET). Spanish government. AEMET OpenData. 2017. http://www.aemet.es/en/datos_abiertos/AEMET_OpenData.
[41] Red Eléctrica de España Co. Red Eléctrica de España. 2017. http://www.ree.es/en.
[42] Teräsvirta T. Specification, Estimation and evaluation of smooth transition autoregressive models. J Am Stat Assoc 1994;89:208–18. https://doi.org/10.2307/2291217.
[43] National Statistics Institute of Spain. Ministry of Economy and competitiveness. Survey on households and the environment. 2008. p. 2008.
[44] Smullin SJ. Thermostat metrics derived from HVAC cycling data for targeted utility efficiency programs. Energy Build 2016;117:176–84. https://doi.org/10.1016/j.enbuild.2016.02.018.
[45] Daikin Daikin 2015. http://www.daikinac.com/.
[46] Carrier. Home heating & cooling products. 2015. http://www.carrier.com/homecomfort/en/us/products/heating-and-cooling/.
[47] Fujitsu. Cooling products. 2015. http://www.fujitsu-general.com/eu/products/.
[48] Dimplex. Domestic heating products. 2015. http://www.dimplex.co.uk/products/domestic_heating/portable_heating/index.htm.
[49] Stamminger R. Synergy potential of Smart appliances. D2.3 of WP2 from the smart-a project. 2008.
[50] ENTRANZE. Project. Heating and cooling energy demand and loads for building types in different countries of the EU. 2014.
[51] U. S Energy Information Administration. Residential energy consumption survey (RECS). 2009. http://www.eia.gov/consumption/residential/data/2009/.
[52] de Almeida A, Fonseca P, Bandairinha R, Fernandes T, Araújo R, Nunes U, et al. REMODECE-Residential monitoring to decrease energy use and carbon emissions in Europe. 2008. Final Repo:96.
[53] Kuster C, Rezgui Y, Mourshed M. Electrical load forecasting models: a critical systematic review. Sustain Cities Soc 2017;35:257–70. https://doi.org/10.1016/j.scs.2017.08.009.
[54] Ma W, Fang S, Liu G, Zhou R. Modeling of district load forecasting for distributed energy system. Appl Energy 2017;204:181–205. https://doi.org/10.1016/j.apenergy.2017.07.009.
[55] Hsiao YH. Household electricity demand forecast based on context information and user daily schedule analysis from meter data. IEEE Trans Ind Informatics 2015;11:33–43. https://doi.org/10.1109/TII.2014.2363584.
[56] Jurado S, Nebot À Mugica F, Avellana N. Hybrid methodologies for electricity load forecasting: entropy-based feature selection with machine learning and soft computing techniques. Energy 2015;86:276–91. https://doi.org/10.1016/j.energy.2015.04.039.
[57] Li X, Wen J, Bai EW. Developing a whole building cooling energy forecasting model for on-line operation optimization using proactive system identification. Appl Energy 2016;164:69–88. https://doi.org/10.1016/j.apenergy.2015.12.002.
[58] Platon R, Dehkordi VR, Martel J. Hourly prediction of a building's electricity consumption using case-based reasoning, artificial neural networks and principal component analysis. Energy Build 2015;92:10–8. https://doi.org/10.1016/j.enbuild.2015.01.047.
[59] Massana J, Pous C, Burgas L, Melendez J, Colomer J. Short-term load forecasting in a non-residential building contrasting models and attributes. Energy Build 2015;92:322–30. https://doi.org/10.1016/j.enbuild.2015.02.007.
[60] Fischer D, Härtl A, Wille-Haussmann B. Model for electric load profiles with high time resolution for German households. Energy Build 2015;92:170–9. https://doi.org/10.1016/j.enbuild.2015.01.058.