Stochastic model for electrical loads in Mediterranean residential buildings: validation and applications

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ABSTRACT

A major issue in modelling the electrical load of residential building is reproducing the variability between dwellings due to the stochastic use of different electrical equipment. In that sense and with the objective to reproduce this variability, a stochastic model to obtain load profiles of household electricity is developed. The model is based on a probabilistic approach and is developed using data from the Mediterranean region of Spain. A detailed validation of the model has been done, analysing and comparing the results with Spanish and European data. The results of the validation show that the model is able to reproduce the most important features of the residential electrical consumption, especially the particularities of the Mediterranean countries. The final part of the paper is focused on the potential applications of the models, and some examples are proposed. The model is useful to simulate a cluster of buildings or individual households. The model allows obtaining synthetic profiles representing the most important characteristics of the mean dwelling, by means of a stochastic approach. The inputs of the proposed model are adapted to energy labelling information of the electric devices. An example case is presented considering a dwelling with high performance equipment.

KEYWORDS

Stochastic model; electric load; residential building; Mediterranean region; cluster of buildings; energy labelling

1. Introduction

The detailed modelling of a household's energy consumption is a complex task that involves different issues and requires different skills. In detail, the main energy consumption sources in a household are: space heating/cooling [1, 2], domestic hot water, appliances and lighting. A major issue in modelling is to estimate the uncertainties implicit in the building model. There are many unknown and uncertain parameters that affect directly the results, especially when the model reproduces existing buildings. The uncertainties can be related to the quality of building works, real properties of materials and their performance degradation, real performance of heating and cooling systems and their efficiency reduction, quantification of air infiltrations, subjectivity in comfort condition, and an important group of uncertainties related to the user behaviour (appliances, lighting, set points...). In particular, for modelling the consumption of appliances, a difficult aspect is the quantification of purely stochastic variables, namely the simulation of electrical consumption profiles for appliances and plug loads. In practice, electricity consumption caused by appliances has been often based on fixed profiles derived from statistical data. Although this kind of approach has some strong points (e.g., simple calculations, perfect for first stage analysis), it is not useful when a detailed characterization of the household consumption is needed, as for example in models for studies on the energy interactions of a "prosumer" (producer and consumer) building [3-7]. From this perspective, a good and solid modelling approach should comprise both average and peak value estimation: the first being useful for an early design of the systems, the latter for grid interaction, storage sizing issues and optimization of demand side management strategies. For such applications, transient modelling approaches are used worldwide to represent both building physics and energy generation systems, but it is important to make progress also in the field of user-related energy consumption modelling with models with the same level of detail. In other words, at least hourly time-steps should be adopted to obtain meaningful results and to make comparisons to energy generation data. The modelling of user-related energy consumption is crucial when the focus of the study is the residential sector. Residential energy consumption profiles are much more difficult to predict than for e.g., offices, for several reasons: occupant behaviour can vary widely and therefore have notable impacts on energy consumption, privacy issues limit the collection and distribution of energy data related to individual households and usually the detailed metering of end-uses consumption have high costs. The importance of the demand side modelling is particularly high when demand-response studies are being performed: having a detailed insight on how energy use in the households might vary following the designer's input, is of the uttermost importance to develop a solid study.

This paper proposes a model aimed at describing the energy consumption of building clusters and neighbourhoods. The model uses a stochastic approach to simulate more than one household at the same time. The idea behind the model is having a high-resolution tool, dependent on easily modifiable parameters. The model allows a simple and effective customization by the user, keeping it robust. The parameters of the model are also related with energy standards of appliances, making possible an analysis of their effect at neighbourhood level. The modelling environment chosen for the implementation of the model is TRNSYS, in order to complement the simulation of thermal loads in buildings. Considering existing literature, the model could be one of the first implementations in an environment of user-related energy consumption models. The aim of the paper is the analysis of the performance of the model by considering that main inputs and parameters to the model are derived from empirical analysis of real data from existing research projects. A detailed sensitivity analysis of parameters and a comparison of the results with other studies available in the literature are done. Although many household electrical consumption studies are available in the literature, the proposed model is one of the first to be implemented in Mediterranean regions.

1.1. State of the art

Residential energy use modelling is usually very dependent on the level of accuracy of the input data. Therefore, different modelling approaches have been developed in the last decades, with different strengths and weaknesses, as well as different model resolutions and modelling capabilities.

The main techniques used to model residential energy uses can be grouped up into two main categories [8]: “top-down” and “bottom-up”. Top-down models underwent a major development during the energy crisis of the late 1970s. The major aim of such research effort was to understand better consumer behaviour with changing supply and pricing. Such models analyse residential sector as a whole and their objective was to determine and to analyse trends of the sector. The strength of “top-down” models is that they do not need very detailed input data to work. They just need widely available energy aggregate data and rely on historic residential sector energy values. The heavy reliance on historical trends and data for these models is also a major drawback, since they are not able to handle discontinuities in the major trends.

Saha and Stephenson [9] developed a “top-down” model for New Zealand, modelling in separate sub-models space heating, domestic hot water and cooking, that are added up to obtain total consumption. The proposed method used historical data to predict future energy use levels as function of stock, ownership, appliance ratings and use factor. Its prediction was excellent during the 1960s, but in 1970s the shifts in home insulation levels caused a major deviation between monitored and simulated data.

The “bottom-up” approach goes beyond the limits of the “top-down” one, accounting in detail for individual houses and energy end-uses. After that, the results of the model may be extrapolated to represent a region or a nation, according to the level of detail of the inputs. Common input data to bottom-up models are dwelling properties, equipment and appliances, climate characteristics, occupancy schedules and use levels of equipment. This detail in characterization is the strength of these methods. It allows a very accurate modelling, but has as drawback the difficulty of obtaining all the needed data. No historical data are required. However, in order to extrapolate the results for a whole region or country, data must be representative of the zone. A peculiar characteristic of these models is the modelling of occupant behaviour. The main modelling approaches in this field may be summarized as: statistical techniques (regression and conditional demand analysis) and neural networks.

Widen et al. [10] proposed a Markov-Chains method with a wide use of Time Use Data (TUD) information for Sweden. TUD were used to describe occupancy patterns, obtaining transition probabilities of 3 states (outside home, active at home, and passive at home). The model is developed in the field of electrical and lighting demand. Widen et al. used detailed modelling of the time use for each occupant. The fundamental section of the model is the conversion of the TUD into occupancy levels. Subsequently, the model obtains energy use profiles through the use of different patterns and converting functions for each appliance.

Yamaguchi et al. [11] has developed an occupant behaviour model for estimating high-resolution electricity demand profiles of residential buildings. The occupant behaviour is based on statistical treated data of TUD in Japan. The model is based on a set of probabilities related to different behaviours or activities, which are used to define the behaviour of each occupant and then its electrical consumption. One of the advantages of this model is that not detailed data are needed. Richardson et al. [12] proposed a method having as input the value of natural light entering windows and the activity level of the household residents. The main input of the model is a time-series representing the number of active occupants within a dwelling and is based on Monte-Carlo technique. The statistical information used is from the United Kingdom. Paatero and Lund [13] built a model for generating electricity load profiles for a dwelling using representative data sample and statistical averages from Finland. The randomness has been included using stochastic processes and probability distribution functions (starting probability function based on the seasonal, hourly and social factors). Paatero and Lund use the model to simulate strategies of Demand Side Management (DSM). Another key element is the high influence of the occupancy activity with heating and cooling loads and in consequence, with the size of the systems. Baetens and Saelens [14] simulated in Modelica user behaviour and use of lighting and appliances. The use of appliances has been implemented by a semi-Markov process based on the presence of an occupant and their activity profiles. In a similar way, Neu et al. [15] integrate a Markov Chain Monte Carlo approach in EnergyPlus platform to simulate multi-zone single-storey detached building. The model is based on TUD of Ireland to obtain disaggregated residential appliances uses profiles, as Widen et al. did. The model generates occupancy profiles at a fifteen-minute time resolution, electrical appliances load and lighting load profiles. They relate these profiles with the building models, including the associated heat gains of each element (occupancy, appliances and lighting).

Even though the use of Neural networks methods has been historically limited in this field, they have had some applications to the modelling of electrical consumption in households [16, 17] due to their capability of modelling non-linear phenomena with forecasting purposes.

2. Stochastic model description

In the simulation, the energy uses are selected and modelled for each household, through a stochastic approach. Main outputs of the model are energy consumption of both neighbourhood and household, in terms of aggregated and single energy use consumption. The simulation is divided in two steps, which are related to two different sources of stochasticity: dwelling characterization and use of equipment.

The characterization of each dwelling is performed at the first time step by the routine. In this first phase, a set of energy uses is selected randomly for each household. In other words, the model defines stochastically which and how much equipment there is in each simulated dwelling. In the equations (1) are represented the conditions to choose the equipment of each dwelling, using the parameters of the stock characterization described in Table 1.

$$\left.\begin{array}{ll} RNE_e^d < (1-\Pr_e) & \rightarrow \text{There is no equipment e in dwelling d} \\ RNE_e^d \geq (1-\Pr_e) \begin{cases} (1-Mp_{e1}) > RNE_e^d \\ (1-Mp_{e1}) \leq RNE_e^d < (1-Mp_{e2}) \\ (1-Mp_{e2}) \leq RNE_e^d < (1-Mp_{e3}) \\ (1-Mp_{e3}) \leq RNE_e^d < (1-Mp_{e4}) \end{cases} & \begin{array}{l} \rightarrow \text{There is 1 equipment e in dwelling d} \\ \rightarrow \text{There are 2 equipment e in dwelling d} \\ \rightarrow \text{There are 3 equipment e in dwelling d} \\ \rightarrow \text{There are 4 equipment e in dwelling d} \end{array} \end{array}\right\} \quad (1)$$

Where RNE_e is the random number for each type of equipment *e* and dwelling *d*. Pr_e is the penetration rate for each type of equipment *e*. Mp_e1, Mp_e2, Mp_e3 and Mp_e4 are multi-equipment probabilities for each type of equipment *e*.

Once the dwelling characterization is done, the model has to choose randomly which equipment is ON or OFF (or Stand-by), using the probability values for each of them. Then, in each time step another set of random number have generated ($RNP(t)_e$) in order to be compared with the probabilities of use of each equipment type. In the equation (2) the comparison done and the energy consumption calculation at each time step is shown.

$$\left.\begin{array}{ll} RNP(t)_e^d \geq prob(t)_e \rightarrow E(t)_e^d = Pstb_e \cdot \Delta t & \rightarrow \text{The equipment is OFF or in Stand-by} \\ RNP(t)_e^d < prob(t)_e \rightarrow E(t)_e^d = P_e \cdot PF_e \cdot CF_e \cdot \Delta t & \rightarrow \text{The equipment is ON} \end{array}\right\} \quad (2)$$

Where $RNP(t)_e$ is the random number generated for the equipment *e* of the dwelling *d* at time *t*. $prob(t)_e$ is the probability of use at the time *t* of the equipment *e* (*t* refers to the season, type of day and hour of day). $Pstb_e$, P_e, PF_e and CF_e are the parameters of the equipment *e* described in the Table 1. Δt is the time step (1 hour). Finally, the $E(t)_e$ is the energy consumption for the equipment *e* of the dwelling *d* at time *t*.

In Figure 1 an example of the hourly probability of use for a dishwasher and a television is shown.

2.1. Basis of the model

Recently, "Instituto para la Diversificación y Ahorro de la Energía" (IDAE) has carried out the SECH-SPAHOUSEC project [18]. This project characterizes the energy consumption of the residential sector in Spain, including detailed information about the equipment stock and the main energy uses. The information is aggregated by regions (Atlantic, Continental and Mediterranean) and by building type (detached houses and apartment buildings).

Data collection done in SECH-SPAHOUSEC has been performed by three complementary methods: telephone surveys, in-person surveys and electrical measurements of individual equipment in 600 dwellings. The main information obtained from surveys is related to the occupancy, the equipment stock and the annual energy consumption (based on estimations and bills). The electricity measurements give information about the use and the hourly consumption profile of each equipment and the hourly aggregate profile of the electricity consumption for each dwelling. In addition, the energy label of the characterised equipment is known, thus allowing a detailed knowledge of the energy efficiency level of the equipment stock.

The study presented in this paper uses detailed data from an apartment building from the Mediterranean region, taken as an example of the whole study. The general considerations on the method presented in the following paper may be extended to the other regions and building typologies as well. A post-processing of the data is done to obtain the parameters and inputs of the stochastic model.

2.2. Input and parameters of the model

The model is arranged in two different sub-routines, describing two different families of energy uses. The first one deals with electrical appliances: refrigerator, freezer, washing machine, dishwasher, television, tumble dryer, microwave, PC, lighting and other (which includes a group of small appliances that do not strongly impact the overall energy consumption, e.g., electrical radios, computer games, etc.). The second sub-routine models kitchen devices: gas and electric stoves and ovens. The model does not include heating and cooling systems consumption because their use mainly depends on weather data and building typology.

The chosen time resolution is one hour. The main parameters required for the characterization of equipment are reported in Table 1. They are mainly derived from the analysis of empirical data. In addition, more general parameters are needed to carry out the simulation, e.g., the number of simulated dwellings, start time of the seasons, seed numbers…

Table 2 and Table 3 show the values of the different inputs and parameters used in the Base Simulation (stock characterization and technical data, respectively).

3. Validation of the model

In this section a detailed validation of the model and their results are done. In previous works [19], a general validation of the model has been done. The validation is based on the analysis of aggregated results of the SECH-SPAHOUSEC project, starting from annual energy consumption per equipment and dwelling. A first analysis on the full database has been performed in [20], using more detailed information of the measurement campaigns. The obtained results show that the model is able to reproduce the patterns of electricity consumption of a residential building. However, slight differences with the reference data were observed. This fact, together with the analysis performed on the whole database from [18] suggested the need to carry out a more detailed validation of the model.

The detailed validation consists of three levels of analysis: a verification of expected results, a verification of equipment profiles and a comparison with other studies.

3.1. Verification of expected results

The objective of this section is to check that the model works properly and their results are reliable. Three classes of parameters have been checked in detail: penetration rates, multi-equipment probabilities and probability of use. To carry out that, a simulation of 1000 dwellings has been performed, using the inputs and parameters of Table 2 and Table 3. In addition, a comparison with the complete database of the SECH-SPAHOUSEC is done.

Table 4 shows the comparison of the penetration rates (*Pr*) and the values obtained by the simulation. The relative errors between the penetration rates and the results of the model are lower than 5%. Differences are low enough to conclude that they are caused by mere stochastic fluctuations.

The evaluation of the multi-equipment probabilities is done by comparison of different results: annual consumption per dwelling and multi-equipment probabilities. Computer and television are the equipment included in this validation. In Figure 2 results of simulation are presented graphically by a box-plot and numerically through mean dwelling consumption and their fraction of multi-equipment. The results obtained show how the mean number of equipment of the simulation is lower than the input data, just as it happens with the mean annual consumption. Notice that the multi-equipment probability is not directly available from the SECH-SPAHOUSEC information. They have been estimated using the total number of equipment, the penetration rate and the mean number of equipment per dwelling. In spite of this fact, the multi-equipment probabilities (input) are quite similar to the simulated data results. Then, the estimation of the multi-equipment probabilities is considered good enough based on the available data (relative error lower than 10%).

The last verification of the model is the probability of use of each equipment, which is defined as the proportion of appliances that are on at a given hour. In order to compare the input data with the simulation, a t-test is performed. We consider that there are statistically significant differences if p-value is lower than 0.05. As Table 5 shows, the results of the test highlight that the difference between the input data and the simulation is not significantly different for all the equipment.

To complete the verification of the composition profiles, a comparison of the results with the different regions and typologies of buildings in Spain is done. The data used are the complete data from SECH-SPAHOUSEC project, which are not used to develop the model. In Figure 3 an hourly profile of mean dwellings are shown: apartment buildings and detached houses from Atlantic, Continental and Mediterranean regions. The modelled profile has the same trend than the measured profiles. There are slight differences between them, especially with detached houses. These results show that the equipment energy use in Spain is more dependent on the building type than on the region. We can conclude that the model reproduces properly the daily profile.

3.2. Equipment profiles analysis

3.2.1. Representative sample size

The first step of the equipment profile validation is to define how many dwellings need to be simulated in order to be representative. The test is performed under the following assumptions: simulation of 1st month of the year and penetration rates of the equipment equal to 1 (this configuration allows setting up a link between the number of dwelling and the number of equipment). The test consist of 5 sets of simulations, increasing the number of dwellings (*N*=10, 50, 250, 500 and 1000) and changing the seed number of the random number generator (5 simulation are done for *N* number of dwellings, changing the seed number in each simulation; then this test is repeated increasing the number of dwellings).

Figure 4 is an example of the results obtained in this test. The simulations of 1000 dwellings are not included in Figure 4 because there are no appreciable differences with respect to the 500 dwellings results. Figure 4 shows how the variation of the energy profile is lower as the number of dwellings included in the simulation is higher. There are differences between the 5 simulations when 10 dwellings are simulated. However, there are not significant differences between simulations when the number of dwellings is high enough. The results of the test concluded that simulations with 500 or more dwellings are representative of the mean dwelling. Considering these the results, all the subsequent validations have been done with 500 dwellings.

3.2.2. Database comparison

The aim of this comparison is to evaluate the correspondence between the simulation of each equipment and the database (SECH-SPAHOUSEC). Figure 5 presents annual results of a simulation of 500 washing machines chosen as an example, where it is possible to see the variability between the different simulated dwellings. Table 6 summarizes the statistics of the annual energy consumption for all the equipment.

The hourly profile of an average washing machine is compared with results from [18] in Figure 6. The timing of the profile peaks and the average trend of the results fit with the reference data. The main difference is that the value of the peaks is usually underestimated by the model by a small amount (5-25 %, being worse during the winter time). There are three assumptions that could be a reason of these deviations:

- Technical parameters of PF and CF are constant over time.
- Assumption on cycle length of appliances,
- The probabilities of use have been obtained considering the time when the equipment is ON and not just at the moment when the equipment is switched ON.

The comparison of the other equipment shows the same behaviour as with the washing machine example. The trend of the model is quite similar to the reference data with just small differences if the value of the peaks is compared. Despite these differences, the model is completely valid for its purpose and the validation could be considered appropriate.

3.2.3. Comparison with other countries

After the detailed validation of the model with the reference data, it is important to compare it with other studies and countries. There are two scopes in this analysis:

- To check that the model reproduces realistic profiles and annual consumption compared with other studies
- To establish differences or similarities with Mediterranean and/or European countries

The data used for the comparison has been obtained from the project Remodece, making use of one of its output: an updated database of consumption of EU-27 countries [21]. The database includes data of different measurement campaigns. The monitored data consists of annual, monthly and hourly consumption, for most of the appliances of the households (using electricity, gas, wood...).

In Figure 6 and Table 7 a comparison of the model results with the different data from different countries are presented. For all the equipment, the annual consumption obtained by the simulation is in the range of the Remodece data, with the exception of the television which is higher. Nevertheless, these differences do not diminish the validation of the model and the results of the comparison with other measurement data is considered correct.

4. Applications of the model

4.1. Analysis of building cluster simulations

Several profiles have been generated. The objectives are to simulate the electrical demand of a building block or neighbourhood and to evaluate when the uncertainty demand is low enough. Figure 8 is an example of an output of the model. One week of two random dwellings and mean consumptions among all the simulated dwellings are presented. The random dwellings have different profiles between them as well as the annual consumption, the maximum peak and the number of equipment. Such information is stochastically generated for each household. One of the most important characteristics of the output is that it is able to reproduce the peak values of the load profiles, which are different between days and dwellings.

Figure 9 is an empirical distribution of annual electrical consumption. The X-axis is the number of simulated dwellings, and as it is expected, the distribution is better defined as the number of dwellings increase. The distribution becomes symmetric and the main statistics are stable. Two main statistical parameters of the distribution converge over 100 dwellings. The mean is around 2800kWh/yr and the standard deviation around 490kWh/yr. The distribution of the annual energy consumption is slightly left-skewed, but it performs quite similar to a Normal distribution.

4.2. Determination of synthetic profile

The model is able to reproduce stochastic profiles of electricity consumption, as in the previous sections are shown. Taking the perspective that the buildings will go toward NZEB and will be integrated in smart grids, the electric consumption will become more and more important. In that situation and to simulate these systems, a detailed consumption profile representative of all the simulated dwellings could be useful. Here a synthetic profile is defined as a dwelling with a stochastic behaviour and whose annual and daily consumption are equal to the mean dwelling. A simulation of 500 dwellings has been performed in order obtain the synthetic profile. Among these 500 dwellings, the ones with an annual consumption equal to the mean consumption with only small differences (+/-1%) are selected. Figure 10 describes the electric consumption profile of the resulting 22 dwellings. For clarification, only the results from a simulated week have been included.

After this first selection, a detailed analysis of the equipment of 22 dwellings is done. The purpose is to choose a dwelling with an equipment distribution as close as possible to the mean dwelling (compared with a penetration rate). As Table 8 shows, there are three representative dwellings that meet these criteria, and in addition, their annual and daily consumption is around the mean dwelling consumption. In Figure 11 one of the synthetic dwellings is compared to the mean dwelling (one winter week and one summer week). The variability of the synthetic profile is reflected as a difference from the mean dwelling. One of the most important features of the synthetic profile is that the peaks of consumption are more realistic that the mean dwelling profiles, as it can be seen in Table 8 (hourly maximum peak) and Figure 11.

4.3. High performance appliances simulation

One of the advantages of the proposed model is that equipment characteristics can be changed and adapted to each simulation case. An analysis of the energy labelling data is performed by means of the proposed model, as a solid source of comparison. The energy label is the main information available in new appliances. For this reason, establishing the relationship between the energy label and the input of the model is interesting. This energy label adaptation consists of entering corresponding inputs to the model for each equipment as a function of their energy efficiency class. The method to estimate the annual consumption depending on the labelling, is specific for each equipment type and is described in different directives (washing machine [22], drier [23], dishwasher [24], electric oven [25], refrigerating appliances [26] and television [27]). To apply these methods some assumptions are needed, i.e., capacity, place settings, screen size, etc. Following the different directives, corresponding inputs of the model are defined for each energy efficiency class. Figure 12 shows the results of simulating several dishwashers with the different energy efficiency classes (D to A+++).

In addition, a verification of the energy label adaptation has been done to compare with the database information. Table 9 shows the comparison between the database information regarding to the energy label, the energy label adaptation in terms of hourly consumption, and the input of the model (Table 3). For washing machine, dishwasher and drier there is an agreement between most representative energy label of the database and the input of the model. However, the fitting accuracy is lower for the equipment refrigerator and freezer. In that case, the input model represents an appliance with a lower energy label (less efficient) than the database one. One reason for these discrepancies could be that the Directive of refrigerating appliances needs extra information that is not available in the SECH-SPAHOUSEC project (i.e., type of refrigerating appliance, storage volumes, storage temperature...).

Once the energy label is related with the inputs of the model, it is possible to use the model to test different strategies and policies for reducing the energy consumption in households. For example, it is possible to use the model with different DSM strategies as Paatero and Lund [13]. In the present paper, a comparison between the results of the simulated average dwelling to a high performance appliance dwelling is done. The objective is to evaluate the energy savings resulting from an overall improvement of the appliances efficiency. Only the equipment with labelling has been included in this test, which represent around the 70% of the annual consumption of the mean dwelling (without considering lighting).

In Figure 13 and Figure 14 a comparison between the dwellings with high performance appliances (A+++) and the dwelling with the average energy efficiency class (Avg. EE class) is presented (hourly profile and annual consumption, respectively). The highest potential savings may be obtained by a substitution of the appliances with the poorest performance (refrigerator, freezer and television). The annual mean energy saving achieved using high performance appliance is closed to 40%. This reduction is also observed in the daily maximum value, as Figure 13 shows. The results show that the energy label of appliances is a first step to achieve important energy savings in the electric consumption of households.

5. Discussion

The proposed TRNSYS routine is a “bottom-up” model, where input data are derived from aggregated data. Such data are typical average consumption 24 hours profiles defined by geographical zone, season and type of day. The data is analysed with regression techniques (penetration rates, equipment information) into a set of different parameters that are used as input to the model. The work done can be divided in two parts: validation of the model (section 3) and their applicability and usefulness (section 4).

The initial validation of the model is done in the section 3.1, where it has been proven that the model is solid and works properly. The outputs are very close to the input data when simulating a statistically relevant number of elements, in terms of characterization of the households (e.g., number and kind of appliances used in each flat) and the average use of the equipment. A comparison of the simulation results with the SECH - SPAHOUSEC database has been done. The model is able to resolve the timing of the peaks and the general trends of the resulting profiles. However the value of the peaks is usually under/overestimated. The reason could be due to some of the assumptions done in the estimation of the technical parameters.

The simulation approach allows a detailed representation of household electrical consumption, distinguishing between different energy use activities. The model allows a very high customization rate, and takes implicitly in consideration the average occupants' habits. However, the number of occupants cannot be changed and it is represented by the average of the Mediterranean region in Spain. This approach could be a limitation if dwellings with a very different occupancy would be reproduced.

Another validation step comprises the comparison with other European studies. The comparison strengthens the reliability of the model, since the trend of the simulated results is quite similar to results in other studies. In particular, when comparing them to other Mediterranean countries, the habits of these countries are reflected (e.g., there is a peak during the lunch time in Mediterranean countries, while in other countries this peak does not exist).

The usefulness of the model is shown in three different cases: analysing the simulation of building clusters; defining a synthetic profile; and evaluating the energy savings using high performance appliances.

In the case of analysing cluster of buildings, the tool generates random profiles, all different between them. The output of the model makes possible to work at individual or aggregate level. The results show that the energy consumption is smoothed into average values as the number of dwellings in the neighbourhood increase.

The definition of a synthetic profile allows to have a dwelling with the main characteristics of the mean dwelling (type of equipment, and annual and daily consumption), and also a stochastic behaviour (realistic profiles). The synthetic profile could be used to estimate with more accuracy the electrical consumption of a household, the design of renewable systems and the grid integration of net zero energy buildings (NZEB).

Finally, a potential application of the model is connected to the quantification of benefits for improving the energy efficiency of appliances. The simulated case-study with the average energy efficiency class of the Spanish-Mediterranean household is compared with a dwelling with high performance appliances. The results of this comparison show that a dwelling could reduce nearly half (40%) of its energy consumption if high performance appliances would be used.

However, the model is, as for most bottom-up models, highly dependent on the input data, since the modelling capabilities of the TRNSYS component have been tuned up to fit the detailed monitoring databases.

6. Conclusions

The detailed modelling of household energy consumption is a complex task that involves different issues and requires different competencies. Often in practice, electrical consumption caused by appliances is based on statistical data. Although this kind of approaches has some strength (e.g., simple calculations, perfect for first stage analysis), they are not useful when a detailed characterization is needed. For example, to model the energy interactions of a building that has complex interactions with the energy grid (e.g., NZEB). The proposed model, being one of the first implementations of stochastic models in TRNSYS environment, focuses on the simulation of a Spanish Mediterranean apartment building. The TRNSYS implementation allows for an easy integration in building simulation, as a complement of deriving heating and cooling consumption. With the total energy consumption of a building, one can study matching between load and generation from renewables systems.

The paper has presented a detailed validation of a household energy consumption model, in addition to some typical output profiles for a simulated household district. The model is able to reproduce random realistic profiles with the preservation of the important qualitative features of residential consumption of the Mediterranean countries, complementing similar models available for other regions (e.g., Nordic European countries). Some of the potential applications of the model are demonstrated. The model can be used to analyse cluster of buildings, with the option to focus on each individual building or on the combination of them. This kind of analysis can be used to analyse the uncertainty of their energy consumption. The model has proven its usefulness to define synthetic profiles. The synthetic profile could be applied in high time resolution studies that aim to model peak loads as well as average data. A direct relationship between the input of the model and the energy labelling of appliances is established. This relationship helps to easily evaluate the potential savings of high performance appliances.

After this analysis of the model and their results, some improvement points have been detected. On one hand, the model could include the occupant as a variable of the model, in order to reproduce a wider range of households. On the other hand, the time step could be lower than one hour, increasing the detail of the energy use events in order to improve the energy peaks simulation.

It can be concluded that the model is a validated approach to be integrated into simulation tools. The model is a simplified tool that brings detailed information about electrical consumption profiles, as part of studies of residential neighbourhoods or net zero energy districts.

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FIGURE CAPTION

Figure 1 Hourly probability of use for dishwasher (left) and television (right).

Figure 2 Multi-equipment verification (top: television, bottom: computer). Left: Distribution of the annual energy consumption for the equipment of 1000 multi dwelling households of Mediterranean region (energy consumption in the left axis and number of equipment in the right one. Description of the box plot parameters: mean by square; median by horizontal line; 25-75% and 10-90% percentile by box; 5% and 95% by whiskers; 1% and 99% percentile by cross; minimum and maximum by dash. Right: Comparison of the database information with the model results (input data vs. simulated).

Figure 3 Comparison of the models result with the different regions of Spain and types of buildings (SECH-SPAHOUSEC).

Figure 4 Results of the representative sample size test. Comparison of the simulations with different configurations. Example of the cooking devices: electrical kitchen, electric oven and microwave.

Figure 5 Distribution of the annual energy consumption for 500 washing machines in a multi dwelling of Mediterranean region. Description of the box plot parameters: mean by square; median by horizontal line; 25-75% and 10-90% percentile by box; 5% and 95% by whiskers; 1% and 99% percentile by cross; minimum and maximum by dash.

Figure 6 Average hourly profile of the energy consumption for a washing machine: simulation vs. reference data.

Figure 7 Average hourly energy consumption for dishwasher, electric oven, television and computer. Comparison of different studies and countries. Left: Mediterranean Countries; Right: Center-North EU Countries.

Figure 8 Hourly electric consumption for a winter week. Example output of the model, two random dwellings and the mean dwelling (reference data).

Figure 9 Distribution of the annual energy consumption for dwelling, increasing the number of dwellings.

Figure 10 Winter week profile of the mean dwelling (black line) and the dwellings with an annual consumption equal to mean +/- 1% (grey lines).

Figure 11 Week profile of the synthetic profile (SP1). Left: winter week. Right: summer week.

Figure 12 Hourly energy consumption for dishwasher with different energy labels. Capacity: 12 place settings (without stand-by).

Figure 13 Comparison of the mean hourly energy consumption for dwelling with high performance equipment (A+++) and the dwelling with the average energy efficiency class of Mediterranean region (Refrigerator: B; Freezer: B; Washing machine: A; Dishwasher: A; Television: C; Drier: A).

Figure 14 Comparison of the annual consumption for a dwelling with high performance appliances (A+++) and the dwelling with average energy efficiency class of Mediterranean region.

Table(s) with Caption(s)

Table 1 Description of the parameters and inputs of the stochastic model of electrical load profiles for dwellings

Data type	Parameter	Units	Description
Stock characterization	Penetration rate (Pr)	%	Fraction of dwellings with at least one equipment.
	Multi-equipment probabilities (Mp)	%	These values represent the probability to have a different number of the same equipment in the same dwelling (e.g. having multiple televisions). The input of the model is defined as the cumulative fraction of dwellings with 1, 2, 3 or 4 equipment, based on the initial penetration rate (1-*Pr*). As an example, the fraction of dwellings with 1 equipment is (Mp_1-(1-*Pr*)) while the one with 2 equipment is (Mp_2-Mp_1).
	Fraction of electric devices (FE)	%	In the case of the kitchen devices, it is necessary to include the fraction of electric devices. The gas devices fraction is calculated as (1 – *FE*)
Technical data	Power (P)	kW	*P* is the nominal power. This information is available in the technical sheet of the equipment..
	Power Fraction (PF)	%	PF is the hourly mean power when the equipment is ON to the nominal the power (*P*) ratio of the equipment. This parameter is constant over time.
	Cycle Length Fraction (CF)	%	*CF* is the ratio between the cycle length and the corresponding integer hours, rounded to the upper value. For example, the duration of the cycle of a washing machine is 1.5 hours, then the integer hours is 2, and CF is 1.5/2.
	Power of Stand-by (Pstb)	kW	*Pstb* is the power of the stand-by mode. If the equipment does not have stand-by, the value is zero.
Statistics of use	Hourly profile of probabilities of use (prob(t))	%	The probabilities of use represent the probability to use one equipment at each hour. Hourly profiles for each season (summer, winter and intermediate season) and type of day (weekday and weekend) have been derived in the study.

Table 2 Stock characterization of the block of apartments in the Mediterranean Region.

Equipment	Pr %	Mp_1 %	Mp_2 %	Mp_3 %	Mp_4 %	FE %
Refrigerator	99	100	-	-	-	-
Freezer	16	100	-	-	-	-
Washing machine	92	100	-	-	-	-
Dishwasher	49	100	-	-	-	-
Television	100	35	75	90	100	-
Tumble drier	31	100	-	-	-	-
Microwave	89	100	-	-	-	-
PC	50	60	85	97	100	-
Others	100	100	-	-	-	-
Lighting	100	100	-	-	-	-
Kitchen	100	100	-	-	-	62
Oven	77	100	-	-	-	78

Table 3 Technical data of the equipment used in the Base Simulation (block of apartments in Mediterranean Region).

Equipment	P	PF	Cycle Length			E_{ON}	E_{STB}
	W	%	hh	mm	%	Wh	Wh
Refrigerator	180	45	23.0	-	96	77	-
Freezer	130	40	23.0	-	96	50	-
Washing machine	2200	19	-	111	93	380	7
Dishwasher	2200	17	-	170	94	350	-
Television	125	73	6.9	-	99	90	5
Tumble drier	2000	25	-	162	90	450	-
Microwave	1100	10	-	30	50	55	3
PC	225	45	7.9	-	99	100	5
Others	3000	10	-	40	22	65	1.4
Lighting	200	100	-	60	100	200	-
Kitchen (electric)	5000	12	-	204	85	510	-
Kitchen (gas)	6176	12	-	204	85	630	-
Oven (electric)	2500	17	-	144	80	340	-
Oven (gas)	3162	17	-	144	80	430	-

Table 4 Comparison of the Penetration rate (*Pr*) with the Fraction (*F*) of dwellings with each equipment (input vs. output).

Equipment	Pr %	Fraction %	Relative error[a] %
Refrigerator	99.4	99.7	0.3
Freezer	15.8	15.7	0.8
Washing machine	92.2	91.6	0.7
Dishwasher	48.8	47.1	3.5
Television	100.0	100.0	0.0
Tumble drier	31.3	29.9	4.5
Microwave	89.4	89.6	0.2
PC	49.7	50.4	1.5
Others	100.0	100.0	0.0
Lighting	100.0	100.0	0.0
Electric Kitchen[b]	62.1	61.6	0.9
Electric Oven[b]	60.0	62.3	3.9

[a] $E_r = \frac{|F - Pr|}{Pr} \cdot 100$

[b]Obtained by: *(Pr x FE)/100*.

Table 5 Comparison of the daily proportion of equipment in state ON (Two sample t-Student test, *α=0.05* confidence level).

Equipment	Daily proportion mean of equipments ON			
	Simulation	Input Data	t	p-value
Washing machine	0.0742	0.0728	0.0510	0.95
Dishwasher	0.0825	0.0822	0.0079	0.99
Television	0.2152	0.2148	0.0057	0.99
Tumble drier	0.0651	0.0620	0.1461	0.88
Microwave	0.0762	0.0751	0.0288	0.98
PC	0.2673	0.2582	0.1467	0.88
Kitchen	0.1022	0.1024	-0.0032	0.99
Oven	0.0508	0.0512	-0.0127	0.98

Table 6 Statistics of the annual energy consumption for 500 simulated equipment in a multi dwelling of Mediterranean region.

Summary statistics	Wash. mach. kWh	Dishwasher kWh	Television kWh	Drier kWh	Ele. kitchen kWh	Ele. oven kWh	Microwave kWh	Computer kWh
Mean	303.9	246.3	210.6	248.8	435.6	163.3	61.0	290.7
Standard deviation	8.8	7.1	2.8	9.8	11.9	6.7	1.1	3.5
Minimum	277.6	223.6	200.9	216.9	401.9	142.1	57.1	278.9
Maximum	331.7	272.6	319.7	281.3	485.0	190.0	64.6	302.96

Table 7 Comparison of the annual energy consumption obtained in different studies and countries by measurement campaigns (Nº is the number of equipments). In grey the Mediterranean countries.

Study	Country		Dishwasher		Electric Oven		Television		Computer	
			Nº	kWh/yr	Nº	kWh/yr	Nº	kWh/yr	Nº	kWh/yr
Ciel 1995/96	FR	France	45	277	22	95	122	137	-	-
Irise 1997/99	FR	France	49	306	27	186	113	133	-	-
Eureco 2000-2001	DK	Denmark	46	289	-	-	91	31	-	-
	GR	Greece	40	159	-	-	142	35	-	-
	IT	Italy	49	369	8	130	123	131	-	-
	PT	Portugal	42	256	8	144	92	66	-	-
Remodece 2006-2008	BE	Belgium	11	288	-	-	145	24	22	194
	BU	Bulgaria	7	151	-	-	166	106	15	294
	CZ	Czech Rep.	32	223	7	169	171	57	25	393
	DE	Germany	17	146	3	65	112	63	12	225
	DK	Denmark	-	-	-	-	239	81	54	743
	FR	France	68	250	-	-	180	137	13	228
	GR	Greece	-	-	-	-	166	135	42	322
	HU	Hungary	18	330	4	100	97	51	12	177
	IT	Italy	41	206	9	146	101	53	6	263
	NO	Norway	9	188	7	298	223	49	3	312
	PT	Portugal	-	-	-	-	108	71	4	123
Simulation results (ON+STB)				246		163		177+34		260+31

Table 8 Characteristics of the dwellings with a synthetic profile: equipments, annual and daily consumption. Comparison with the mean dwelling.

	Synthetic Profile			Mean dwelling	
	SP1	SP2	SP3	Pr (%)	Mp (nº)
Refrigerator	1	1	1	100	1
Freezer	0	0	0	16	1
Washing Machine	1	1	1	92	1
Dishwasher	0	1	1	49	1
TV	2	1	1	100	1.9
Drier	0	0	1	31	1
Microwave	1	1	1	89	1
PC	1	1	0	50	1.08
Others	1	1	1	100	1
Lighting	1	1	1	100	1
Ele. kitchen	1	1	1	100	1
Ele. Oven	1	1	1	77	1
Annual consumption (kWh)	2939	2944	2923	2932	
Hourly maximum peak (Wh)	187	213	213	93	
Weekday consumption (Wh)	800	796	794	795	
Weekend consumption (Wh)	818	835	816	821	

Table 9 Energy label comparison: database, label adaptation and input model (hourly consumption).

	DDBB		Label adaptation		Input model
	%	Label	Min Wh	Max Wh	Wh
Washing Machine	20	A+	339	384	380
	41	A	384	443	
	19	B	443	502	
Dishwasher	11	A+	308	347	350
	60	A	347	391	
	23	B	391	440	
Drier	29	A	444	687	450
	20	B	687	803	
	27	N/A	-	-	
Refrigerator	30	A+	37	49	77
	38	A	49	61	
	24	B	61	84	
Freezer	54	A	34	43	50
	11	B	43	59	
	23	C	59	74	

Fig.1

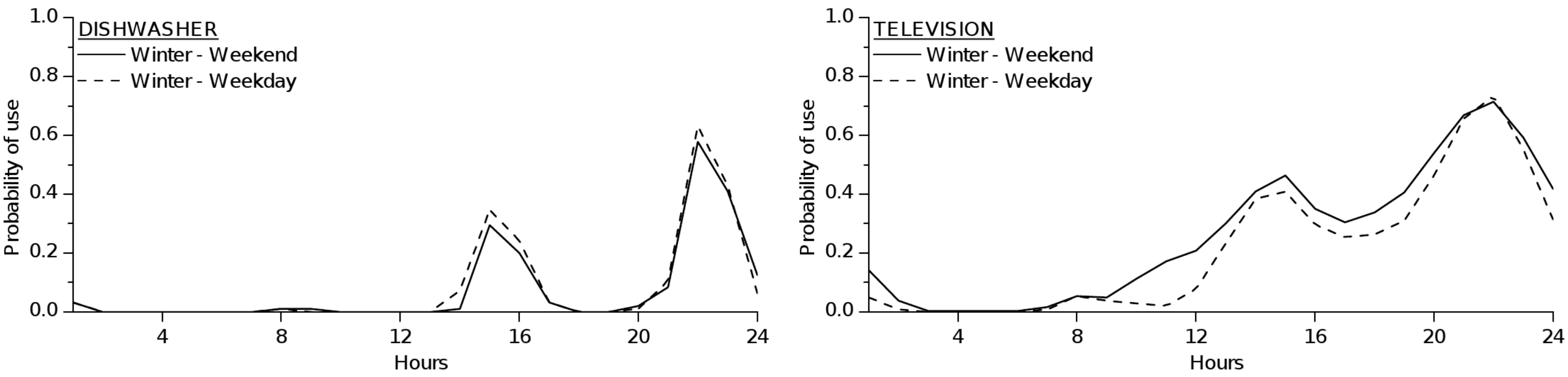
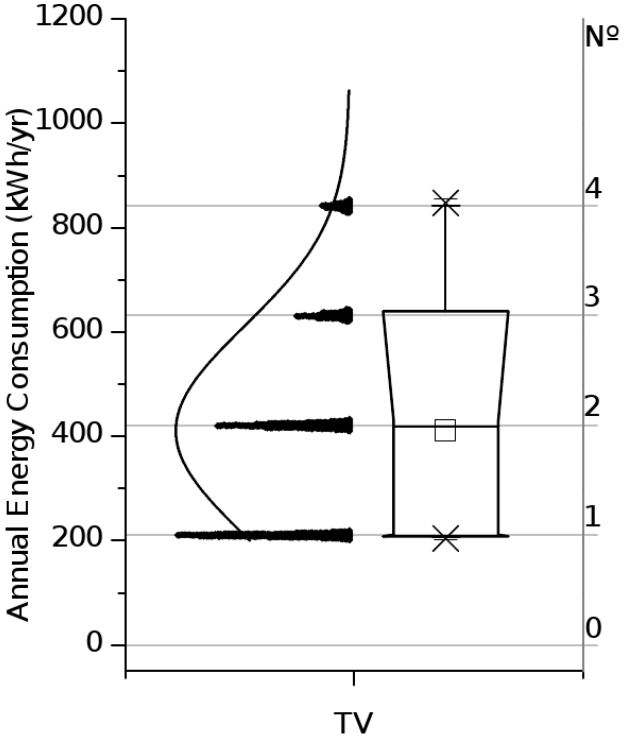

DISHWASHER
Winter - Weekend
Winter - Weekday
Probability of use
Hours
TELEVISION
Winter - Weekend
Winter - Weekday
Probability of use
Hours

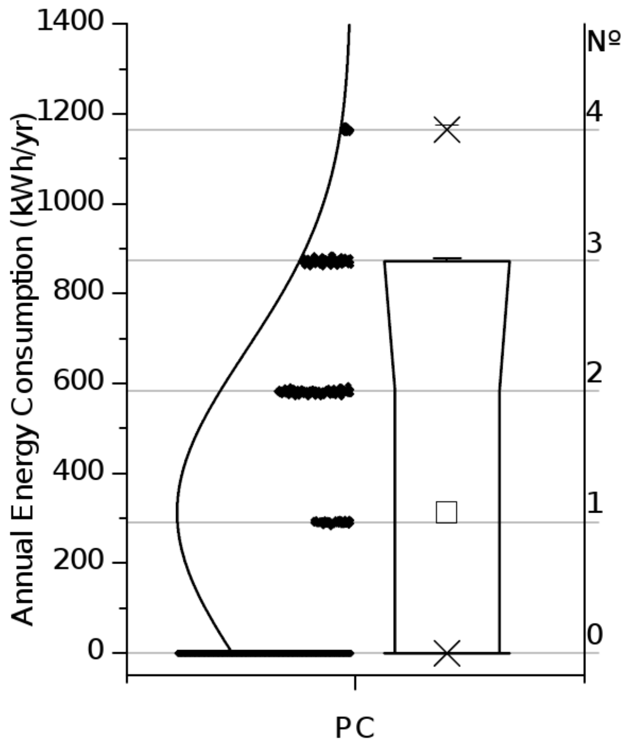
Fig.2



Television Summary statistics	Simulation		Input data	
	kWh/yr	Nºeq.	kWh/yr	Nºeq.
Mean	410.9	1.9	440.9	2.1
Standard Deviation	200.5	0.9	-	-
Minimum	200.9	0.95	-	-
Maximum	855.1	4.1	-	-

Fraction of multi-equipment (%)

Nº	Simulation	Input data
1	35	39
2	40	37
3	15	15
4	10	9

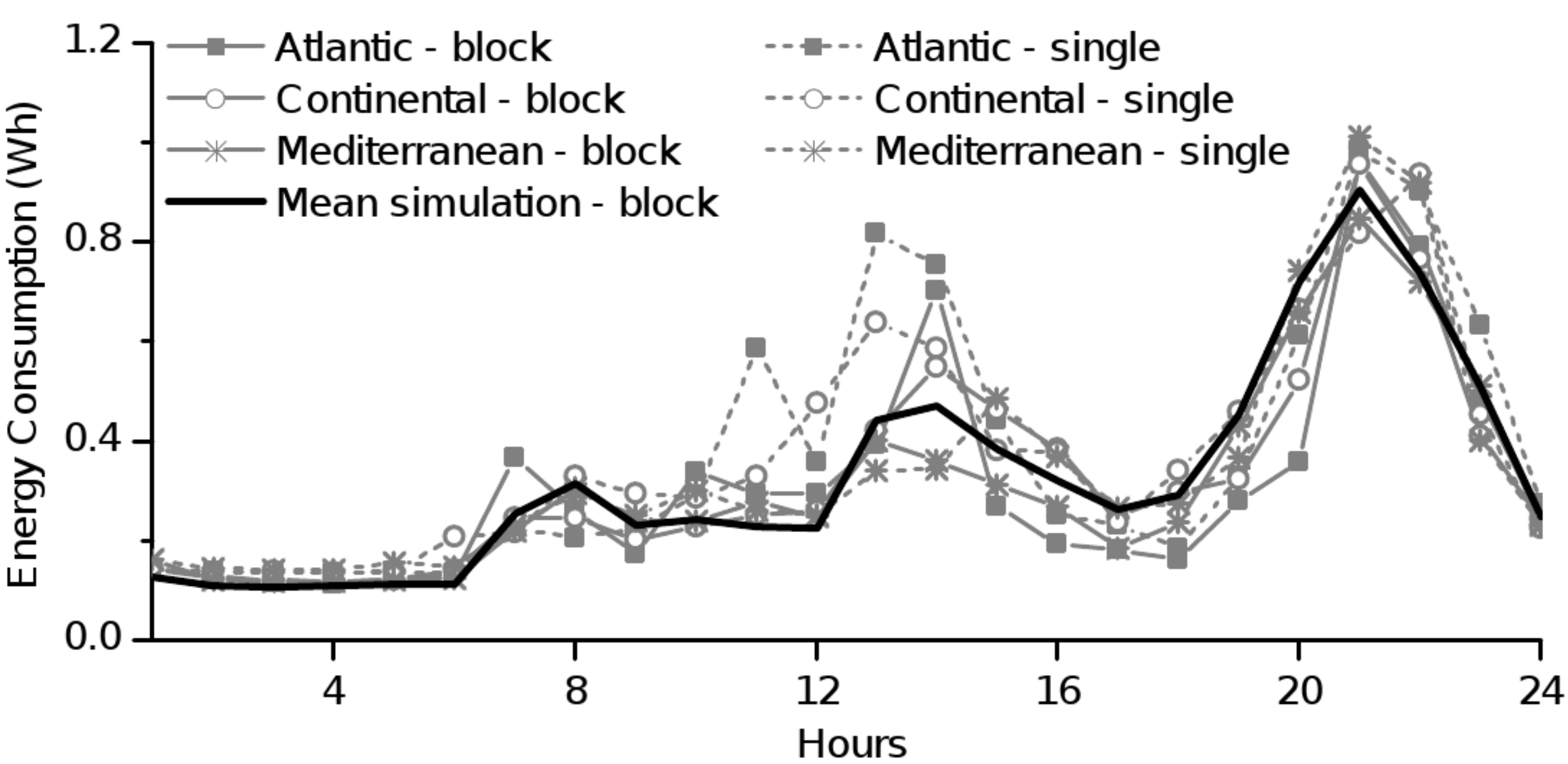


Computer Summary statistics	Simulation		Input data	
	kWh/yr	Nºeq.	kWh/yr	Nºeq.
Mean	313.1	1.08	350.9	1.2
Standard Deviation	358.9	1.2	-	-
Minimum	0	0	-	-
Maximum	1174.3	4.0	-	-

Fraction of multi-equipment (%)

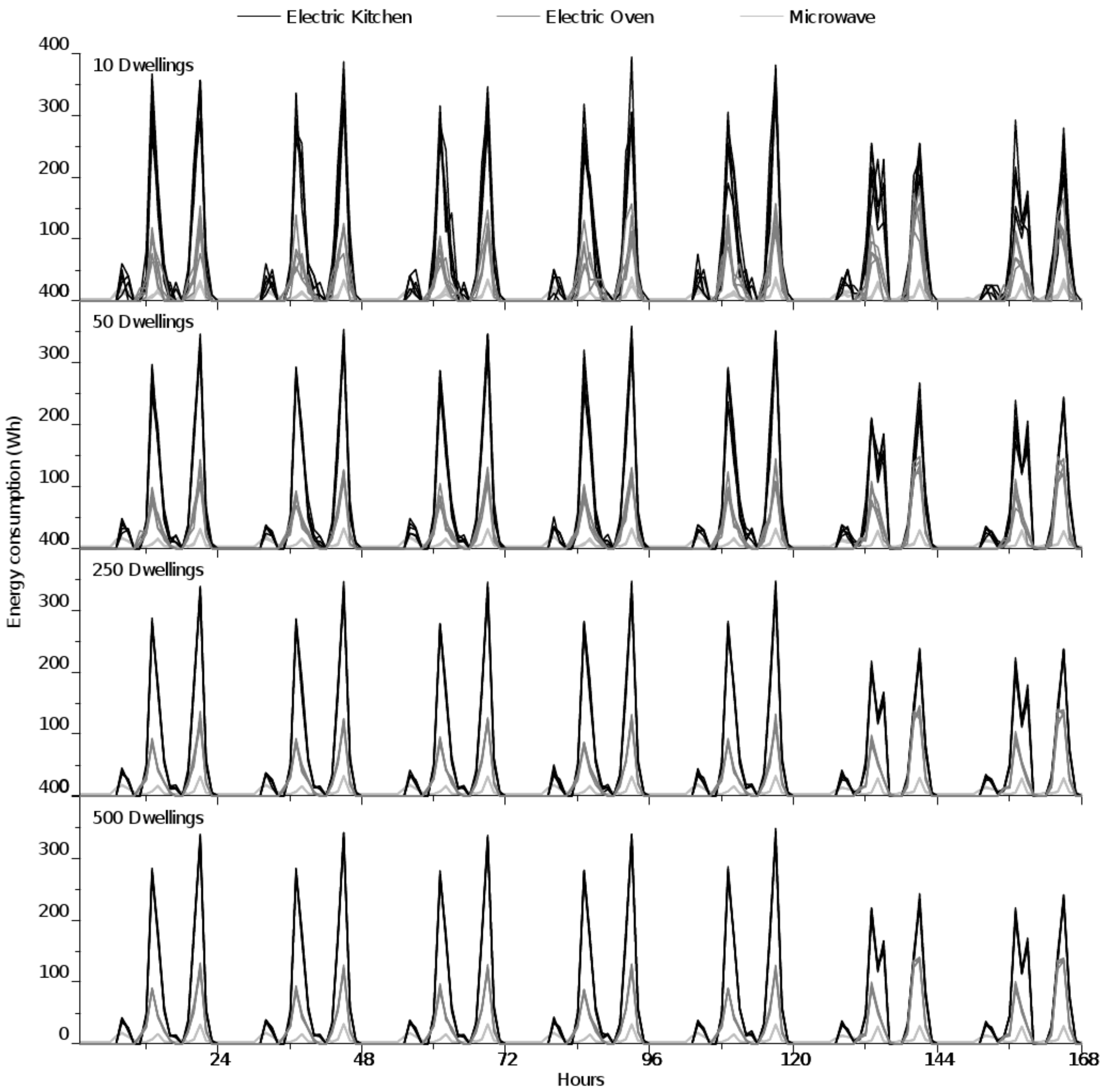
Nº	Simulation	Input data
1	20	20
2	48	50
3	26	25
4	5	5

Fig.3 (NEW)



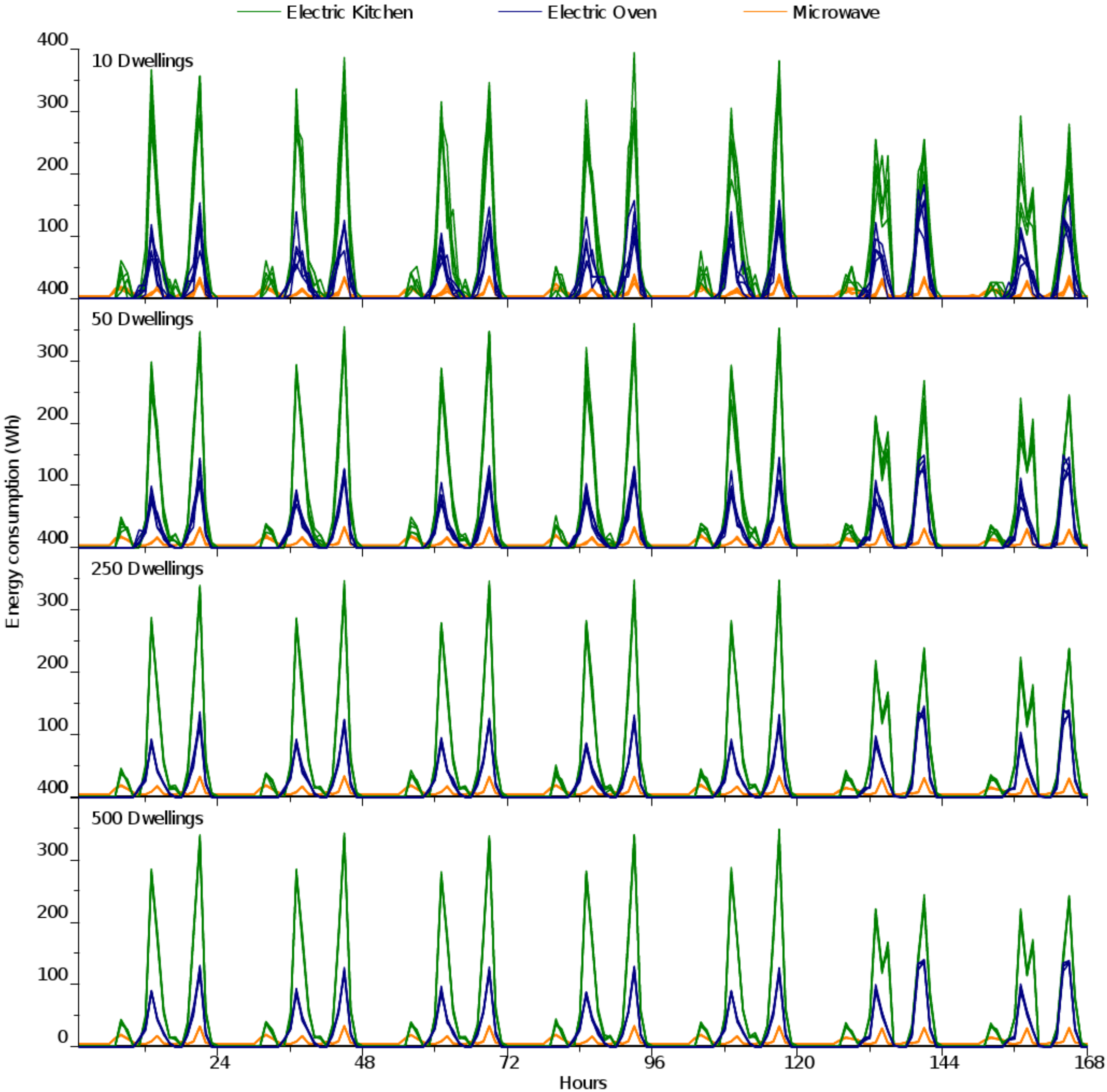
Atlantic - block
Atlantic - single
Continental - block
Continental - single
Mediterranean - block
Mediterranean - single
Mean simulation - block
Energy Consumption (Wh)
1.2
0.8
0.4
0.0
4
8
12
16
20
24
Hours

Fig.4.B&W



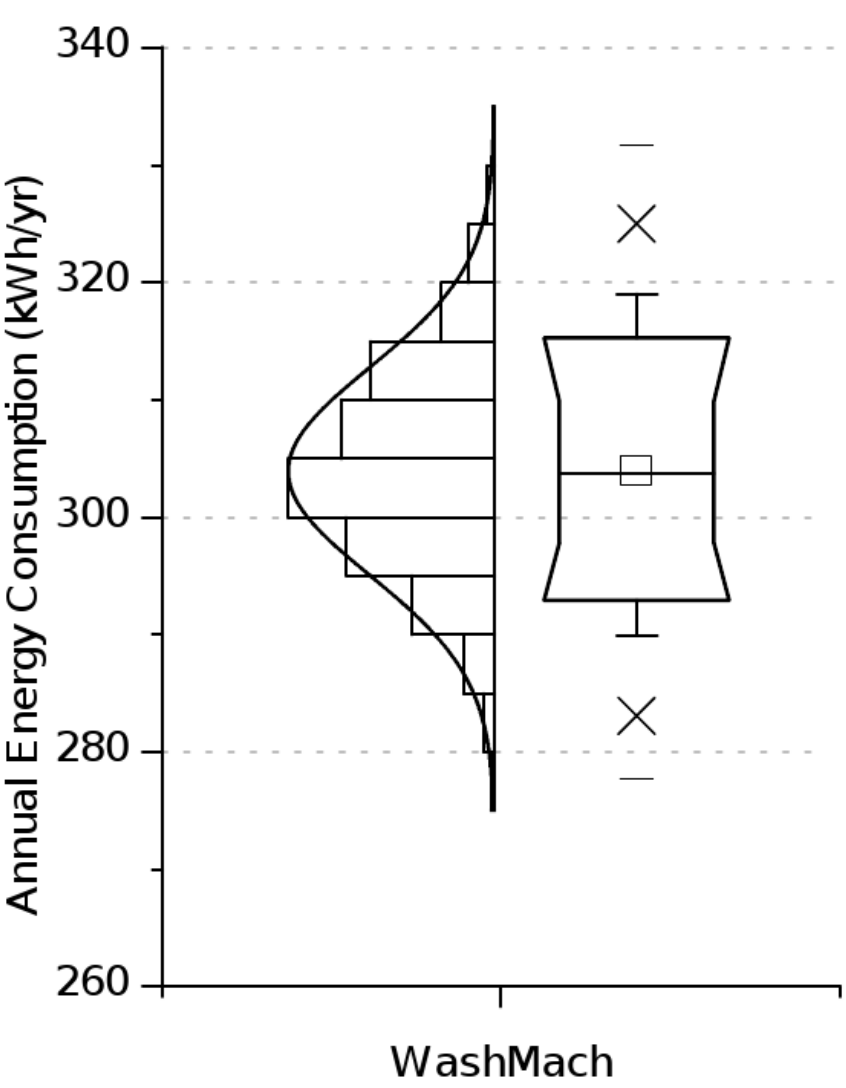
Electric Kitchen
Electric Oven
Microwave
10 Dwellings
50 Dwellings
250 Dwellings
500 Dwellings
Energy consumption (Wh)
400
300
200
100
0
24
48
72
96
120
144
168
Hours

Fig.4.color



Electric Kitchen
Electric Oven
Microwave
10 Dwellings
50 Dwellings
250 Dwellings
500 Dwellings
Energy consumption (Wh)
400
300
200
100
0
24
48
72
96
120
144
168
Hours

Fig.5



Summary statistics	kWh/yr
Mean	303.9
Standard Deviation	8.8
Minimum	277.6
Maximum	331.7

Fig.6

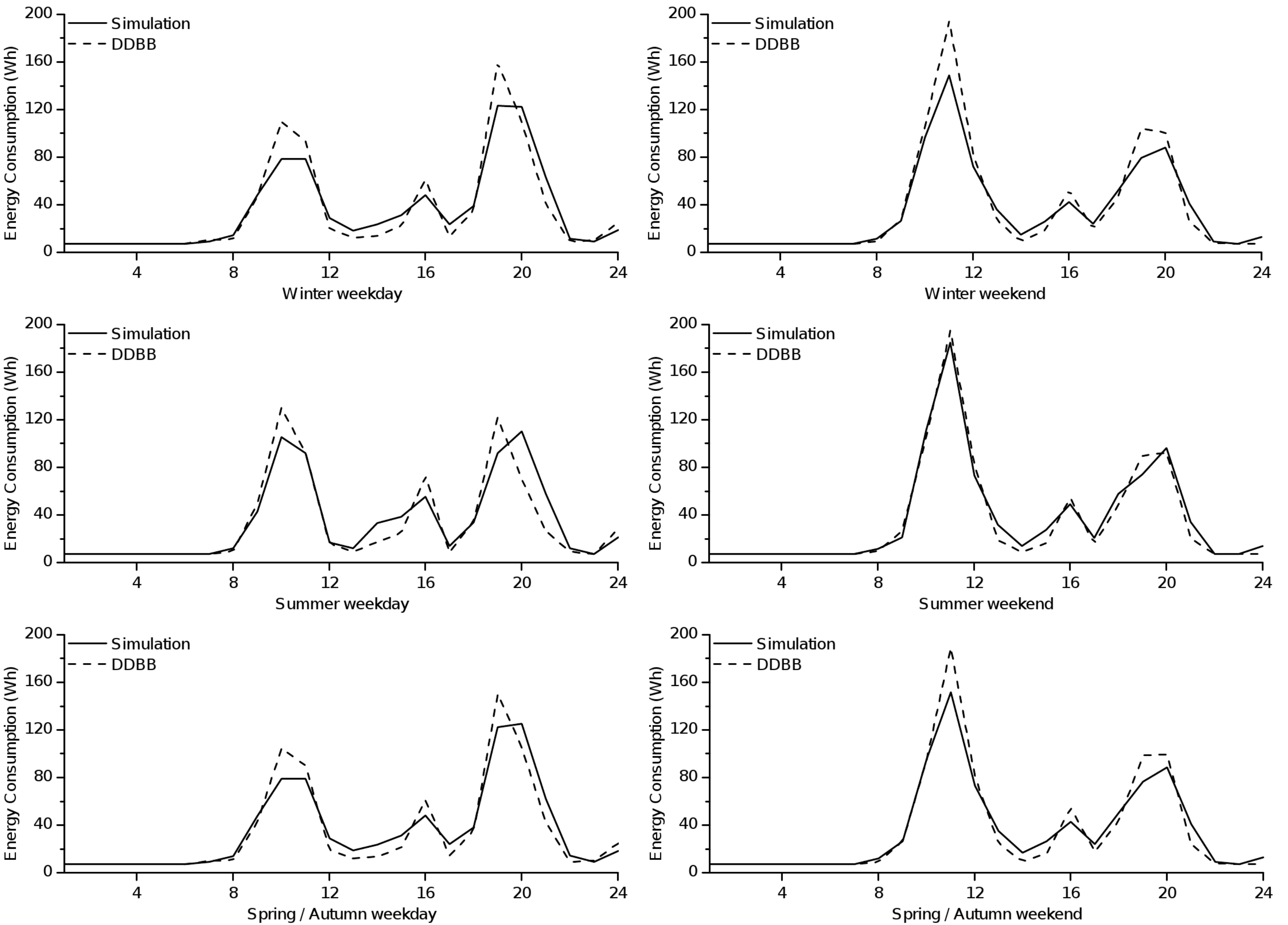

Simulation
DDBB
Energy Consumption (Wh)
Winter weekday
Winter weekend
Summer weekday
Summer weekend
Spring / Autumn weekday
Spring / Autumn weekend
0
40
80
120
160
200
4
8
12
16
20
24

Fig.7.B&W

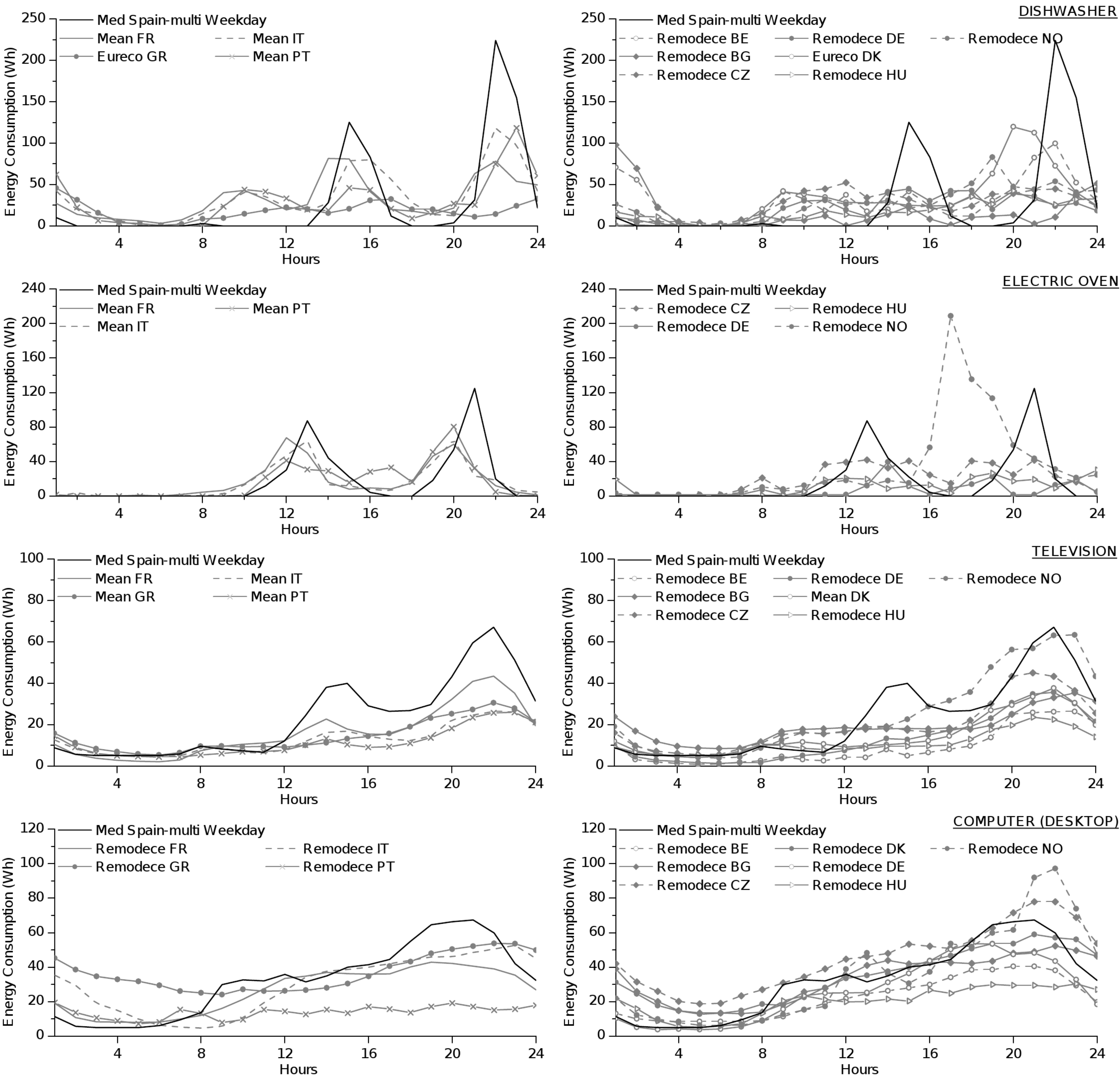

DISHWASHER
ELECTRIC OVEN
TELEVISION
COMPUTER (DESKTOP)
Med Spain-multi Weekday
Mean FR
Mean IT
Eureco GR
Mean PT
Mean GR
Remodece FR
Remodece IT
Remodece GR
Remodece PT
Remodece BE
Remodece BG
Remodece CZ
Remodece DE
Remodece DK
Remodece HU
Remodece NO
Eureco DK
Mean DK
Energy Consumption (Wh)
Hours

Fig.7.color

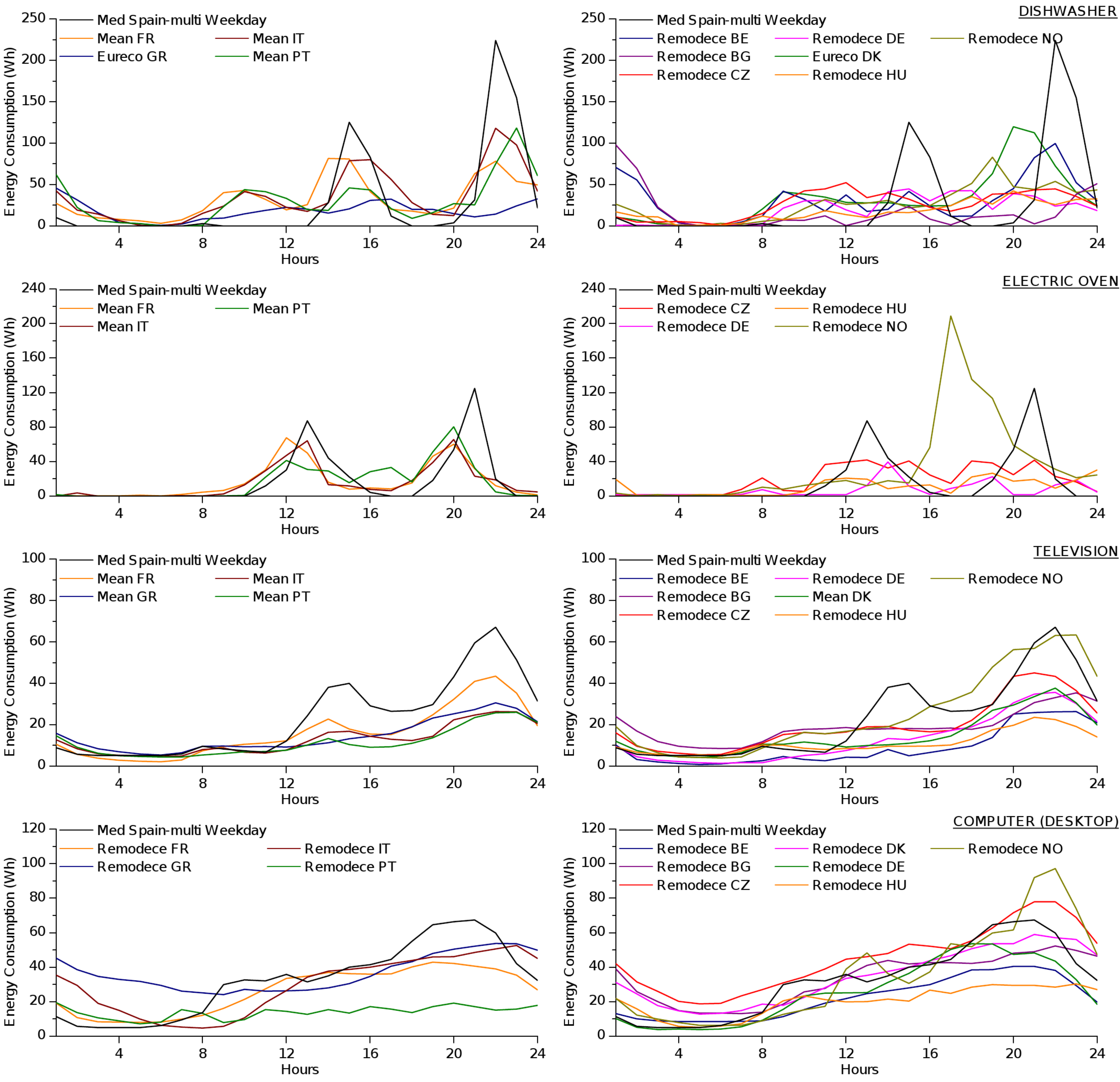
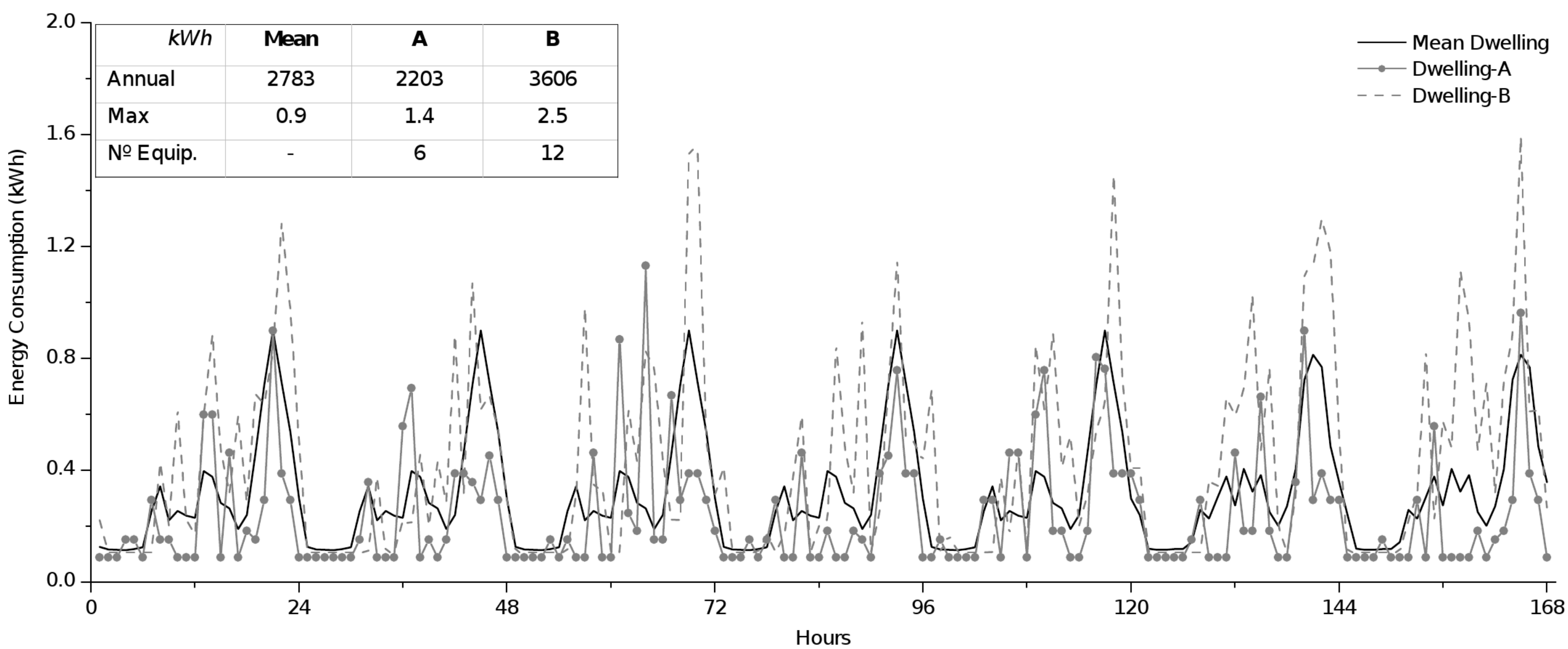
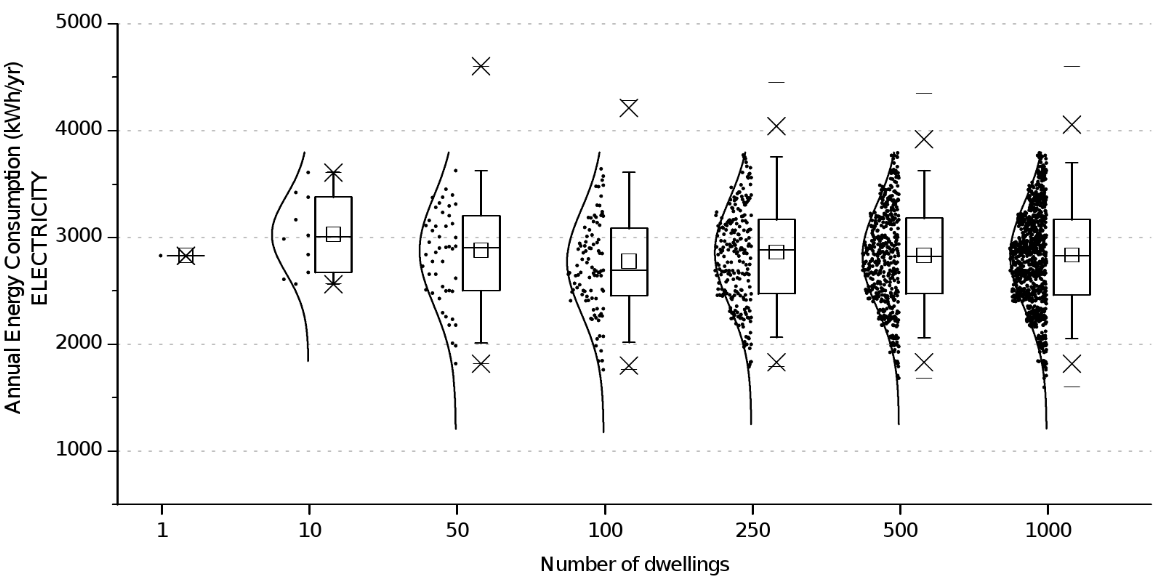

DISHWASHER
Med Spain-multi Weekday
Mean FR
Mean IT
Eureco GR
Mean PT
Remodece BE
Remodece DE
Remodece NO
Remodece BG
Eureco DK
Remodece CZ
Remodece HU
ELECTRIC OVEN
Mean FR
Mean PT
Mean IT
TELEVISION
Mean GR
Mean DK
COMPUTER (DESKTOP)
Remodece FR
Remodece IT
Remodece GR
Remodece PT
Remodece DK
Energy Consumption (Wh)
Hours

Fig.8



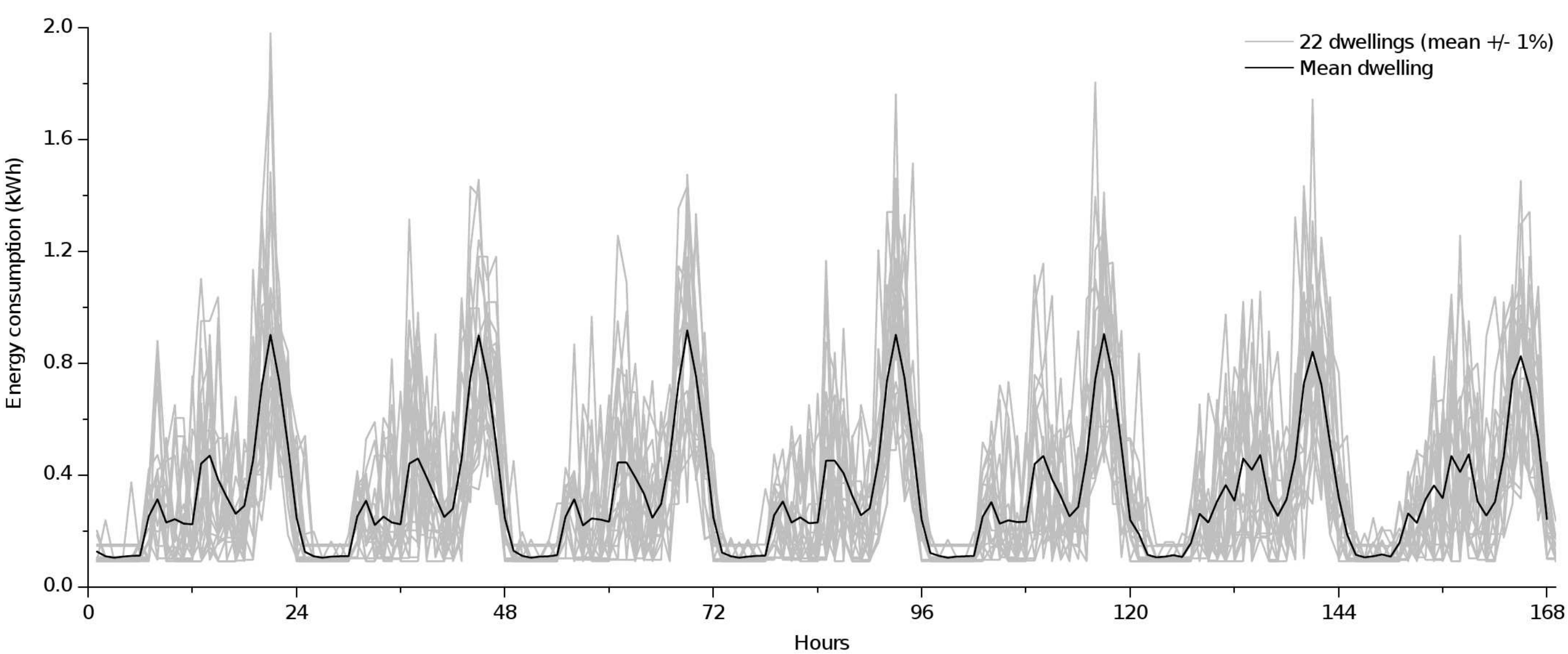
kWh
Mean
A
B
Annual
2783
2203
3606
Max
0.9
1.4
2.5
Nº Equip.
-
6
12
Mean Dwelling
Dwelling-A
Dwelling-B
Energy Consumption (kWh)
0.0
0.4
0.8
1.2
1.6
2.0
0
24
48
72
96
120
144
168
Hours

Fig.9



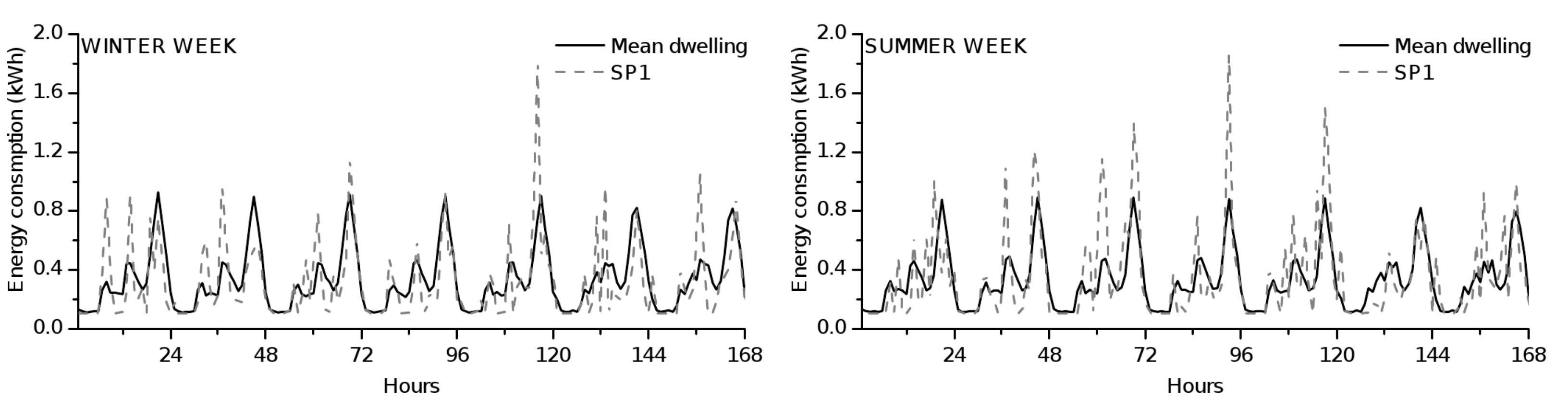
nº dw.	STATISTICS (kWh/yr)			
	Mean	SD	MIN	MAX
10	3028	364	2565	3611
50	2877	513	1822	4606
100	2777	492	1763	4287
250	2861	495	1791	4452
500	2829	484	1683	4354
1000	2834	499	1600	4606

Fig.10



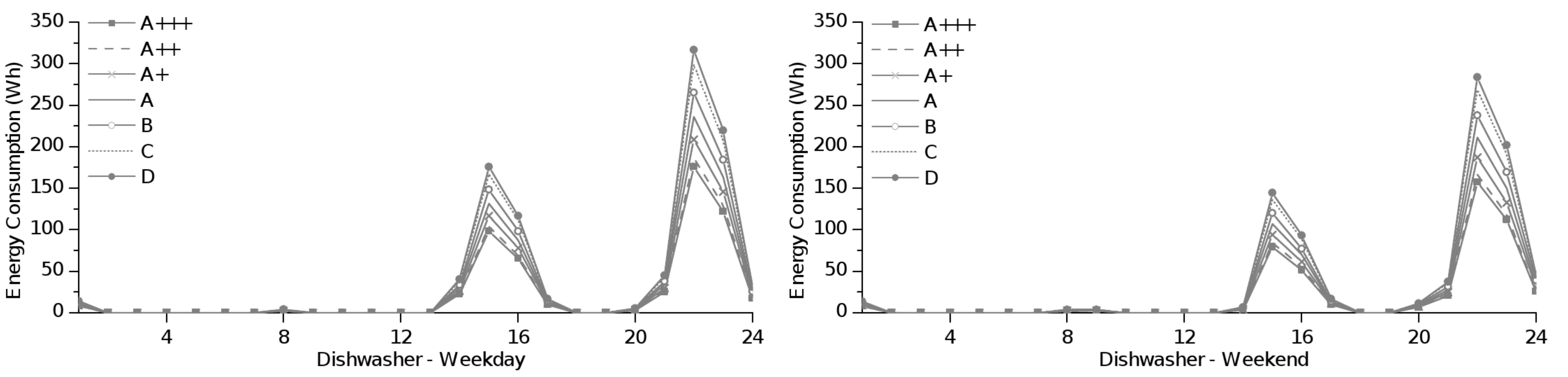
2.0
1.6
1.2
0.8
0.4
0.0
Energy consumption (kWh)
0
24
48
72
96
120
144
168
Hours
22 dwellings (mean +/- 1%)
Mean dwelling

Fig.11



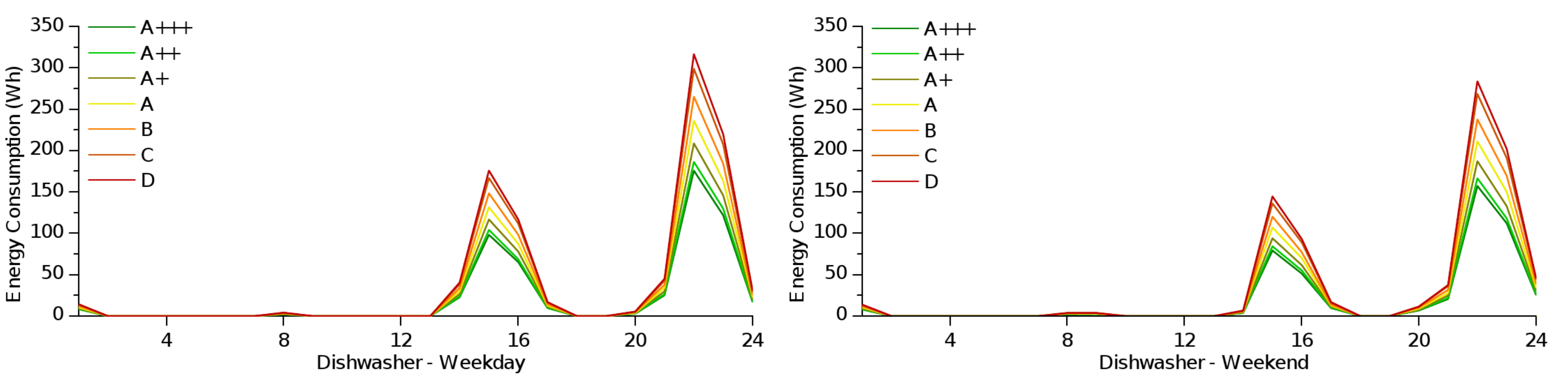
WINTER WEEK
Mean dwelling
SP1
Energy consmption (kWh)
Hours
SUMMER WEEK
Mean dwelling
SP1
Energy consmption (kWh)
Hours

Fig.12.B&W



350
300
250
200
150
100
50
0
Energy Consumption (Wh)
4
8
12
16
20
24
Dishwasher - Weekday
A+++
A++
A+
A
B
C
D
Dishwasher - Weekend

Fig.12.color



350
300
250
200
150
100
50
0
Energy Consumption (Wh)
A+++
A++
A+
A
B
C
D
4
8
12
16
20
24
Dishwasher - Weekday
Dishwasher - Weekend

Fig.13

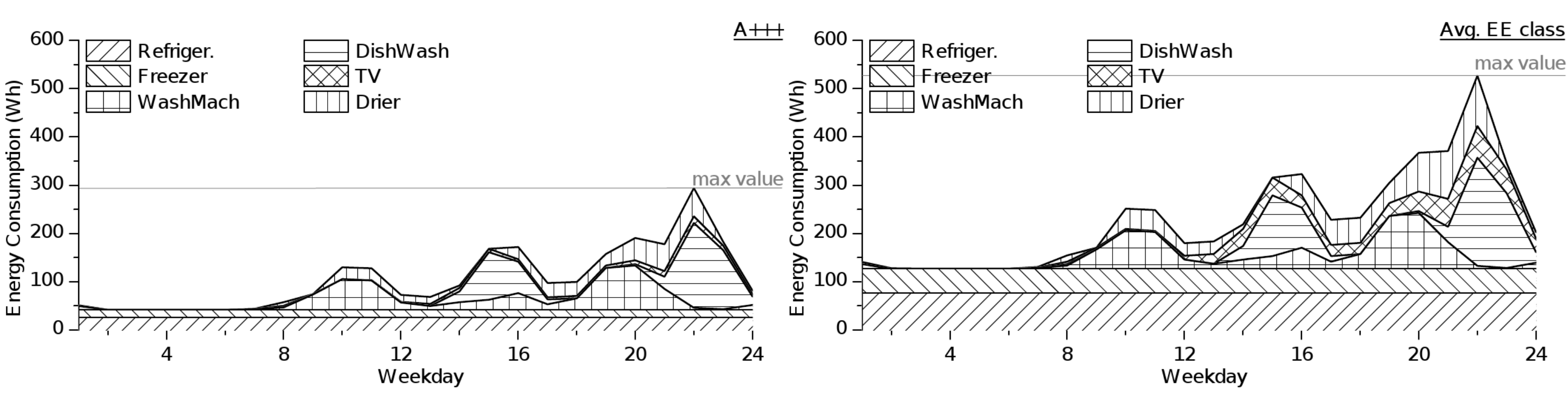
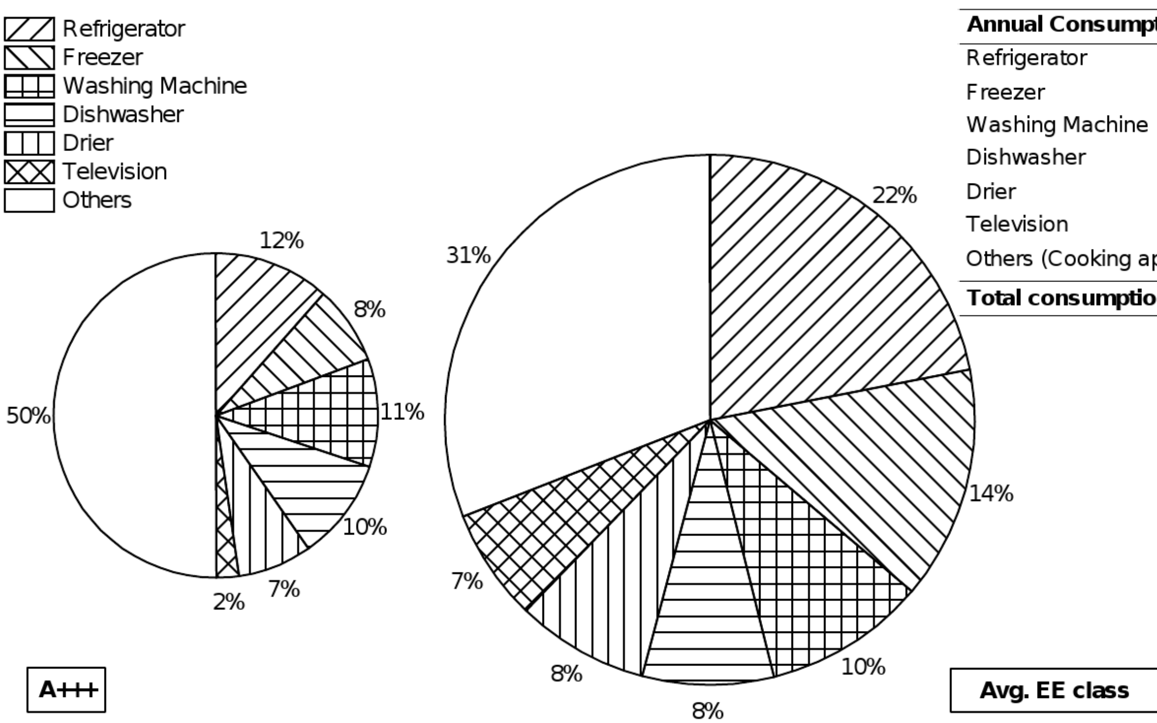

A+++
Refriger.
DishWash
Freezer
TV
WashMach
Drier
max value
Energy Consumption (Wh)
Weekday
0
100
200
300
400
500
600
4
8
12
16
20
24
Avg. EE class
Refriger.
DishWash
Freezer
TV
WashMach
Drier
max value
Energy Consumption (Wh)
Weekday

Fig.14



Annual Consumption (kWh)	A+++	Avg. EE class
Refrigerator	219	674
Freezer	149	438
Washing Machine	204	304
Dishwasher	194	246
Drier	141	249
Television	42	211
Others (Cooking appl. and PCs)	951	951
Total consumption	1900	3073

HIGHTLIGHTS

- We develop a stochastic model for electric loads in Mediterranean households
- The model is able to reproduce the most important features of residential loads
- The model can be used for simulated detailed profiles for a cluster of buildings
- Generation of stochastic dwellings with real peaks and annual and daily mean loads
- The model can use the energy labelling information of appliances as input