MODELING OF SPANISH HOUSEHOLD ELECTRICAL CONSUMPTIONS: SIMPLIFIED AND DETAILED STOCHASTIC APPROACH IN TRNSYS ENVIRONMENT

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ABSTRACT

The initial assessment of electric energy demands of a building is a key element in the design process, that should be integrated in the earlier stages of the design of a net zero energy building. The objective of the study is the creation of predictive models of household electrical consumptions in the Mediterranean/Spanish climate and its implementation in TRNSYS 17 environment. The models offer both a simplified level of analysis, based on average seasonal electrical consumptions trends and a stochastic in-depth level for the simulation of peak loads through the compiling of multiple TRNSYS types.

INTRODUCTION

The preventive assessment of the household electrical consumptions (Cellura, M. et al., 2012) is gaining attention, in the domain of integration of renewable technologies in Net zero energy buildings (Net ZEBs). Although the importance of a preventive knowledge of the electrical consumptions is not usually as stressed as other aspects (e.g. energy efficiency, energy savings), it is one of the key elements for sizing of equipment and systems and to evaluate the behavior of the building in terms of interaction with the energy grid (Carbonell, J. et al, 2010).

The estimation of electrical loads has always been based on statistical data; although this kind of approach has some strengths (e.g. simple calculations, perfect for first stage analysis) but it is not useful when it is needed to model the energy interactions of a “prosumer” building. From this perspective a good and solid modeling approach should comprise both average values and peak values estimation: the first being useful for an early “charrette design” sizing of the systems, the latter for grid interaction, storage sizing issues and to optimize demand side management (DSM) strategies.

Those are some of the core topics analyzed in detail (Salom J. et al, 2011) in the context of the Net Zero Energy Buildings framework defined within the joint implementing agreement of the Solar Heating and Cooling (SHC) and Energy Conservation in Buildings and Community Systems (ECBCS) SHC Task 40-ECBCS Annex 52 of the International Energy Agency (IEA) “Towards Net Zero Energy Solar Buildings”.

The capability of assessing in advance electrical energy consumptions can be crucial in performing correct sizing of energy storages or energy production systems reducing the need of retrofit action caused by a non-perfect design stage: the use of building simulation tools in the first design stages in thermal non-steady state conditions field, daylight and assessment of electrical consumptions could allow multi-objective optimizations, resulting in an optimal design of the building as a whole and in its interaction with the grid .

Another key element in the definition of the rationale of the work presented in this paper is the importance of uncertainty caused by occupants’ behavior in the definition of thermal loads and electrical consumptions in buildings’ simulations. Occupants thermal loads may have a significant incidence on the H/C loads requested in buildings; occupants’ habits (e.g. using appliances at night, watching television in the afternoon, etc.) and status (e.g. family with children, single unemployed, etc.), type, efficiency and number of appliances used in the household have huge impacts on electrical energy demand peaks and average profiles.

The topic proposed in the paper has been studied before in similar ways.

Widen et al. (Widen, J. 2010) proposed a Markov-Chain transition probabilities driven method, with a wide use of Time Use Data (TUD) information for Sweden. TUD were used to describe occupancy patterns in a stochastic Markov chain (3 modeling states) based model in the field of electrical and lighting demand. Widen used detailed modeling of the use of time (household care, recreation, transports, food preparation, work etc.) for each occupant. The fundamental section of the model is the conversion of the TUD into occupancy and end uses energy profiles, through the use of different pattern and converting functions according to the appliances modeled in the paper.

Richardson et al. (Richardson, I et al. 2009) proposes 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 a transition probabilities-Monte Carlo technique.

The study described in this paper aims to create a tool able to model both average trends and stochastic variability in terms of average trends and "switch-on events" (Turning the state of the i^{th} appliance of the n^{th} household from off to on, at the j^{th} timestep) description for each of the appliances considered. The models allow the user to describe both the single household case and the multi-household scenarios in TRNSYS environment; the results included in the paper are evaluated tuning the input data and the probabilities of switch-on events to happen on the Spanish case, through the analysis of projects dealing with the use of energy in households for Spain.

METHODS

The study has been performed on different levels, each one with a different aim, different resolution and using different techniques. Modeling needs vary according to the modeling aim and are very different in the two levels that have been analyzed in the paper. Before analyzing in detail the differences among the two approaches, a common ground will be briefly described.

The study aims to model the electrical consumptions of the household sector of the Spanish background. All the models analyze electrical consumptions that are not forced by external phenomena (heating/cooling and artificial lighting) under the following classification: cooking devices, washing machine, dish washer, television, dryer, oven, computers, washer-dryer, microwave.

Other nearly constant consumptions appliances (e.g. fridge, freezer), an estimation of the standby equipment electric consumptions are also considered in both analyses.

The simulations models have been implemented in TRNSYS 17.1 environment, arranged in single household projects at first and, after a FORTRAN programming process, implemented into multiple TRNSYS types for every level of modeling depth, in order to handle multi-dwelling simulations. Although the implementation of the model would fit in any simulation environment, the possibility of running generation-side and both thermal and electrical load-side simulation in the same tool and at the same time, like in the case of the proposed TRNSYS type implementation, is an advancement towards a "global" simulating approach. The time-step chosen is one hour, as it guarantees a good balance between computational requirements, scientific robustness of the results (Widen, J. 2010) and validation capabilities according to the available data (Most of them use hourly resolution).

All the models use the detailed data from the Spahousec project led by IDAE (IDAE, 2011) for different aims, that will be clarified in the following. This project delineates an overview on the state of the energy consumptions in Spain, with detailed information also on different sub-regions (Continental, Mediterranean and Atlantic) and different type of households (single detached houses or multi-dwelling buildings). The data are built through both surveys and monitored data.

The main information used as input to the models are: the number of households per kind and zone, penetration ratios of equipment (Number of house with at least one appliance of the i^{th} kind/total number of houses) in each region in conjunction to the average number of appliance per house per region. The IDAE database also contains the Spanish overall electrical consumptions, in detail for every appliance and for every sub-region. These data are organized in the form of hourly average profiles on the 24 hours, with a weekend-weekday and seasonal depth. Three seasons are differentiated: winter, summer and intermediate season.

In general the parameters required for every model to run are: number of simulated dwellings, operative parameters (e.g. number of header lines in external files), seed(s) to the random number generators, seasons starting-ending simulation hours.

The last consideration to be done before carrying out the analysis of the two presented approaches is that the models have been conceived and realized in order to allow future studies, also not directly connected to the Spanish background or the household sector. In other words, the structure of the TRNSYS Types has been compiled with a high customization possibility, arranging the description of the case study only into external text files that can be easily replaced or modified.

First modelling level: simplified

A first level of analysis deals with the creation of a simplified tool, able to describe average trends in the domain of household electrical consumptions.

The idea is to have a simple tool to be used when in need of some quick assessment on the expected electricity consumptions of a building or in the case of a target of a neighborhood. Obviously the model does not take in consideration peak loads as they are smoothed in the average values, but modeling peak loads isn't the target of this section of the work. This model answers the need to assess the overall energy consumptions for a building target in a period of time and to know when to expect the highest overall energy demand.

The idea is to manipulate the overall electric energy consumptions for the selected region of the residential sector with the total number of households in the whole nation, number of equipment per house and penetration ratios of the selected equipment in order to obtain an average energy consumption profile per each use of energy per household. The possibility of analyzing some retrofit actions on the selected use of energy (e.g. using more efficient appliances) has been implemented too as coefficients to be selected in the parameters panel of the Type and to be applied to all the simulated buildings.

The described process has been iterated for all the Spain regions the Spahousec project has data on. Every element from the Spahousec project appliance list has been added to the model, including heating, domestic hot water (DHW), cooling, lighting.
These four more terms have been added in this model although they are not exactly independent from external phenomena since the nature of model 1 allowed it.
The point is that the stochastic approach in this model is not added in terms of "switch on" events: all the uses of energy are analyzed as average consumption profiles and therefore heating, DHW, lighting and cooling can be included in this analysis.
At the beginning of every simulation, the stochastic method is added in terms of the generation of a set of appliances and use of energy different for every house. In other words, at the very first time-step, the TRNSYS routine compares random generated numbers to the penetration ratios for each use of energy, in order to determine if each one is present in each one of the simulated households. If the selected appliance is used in a household, the TRNSYS routine would also determine if more of one of the same kind of equipment would be used in the house. As an example, if it is verified that in a house there is at least a personal computer, the TRNSYS routine will multiply the average profiles per the average number of PCs per house that have been set previously.
The possibility of having different appliances of the same kind both on and off at the same time is not considered in this approach as it is an information already included in the average electrical data and as it is not the aim of this simpler modeling approach.
The input data to the type are average 24 hours profiles for weekends and weekdays, for winter, summer and spring/autumn (6 profiles), penetration ratios for every use of energy and average numbers of appliance per house. The expected output is an average energy consumptions profile, for every household and for the whole neighborhood simulated, both in detail for every appliance and use of energy analyzed in the Spahousec project and aggregated. As figure 1 shows, the switch from weekend to weekday is clearly recognizable.

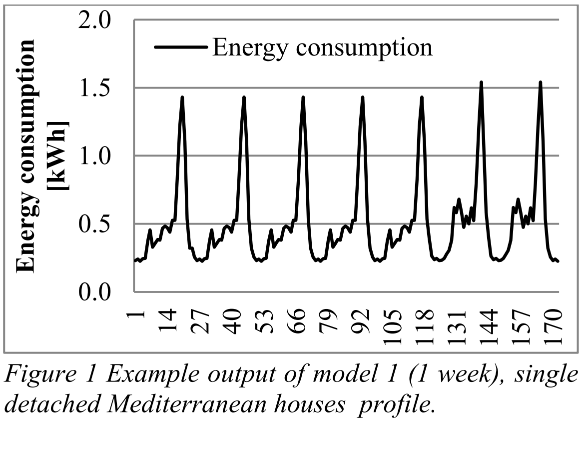

Figure 1 Example output of model 1 (1 week), single detached Mediterranean houses profile.

As expected, for all the weekdays (or weekend days) the profiles are not different as the stochasticity is applied at the beginning of the very first time-step and therefore resulting in the appliance and use of energy list being constant throughout the whole simulating process.

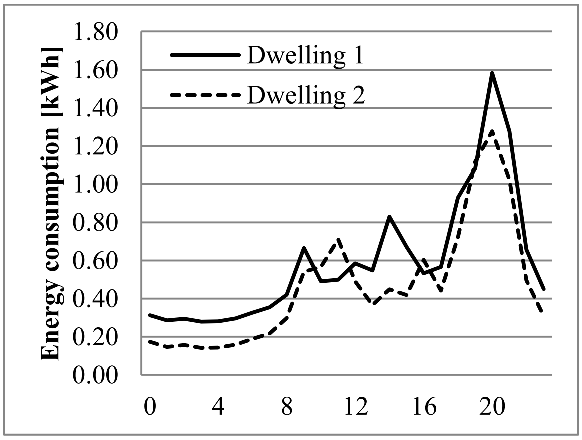

Figure 2 Comparison between two 24 hours dwellings' profiles, model 1

Figure 2, instead, shows two stochastically generated profiles for two different dwellings. As expected, the shape of the two curves is different even though the input data is the same: this is obviously caused by a different setup of the appliances and use of energy list being considered for the two stochastically generated buildings' consumption trends.

Second modelling level: "semi-detailed"

The approach described so far is useful when it is just needed to have a first, base idea on average profiles of electric consumptions.
It is however insufficient when the aim is to assess the interaction of the building with the energy grid, or simply to model peak loads in electric energy consumptions.
A second approach therefore has been developed in order to obtain more realistic patterns in the output of the model.
The second model is much more based on stochastic processes than the first one. The idea is to create a stochastic model using average values but developing a new approach able to keep in consideration peak loads in consumptions: it is "semi-detailed", because there is no modeling of occupancy levels.
The main input to this model is a set of probabilities for every appliance to be on at every time-step. These probabilities are arranged in 24h profiles for weekends and weekdays and for every season. They are extracted from the Spahousec data, through some simplifications and assumptions that will be now briefly discussed.
First of all, an average energy consumption value per hour for every appliance has been chosen through a comparison of average cycle length and average power per equipment. The values used in the

simulations have been derived from those discussed in (Richardson et al. 2009).

Crossing overall number of households, the number of households that own an appliance, the overall energy consumptions for the household sector for the equipment considered and the average energy consumption of a single appliance it is possible to estimate probability factors to be used as input for the models. The idea is to evaluate a ratio between the number of appliances of the same kind switched on at a time *t*, and the total number of appliances installed in every region. This concept is described in equations 1, 2 and 3 :

$$N_{i,j}^{on} = \frac{E_{i,j}}{e_i} \quad (1)$$

$$N_i = H \cdot N_{i,avg} \cdot PR_i \quad (2)$$

$$P_{i,j} = \frac{N_{i,j}^{on}}{N_i} \quad (3)$$

Where $N_{i,}^{on}$ and Ni are the number of appliances switched on and the total number of appliances of the i^{th} kind installed in every region. E_i is the overall energy consumption for the i^{th} appliance, e_i is the average hourly energy consumption for the i^{th} appliance if switched on, PR_i is the penetration ratio of the i^{th} appliance; H and $N_{i,avg}$ are respectively the total number of households and the average number of appliances of the i^{th} kind present in a house that has at least one.

The $P_{i,j}$ probabilities approximate calculation of the i_{th} appliance to be "on" at the "j" hour of the day is therefore calculated as a ratio between the first and the second equation, as stated in equation 3.

At the very starting time-step, the model sets the number, kind of appliances and use of energy that are not external phenomena-driven for every simulated dwelling. Probabilities' profiles for each appliance to be on at every time-step are connected to the types, read and compared with the random generated numbers (RGN), and if they are lower/higher than the RGNs, the electric consumption of the i^{th} kind of appliance, of the h^{th} household would be set to the previously defined average hourly energy consumptions values.

In this way, electric energy consumptions for every building are generated in a semi-random way, under the set of condition the user provides, but allowing a random superposition of different energy uses. The model therefore allows the modeling of electric peak loads for consumptions.

Figure 3 shows an example week of output from model 2 for a single building.

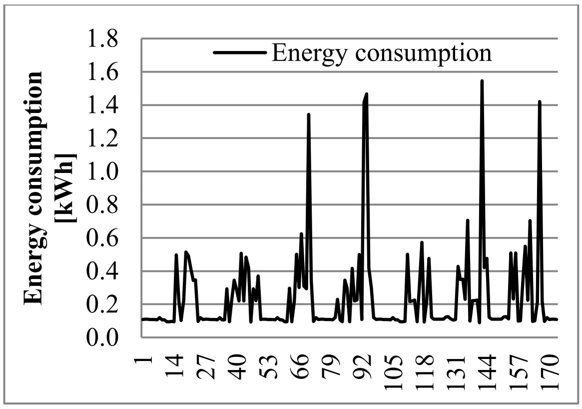

Figure 3 *Example output of model 2 (1 week), Mediterranean single-detached house profile*

Table 1 shows a list containing the assumptions on average energy consumptions used in the simulations, according to the input data. It is worth noting that minor variations on the assumptions on the average energy consumption per hour do not have a high impact on the overall total energy consumptions but they will have in terms of peak loads. The reduced output energy per switch-on event will cause higher probabilities and more switch-on events.

Table 1
List of assumptions on hourly energy (e_i) average consumptions [Wh] per appliance

Appliance	**Hourly consumptions**
Cooking devices	1000
Washing machine	406
Dish washer	1130
TV	125
Dryer	2500
Oven	1200
Microwave	625
PC	200
Washer-dryer	800
Freezer	100

Figure 4 shows that the outputs of the two models are completely different, the first being clearly the average profile and the second showing a non-average peak and an overall trend absolutely stochastically-generated. This results were extracted from model 1 and 2 during winter, for a single household configuration in the Mediterranean region.

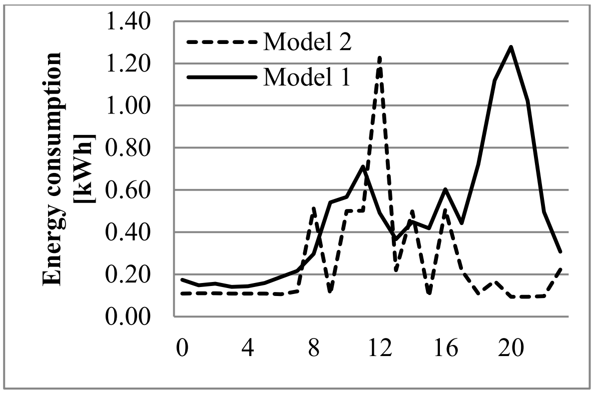

Figure 4 Comparison of the outputs of the two models for a random day and household

VALIDATION AND RESULTS

The validation process has been performed comparing simulation data to the Spahousec data for an adequately high number of dwellings, for every region, for every appliance on a year time base. Figure 5 shows the overall energy consumptions for a neighborhood of 350 dwellings, simulated with the single detached data for the Mediterranean zone.

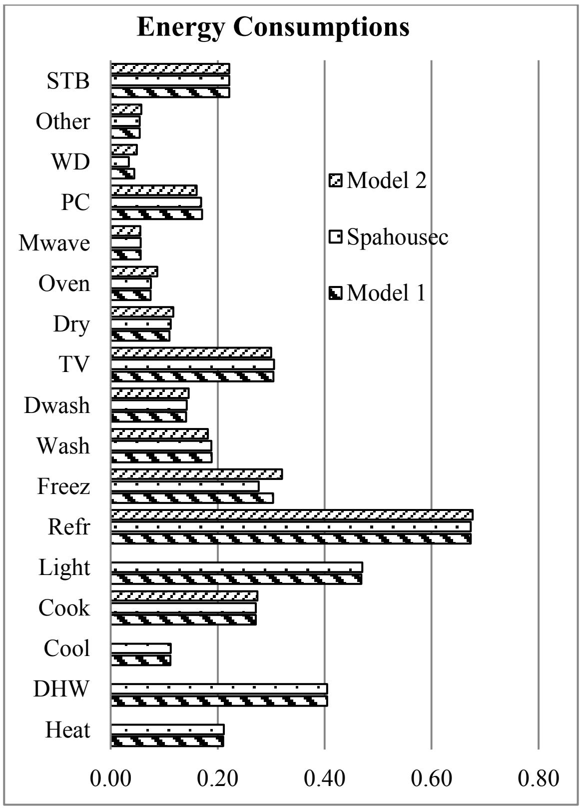

Figure 5 Split energy consumption comparison [MWh/dwelling year] 350 Mediterranean single-detached house

The results show a very good correspondence between simulated results and input data from the Spahousec project. It is worth noting that some of the appliances are simulated in both models, while others are not.

The reason for that is, as stated before, that some of the outputs, namely cooling, domestic hot water, heating and lighting are deeply influenced by weather conditions: they are not pure stochastic variables and therefore cannot be described by model 2. The validation of the model for one category of data based on the incidence of each appliance on overall annual consumptions has been shown in fig.5.
The next step of the validation process is checking the behavior of the models when considering 24 hours average profiles.

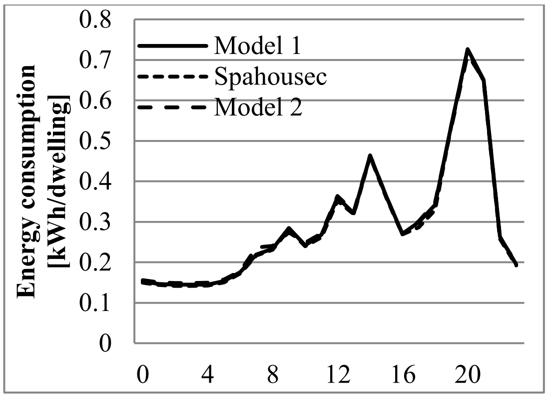

Figure 6 24 hours average profile, 350 households, Mediterranean single-detached houses, winter season

As it is possible to see in figure 6, even though some differences in the profiles are present and unavoidable, since the nature of the modeling is stochastic, the overall trend is similar in all the three cases.
Similar results and trends can be computed also for the other sub-regions or kind of buildings. As an example the following figures (7 and 8) show results for 350 dwellings in multi-dwelling buildings in the Mediterranean region.
Accordance of results to the input data is high enough to state that the models are able to handle the input data and describe the electrical consumptions in the household sector.

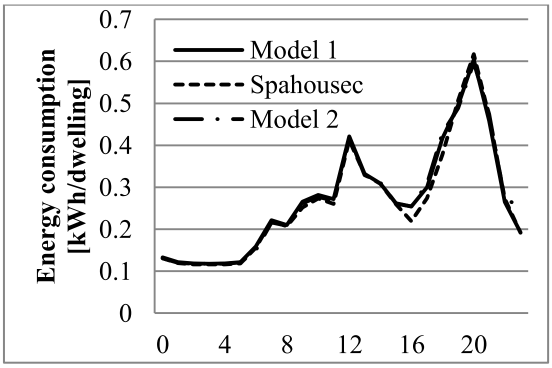

Figure 7 24 hours average profile, 350 Mediterranean multi-dwelling buildings - Mid - season

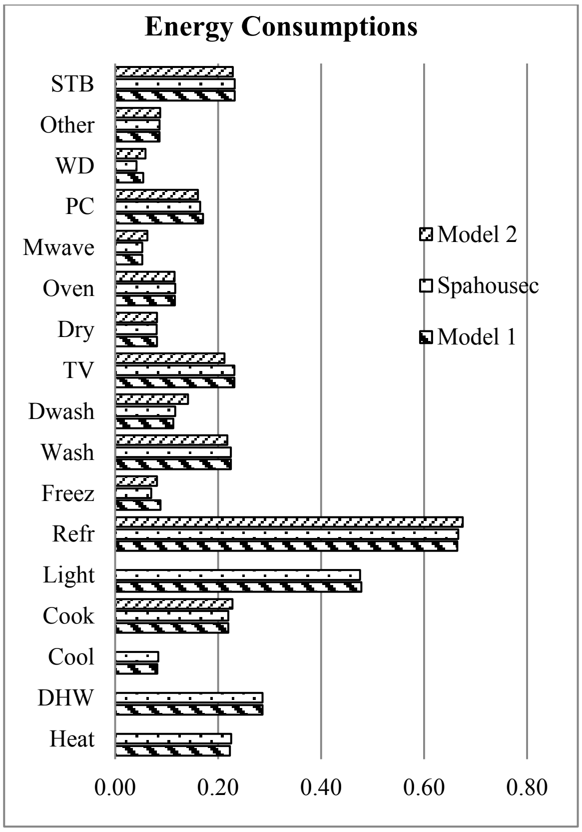

Figure 8 Energy consumptions [MWh/dwelling], 350 Mediterranean multi-dwelling buildings

Some more considerations are useful concerning the applicability of the two models. In the first paragraphs, the second model has been presented as able to handle peak loads, in comparison to the first one, only able to handle average profiles.
This assertion is correct, but it needs some re-tuning. As figure 9 shows, the two approaches are nearly equivalent when simulating a number large enough of dwellings.
Figure 10 instead shows that for a low number of buildings, as expected, the peaks produced by the second model are way higher than those of the first one.

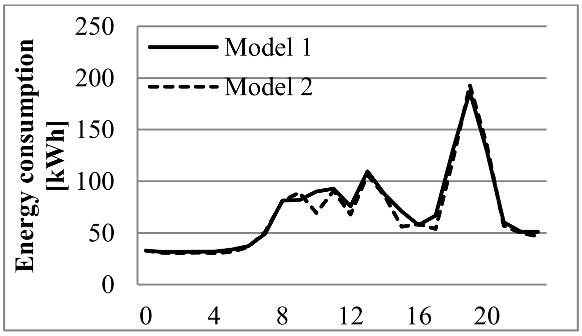

Figure 9 First 24 hours of the simulation, Mediterranean zone, single-detached houses, 200 households simulated

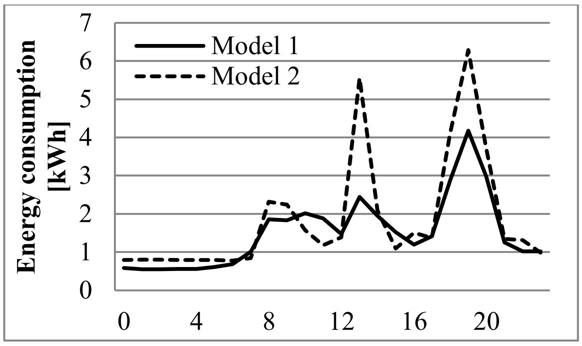

Figure 10 First 24 hours of the simulation, Mediterranean zone, single-detached houses, 5 households simulated

Table 2 shows a sensitivity analysis run on the random numbers (RN) used as seed of the random number generation functions.

Table 2

Sensitivity analysis on the random number generator seed , model 2. Annual energy consumptions [MWh] for 200 households

	RN1	RN 2	RN3	STD
Cooking devices	54.47	54.61	54.73	0.13
Washing m.	38.01	36.55	37.20	0.73
Dish washer	30.11	29.54	29.07	0.52
TV	64.74	60.69	58.09	3.36
Dryer	24.53	23.95	25.34	0.70
Oven	17.24	17.99	17.17	0.45
Microwave	11.30	11.43	11.23	0.10
PC	32.66	31.92	33.98	1.04
Washer dryer	6.22	5.72	5.21	0.51
Freezer	63.07	64.82	63.95	0.88

The maximum standard deviation calculated for each of the appliances is around 3.3 for televisions. It must be noted that the highest standard deviation values are reported for the appliances that need a double level of uncertainty in the modelling process (penetration ratio and multi-appliance per flat): televisions and computers. Some values are closer than others, as expected in a randomness-driven system.

Table 3 shows instead mean values and standard deviation for the 4 simulated configurations shown in figure 9 and 10. The two previously shown figures have a visual value and show with a qualitative approach a very small amount of data (24h); in order to obtain more solid results it is necessary to analyse the trends on the overall annual data. In order to allow a meaningful comparison, the terms considered in the sums are only the pure stochastic variables.

It is clear that for a smaller number of simulated households the mean value might have considerable percentage variations, due to the stochastic nature of the models. Moreover, as confirmation of what has been stated before, the standard deviation of the second model data is way higher than the first one, confirming the highest value of peaks modelled.

As major confirmation to what has been stated before, the results for 200 models are much more similar between the two outputs. The mean value shows differences that can easily be connected with stochastic variations (see table 2), and also the standard deviation is very similar in the two cases.

Table 3

Mean value [kWh] and standard deviation for the cases presented in figure 8 and 9 for model 1 and 2

	Mean value	STD
5 households (1)	0.88	0.88
5 households (2)	1.19	1.28
200 households (1)	32.51	26.89
200 households (2)	34.49	27.47

Table 4 and 5 show a sensitivity analysis that comprises average, peak (overall neighbourhood), minimum hourly values of consumption. It must be noted that some clear trends are easily recognisable: as the number of dwellings grows all the data tend to get closer, between the two models, peak loads for model 2 get lower increasingly, up to being comparable with those from model 1 (Fig. 10).

Table 4

Average hourly and lowest consumptions (kWh/dwelling), highest peak loads (kW/dwelling) for single-detached houses

Dwellings (Model)	Average	Peak max (average)	Min
1(1)	0.3557	1.0070	0.1944
1(2)	0.2296	2.0958	0.0894
5 (1)	0.3504	0.9411	0.1775
5 (2)	0.3042	1.8137	0.1322
20 (1)	0.3046	0.8855	0.1775
20 (2)	0.2829	1.1677	0.1289
50 (1)	0.3027	0.8954	0.1419
50 (2)	0.2952	1.0298	0.1446
100 (1)	0.2996	0.8827	0.1436
100 (2)	0.2990	0.9351	0.1436
200 (1)	0.3001	0.8840	0.1432
200 (2)	0.3044	0.9097	0.1481
350 (1)	0.2985	0.8771	0.1432
350 (2)	0.3023	0.8862	0.1457

In order to correctly read these data anyway, it must be remembered that only the appliances that could be simulated by both models were included in this study, in order to allow the two outputs to be comparable.

Table 5

Average hourly and lowest consumptions (kWh/dwelling), highest peak loads (kW/dwelling) for multi-dwelling buildings

Dwellings (Model)	Average	Peak max (Average)	Min
1 (1)	0.2691	0.7300	0.1059
1(2)	0.2801	2.7083	0.0877
5 (1)	0.2807	0.6546	0.1157
5 (2)	0.2713	1.7171	0.1139
20 (1)	0.2674	0.6351	0.1157
20 (2)	0.2760	1.0793	0.1101
50 (1)	0.2688	0.6491	0.1138
50 (2)	0.2709	0.9082	0.1133
100 (1)	0.2662	0.6409	0.1152
100 (2)	0.2733	0.8784	0.1157
200 (1)	0.2699	0.6471	0.1162
200 (2)	0.2716	0.7595	0.1159
350 (1)	0.2668	0.6400	0.1150
350 (2)	0.2691	0.7273	0.1147

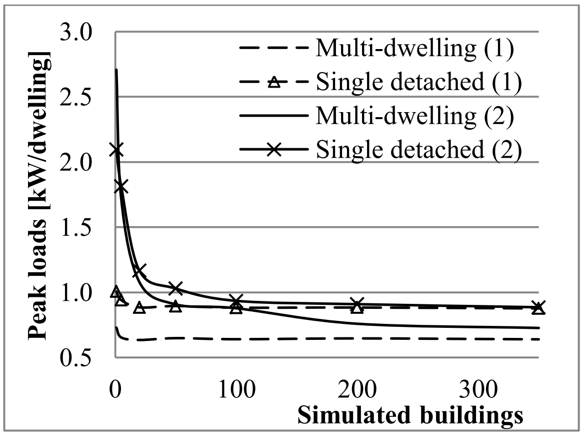

Figure 10 Peak loads assessed for both models

CONCLUSIONS

The authors have presented two different models able to describe household electrical consumptions. A first level of modelling depth is connected to a simplified approach, in which average profiles are used; a second level is used to have a more detailed stochastic approach. Both models were validated by comparing the consumptions of each appliance to the average values of Spahousec and have shown good accordance with the source input files. The two models have different applicability field: the first being useful for a first, qualitative sketch on consumptions in the household sector, the second being more detailed and able to model peak loads.

The number of buildings to be simulated, however, has large impacts on the results. A large number of buildings may cause peak loads to be smoothed into average values, therefore allowing the outputs of the stochastic approach to be very similar to those obtained by using average profiles.

Potential applications of these methods are connected to the sizing of energy generation equipment in buildings and electrical storages for single households and neighbourhoods.

The choice between the two modelling approaches should be carefully oriented to the most appropriate, according to the number of buildings target of the study and to the results of the probabilistic analysis. A sensitivity analysis on the number of buildings is always the best choice when evaluating the two options.

The models have been built with increasing level of detail of the outputs: but this resolution can be only achieved with more detailed input information (e.g. "switch-on" probabilities). In order to connect occupancy to electrical consumptions, as an example, it would be needed much more detailed information on the use of time of occupants. Higher resolution means higher calibrating needs, that usually cannot easily be satisfied because obtaining reliable, complete and detailed monitored data to validate the models on, can prove challenging.

The study will foresee future developments, completing the analysis of the described database and will find new application in the field of load match and grid interaction (LMGI) (Salom, J. 2011) indicators assessment and in the sizing of electrical storages in neighbourhoods simulations.

NOMENCLATURE

I = Kind of appliance
$N_{i,j}^{on}$ = Number of appliances of the ith kind switched on
$N_{i,j}$ = Total number of appliances of the ith kind
$E_{i,j}$ = Overall energy consumption for the ith kind
PR = Penetration ratio
H = Total number of households
$N_{i,avg}$ = Average number of appliances of the ith kind present in a house that has at least one
$P_{i,j}$ = Probabilities of the ith appliance to be "on" at the "j"th = Hour of the day
RN = Random number
STB = Standby
WD = Washer-dryer
PC = Personal computer
$Mwave$ = Microwave
Dry = Dryer
TV = Television
$Dwash$ = Dishwasher
$Freez$ = Freezer
$Refr$ = Refrigerator
$Light$ = Lighting
$Cook$ = Cooking devices
$Cool$ = Cooling
DHW = Domestic hot water
$Heat$ = Heating
RGN = Random generated number

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