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A functional analysis of electrical load curve modelling for some households specific electricity end-uses

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Abstract

In the next decades the European residential sector will face a series of deep technical and behavioural breaks. Among them are : the integration of new electrical domestic end-uses, the development of plug-in hybrid and electric vehicles, the increase of heat pumps implementations, the improvement and the technological changes in small electrical appliances. This will imply some behavioural modifications in the lifestyles. For example, the wishes in terms of comfort and the way electrical devices are used will evolve significantly. The energy consumption is likely to increase but the residential load curve will also be strongly modified. We then propose a functional analysis which enables to take into account, for each end-use, according to its own specificities, the key points that allow to build-up a relevant load curve. This will lead us to step down at the appliance level which will be the starting point of our modelling method. After a general description of the methodology, we will present three case studies for the following end-uses: washing, cooling and lighting. We will consider for each device the main determining factors of which are the technical features, the occupancy patterns of the household members, the activity scenarios in the dwellings, the climate. This bottom-up approach will generate intrinsically some kind of diversity needed to represent the temporality and the level of the power demand for a large number of households. This methodology allows, after an aggregation step, the calculation of the load curves for households at various spatial scales.

Introduction

In France in 2008, the buildings (housing stock) are responsible for 27%¹ of the final energy demand and 16%² of the GHG emissions. That is to say that some efforts in demand side management should have noticeable impacts on these two indicators. Contrary to the industry field demand which is quite steady on a day basis, the buildings, depending on the human presence and activities, are characterized by a fluctuating power demand when considering a unique day and between different days in a year. In the near future, the power demand profile will be completely different from what it is today because of many influences:

- best building insulation which will reduce the energy needs for heating and cooling;
- new comfort levels and management scenarios in the dwellings;
- possible huge integration of electrical heating systems such as heat pumps in new building or which will replace old installed fossil fuels based systems;
- integration of new end-uses such as Plug-in Electric Vehicles and an always growing number of electrical devices;
- integration of decentralized energy production and stocking (PV modules with battery for example);

¹ MEDDTL source

² CITEPA source

- new energy prices which will influence the time of use of the domestic appliances.

These evolutions will lead to a modified electrical demand (in terms of consumption) but simultaneously to a very different aggregated load curve (electric power demand over the time). This last representation is very dependent on the time of use and on the way (intensity of functioning) appliances are used. Then the peak load issue on the electric network, which is one of its main dimensioning characteristics, could evolve significantly in terms of shape and level.

That's the reason why the load shape estimation is taking a more and more important role especially in the residential sector where there are no aggregated measurements. In the literature we can find three main types of models:

1. top-down models which analyze total load curves measured on a sample of dwellings in order to get end-uses load curves;
2. bottom-up methodologies that build the load curve from an elementary entity that could be the domestic appliance, the end-use or even the household and aggregate it at the wished modelling level;
3. hybrid methods that combine both bottom-up and top-down approaches.

Various models have been developed according to each typology of method. Yet top-down approaches like what was constructed by Aigner et al. [1] or Bartels et al. [2] fail for the load forecasts in case of non-trend evolutions because of the use of past measures. In order to take into account the future changes the residential sector is likely to face, an estimation model must be explicit in terms of technology that is to say to calculate the load curves with focus on the domestic appliances, their technical characteristics and the ways they are used by the occupants as starting points. A literature survey has identified a series of bottom-up models [3, 4, 5, 6, 7, 8, 9, 10 and 11]. Finally hybrid methods were notably used by Train et al. [12, 13]. Yet all those models don't answer very well to the exposed problem.

Thus we choose the bottom-up approach for our model because it fits the best our needs.

Then we conducted a **functional analysis** enabling to achieve the aimed sophistication of the modelling. In a first time we describe our method. Then we expose the routine of the methodology in order to simulate a specific end-use according to its own characteristics. Finally we conclude on the future possible improvements of our method.

Presentation of the modelling methodology

The aim of the model is to get, for selected simulation duration (up to several decades), daily load curves corresponding to a specified household stock on a territory: the so called **inhabited stock**. This is constituted by three main entities: **typical buildings**, **typical households** and **typical appliances**³. The association of a typical building, a typical household and a set of typical appliances constitutes an **n-tuple**. This segmentation is a result of the functional analysis which showed that the optimal way to calculate domestic load curves has to take into account these influences independently. Moreover it enables an easier management of the evolution of the inhabited stock.

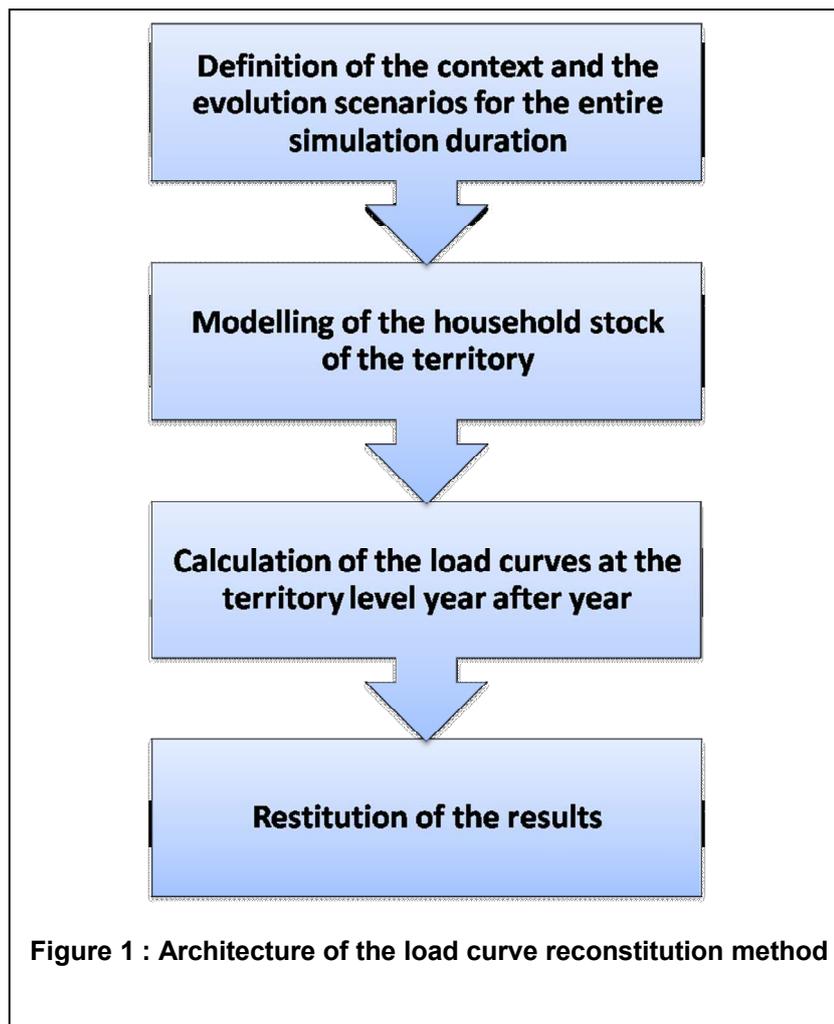
We only chose a reduced number of parameters so as to define the typical elements and we selected a restricted series of domestic appliances because of two main statements of facts:

- in reality each element in the simulated stock could be defined with an important amount of characteristics, themselves show a large diversity;
- our choices focus on the most relevant influences for the domestic power demand.

³ In the rest of this paper, we will alternately use the following nomenclature to design the typical elements too: building-type, household-type and appliance-type.

Therefore our method intrinsically ignores certain diversity sources that are inconceivable to model. For instance some domestic appliances are not considered: we call them the **unexplained appliances**. The model doesn't give any individual load curve for these devices. Yet, these are responsible for certain energy consumption: we call this quantity the **inevitable energy balance**. We have to integrate it in our model that is to say to give it a corresponding load curve pattern.

The developed method is based on four main functions which are explained in details in the following sections. Because of our choices concerning the appliances we present in this paper, we focus the explanations on the procedures and functions of the model that are indispensable for their simulation. The architecture of the methodology is presented in Figure 1.



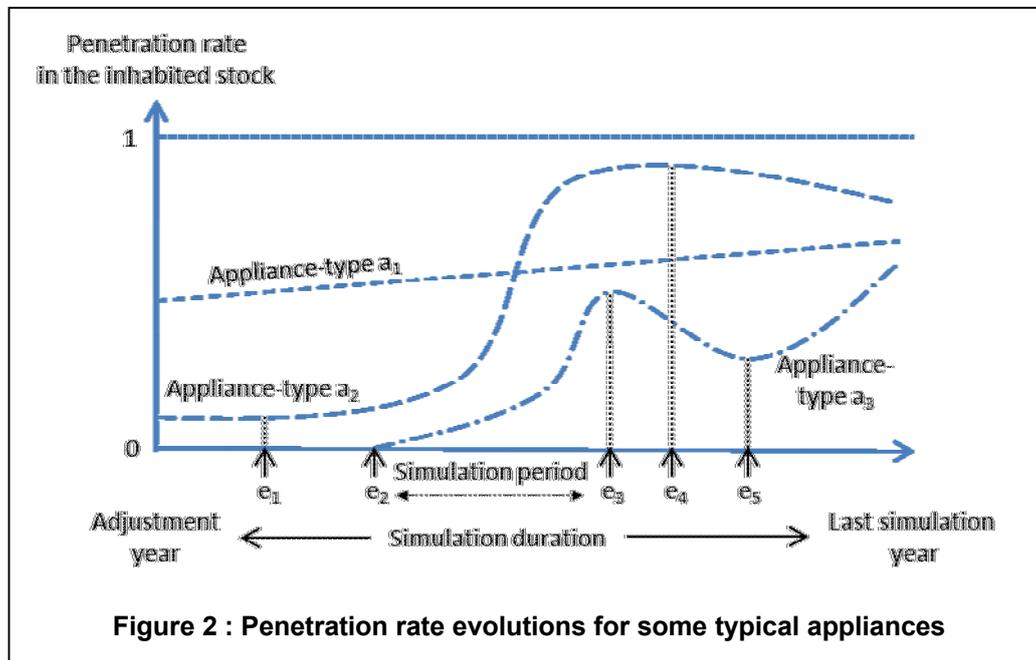
Definition of the context and the evolution scenarios for the entire simulation duration

The first step is to define the temporal scale of the simulation. Concretely, **key events** have to be programmed and set at an annual scale in order to materialize behavioural and technological breaks which are likely to happen during the whole simulation. These events could modify individually the net flows of each typical element⁴ and/or the inevitable energy balance⁵. We call **period** the temporal range between two consecutive key events. On top of the changes in the inhabited stock in terms of breaks, annual evolutions of the simulated entities have to be inserted in the modelling scenario. Thus

⁴ key events could be define specifically for a typical building, a typical household or a typical appliance

⁵ key events which only affect the inevitable energy balance could be set

the user has to define for each period net flows evolution for each typical entity and for the inevitable energy balance. These evolutions could be based on mathematical functions such as linear growth or decrease, exponential evolution, sinusoidal trend. In Figure 2, we propose an illustration of these previous concepts where five different key events (e_i) have been defined throughout the simulation duration. We can underline that the penetration rate of the appliances a_2 and a_3 are directly



dependent on the key events what is not the case of the typical appliance a_1 whose saturation rate follows a linear growth during the simulation.

Modelling of the household stock of the territory

In this section, we describe the method used to characterize the geographical and technical dimensions of the simulation. In fact, the inhabited stock corresponds to a territory which could be divided into some **geographical zones** in accordance with the weather variability on the territory. We first have to define the typical elements constituting the inhabited stock. We then have to construct it for each geographical zone and year. Finally we must ensure the coherence of the proportions of each n-tuple at the territory level.

Definition of the typical elements of the inhabited stock

As we previously said, the inhabited stock is constituted with three main elements:

1. **typical buildings** are characterized with five parameters: dwelling type, dwelling area, global insulation, inertia and ventilation type;
2. **typical households** are defined with four characteristics: composition, socio-economical level, occupation status (active, retired...) and general behaviour towards energy consumption;
3. **typical appliances** are classified according to their corresponding domestic end-use (domestic cold, washing, lighting...) and more precisely characterized with three sets of parameters: nomenclature, functional parameters and control variables.

The typical elements take the form of three **libraries** (see Figure 3), that's to say that the model user may choose each element needed for a simulation in the corresponding one.

In the following tables, we present an example of a building-type (Table 1), a household-type (Table 2) and several typical appliances (Table 3).

Table 1 : Example of a typical building

Properties	Modalities and values
Dwelling type	Detached house
Dwelling area	120m ²
Global insulation	1.0W/m ² .K
Inertia	200kJ/m ² .K
Ventilation type	Heat recovery ventilation

Table 2 : Example of a typical household

Properties	Modalities and values
Composition	2 adults, 2 children
Socio-economical characteristics	Medium income
Occupation status	Active
Behavior towards energy consumption	
Heating/cooling	Energetically responsible
Electricity specific	Indifferent

Table 3 : Examples of typical appliances

Properties	Modalities and values			
Nomenclature				
Corresponding end-use	Domestic cold	Clothes washing	Lighting	
Appliance name	Fridge F ₃	Washing-machine WM ₄	Light-bulb Lb ₁	Light-bulb Lb ₂
Appliance nature	Nomade appliance	Nomade appliance	Nomade appliance	Nomade appliance
Functioning parameters				
Energy grade	B	A+	A	A
Nominal wattage	-	-	80W	50W
Functioning mode(s)	2°C, 4°C, 6°C	30°C, 60°C, 90°C, eco-mode	-	-
Cycle(s) duration	1-5min	75, 85, 100, 45min	-	-
Unitary load cycle(s)	Available in database	Available in database	To be defined	To be defined
Adapted consumption function	No	Yes	-	-
Control variables				
Load shedding adapted	No	Yes	No	No
Programmable	No	Yes	Yes	Yes
Functioning constraints	Non-stop functioning	Runs before the tumble-dryer	-	-

Construction of the inhabited stock for each geographical zone

The above defined typical elements have to be then assembled so as to constitute the n-tuples. The association is based on logic rules and affectation laws so that the complete combinatory of all the typical elements isn't carried out: only the possible combinations are allowed. In this function we associate them according to the geographical area and the simulated year considered. As a result, we get an **n-tuple data basis**. Thus we differentiate this process between the first simulation year, the so called **adjustment⁶ year**, and any other year of the simulation. In fact in the first case the complete association has to be proceeded: we call this the **historical inhabited stock**. On the contrary, in any other case only the modifications affecting the n-tuples with regard to the historical inhabited stock have to be implemented.

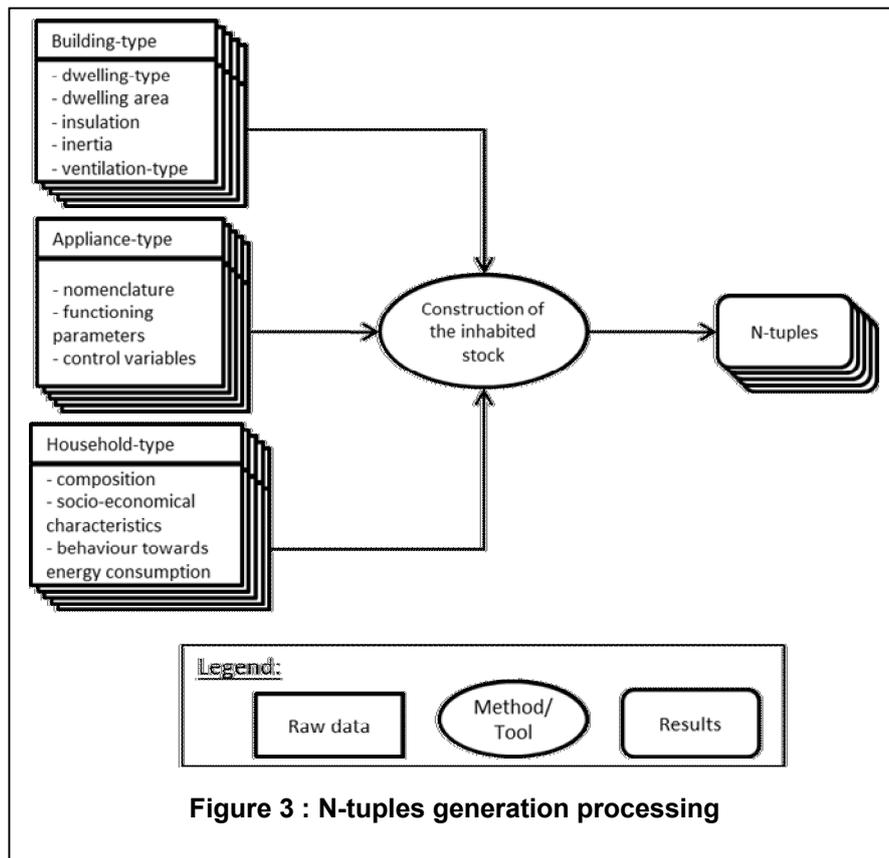
The construction of the historical inhabited stock, schematically illustrated in Figure 3, is a four-step operation:

1. definition of the proportions (numbers) of each typical building in the inhabited stock;
2. definition of the proportions (numbers) of each typical household for each typical building. This association depends on the characteristics of the typical household particularly the socio-economical parameters and the composition of the family;
3. distribution of the typical appliances for each couple typical building / typical household. Here again the parameters values of each typical element guide the association of them because the most and less probably combinations are identified;
4. definition of the participation of each n-tuple in the inevitable energy balance. According to the characteristics of the n-tuple (domestic appliance set, behaviour of the household's members), each of them is responsible for certain unexplained energy consumption.

The modelling of the inhabited stock for another year is a much more complicated task. According to the key events previously defined, all kinds of modifications concerning the n-tuples have to be integrated year after year. Thus on top of deep changes as technological breaks and behaviour modifications which impose the creation of new typical elements, the ageing of each element⁷ must be taken into consideration. This leads to the definition of elements' **generations** in the inhabited stock. Moreover there is an obvious evolution consisting in the possible modification of each element's proportion and the n-tuple participations in the inevitable energy balance.

⁶ for this year real data are available: energy measurements, domestic load curves, saturation levels for a majority of appliances

⁷ with the exception of the ageing of the people in the households. This influence could be taken into account with modifying the proportions of each typical household in the inhabited stock



Coherence control of the n-tuple proportions in the inhabited stock at the territory level

Because of the construction of the inhabited stock at the geographical zone level and the possible need of the aggregated⁸ model results, a coherence control of the n-tuple proportions in the inhabited stock at the territory level seems to be indispensable.

Calculation of the load curves at the territory level year after year

Now that inhabited stock has been defined, the model has then to calculate the corresponding load curves for each n-tuple of the modelled stock. Here is the main richness of the method. This task is realized thanks to a series of functions that are explained in the following paragraphs. The calculation of the load curves is run at the geographical zone level so as to take into account the weather influences on the domestic power demand. Moreover the maximum duration for this calculation is one year because the inhabited stock is unchanged at this temporal scale.

Construction of the simulation calendar for each period

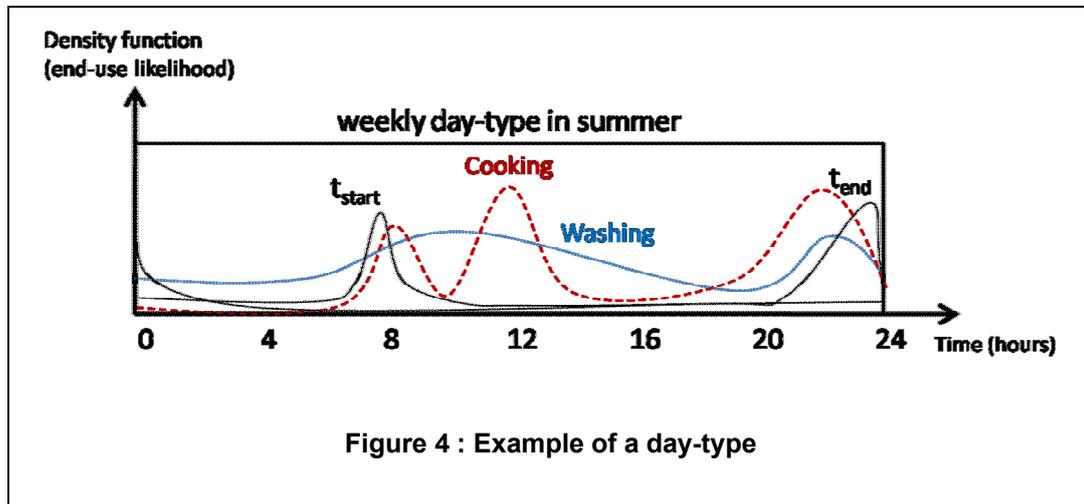
In order to create a simulation calendar, the first thing to do is to select a weather data series from real measurements for the regarded geographical zone and to analyze it. On top of the raw weather data such as outdoor temperature, cloud covering and solar radiation, this step enables the filling of the attributes of each simulated day:

1. season
2. working day (yes / no)
3. holidays period (yes / no)
4. freezing cold (yes / no)

⁸ that is to say for the entire territory

5. scorching heat (yes / no)
6. established regime⁹ (yes / no)

After that, **typical days**¹⁰ have to be defined: it is a question of generic 24 simulated hours whose characteristics represent the transverse lifestyles of the population. A typical day is constituted by several density functions which give information concerning the start and the end of the domestic activities in the households¹¹ and the proclivity of the n-tuples for using a specific end-use. Our method contains various typical days that are available under a library form (see Figure 5).



The end of this step consists in establishing a correspondence between the typical and the simulated calendar days. These must be identified with one of the typical 24-hour duration defined above.

Calculation of the unitary load curves for each n-tuple and each simulated day

A **unitary load curve** is a daily load curve for a specified typical appliance used by a selected n-tuple. The calculation of these elements depends on the modelled end-uses: thus we separately consider appliances for heating, cooling, domestic hot water, ventilation and their respective auxiliary devices on the one hand and specific electricity equipment on the other. In this paper, we only discuss the second calculation way because of the chosen devices.

The calculation method that provides the unitary load curves is an iterative process which consider at each step one typical appliance owned by one specified n-tuple. It calculates the corresponding load curve of this device with regard to the day-type and the behaviour of the n-tuple following a four-step process:

1. definition of a **Time of Use scenario**¹² (TOU) from the time-series use charts¹³ corresponding to the typical appliance (or the end-use). This must respect the coherence with the other selected TOU scenarios for the same n-tuple (there is an end-use diversity inside a household);

⁹ this attribute tells if the simulated day correspond to the beginning, the middle or the end of an unusual weather event

¹⁰ called day-type too

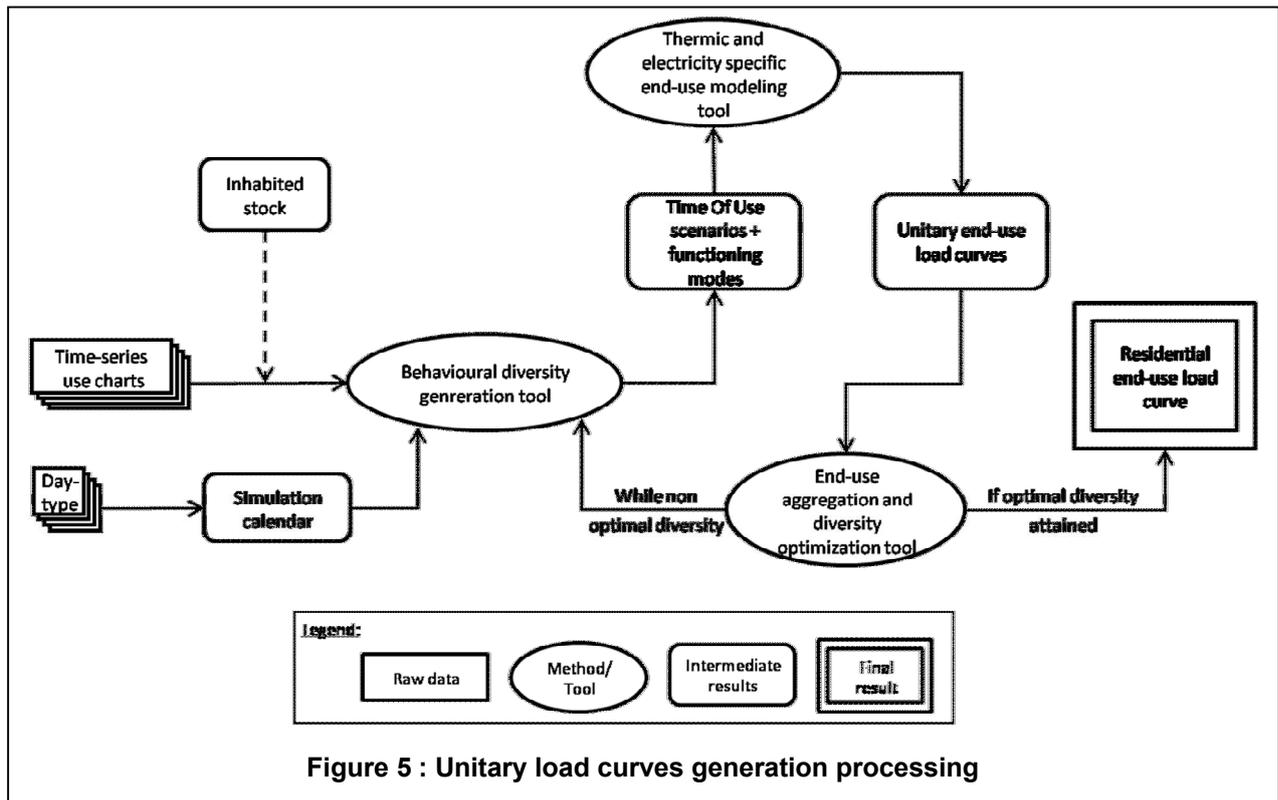
¹¹ it corresponds more or less to the waking-up and the bedtime ranges in the population

¹² a TOU scenario contains the start time(s) at the day level of each typical appliance

¹³ the time-series charts come from real time use survey in the population and they are available under a library form in the model (cf. Figure 5)

2. definition of a **unitary load cycle**¹⁴ for the selected typical appliance and day-type;
3. attribution of representativeness weights for the all-appliances-considered TOU scenarios;
4. attribution of the functioning mode(s) on the defined TOU scenario for each typical appliance and for the selected day-type.

We represent schematically in Figure 5 the iterative processing which give the unitary load curves. This method has to be repeated for each typical appliance of the considered n-tuple.



Calculation of the load profiles for each n-tuple and each simulated day

A **load profile** is the after diversity daily mean load curve for a specified typical appliance, a selected n-tuple and according to the characteristics of the simulated day. This specific load curve is supposed to capture the whole diversity affecting this device. Its construction relies on a four-step method:

1. generation and summation of N unitary load curves and division by N;
2. generation of N unitary load curves and summation of the N+N unitary elements, division by N+N;
3. comparison between the two mean load curves previously obtained;
4. pursuit of the process until either the satisfaction of the predefined convergence criterion or the number of people for this n-tuple in the simulated population.

¹⁴ a unitary load cycle is the power demand of an appliance for one of its functioning mode

In Figure 6 we schematically expose the way enabling the construction of the load profiles.

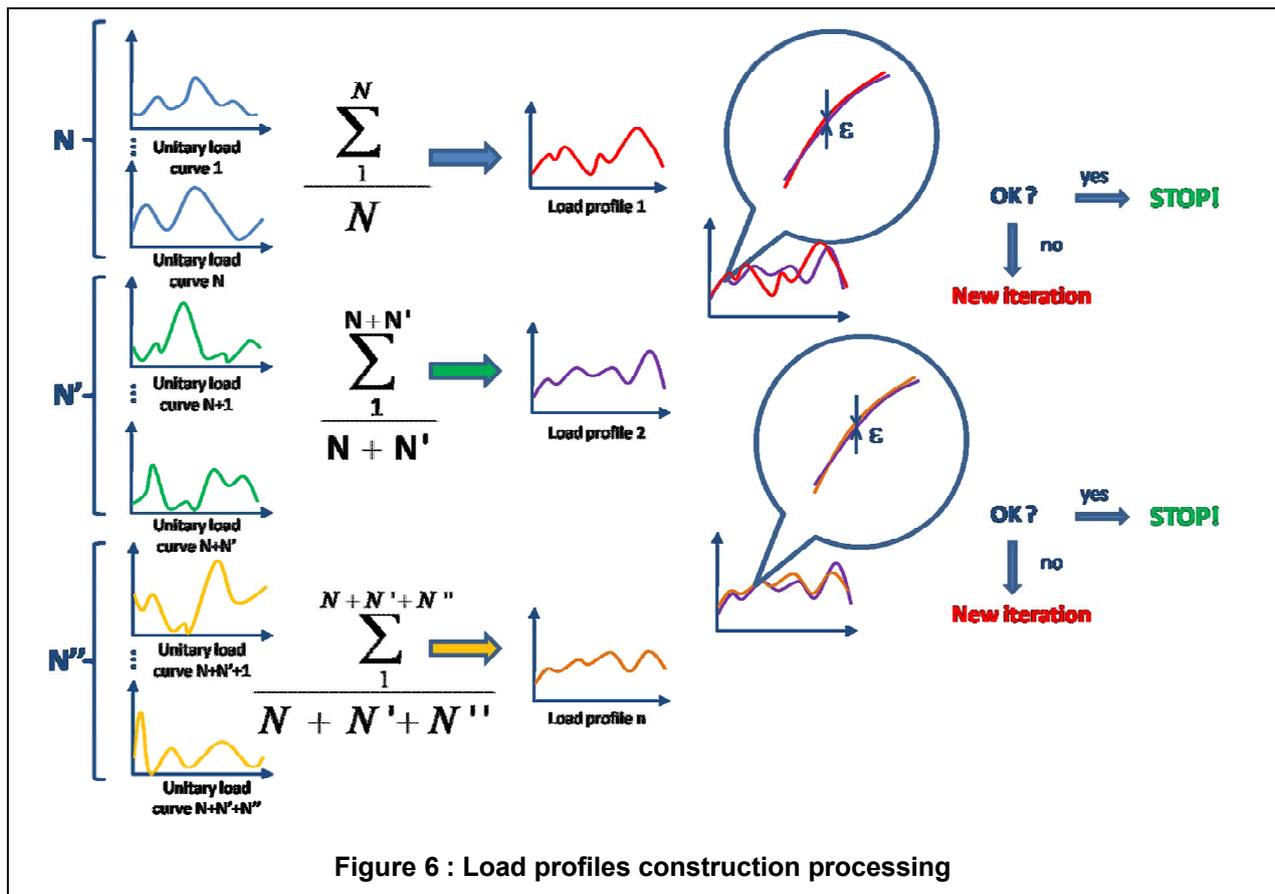


Figure 6 : Load profiles construction processing

In order to get all the load profiles in the population, the previous process must be repeated for each typical appliance in the same n-tuple and for all the n-tuples in the inhabited stock. Convergence criteria could be defined with help of a preliminary study for each typical appliance or end-use. This study would provide some insights concerning the number magnitude of unitary load curves which must be aggregated to obtain the whole diversity that affects this level.

Aggregation of the unitary load curves for all n-tuples and each geographical zone

This function aggregates the previously obtained results in order to get load curves for the global population of the regarded geographical area.

Figure 7 shows the different scaling and aggregation phases that we describe in the next lines.

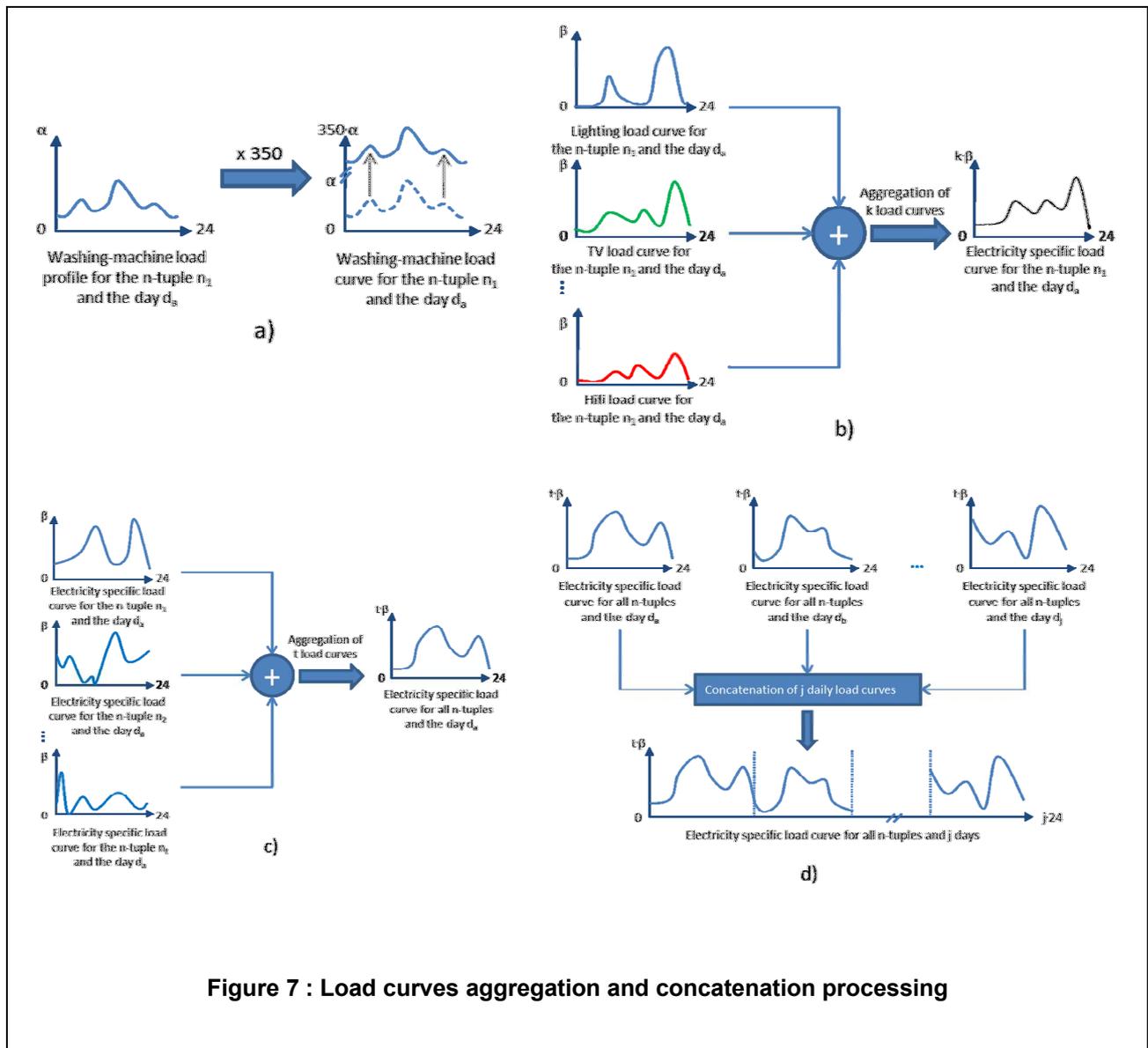
In the first place □ case a) □ load profiles have to be scaled at the n-tuple level with respect to its proportion in the inhabited stock¹⁵. That is to say that each calculated load profile must be multiplied by the size of the corresponding n-tuple (here 350). Thus the daily load curve for each typical appliance, each simulated day, which is function of the n-tuple and for a specified geographical zone is provided thanks to this processing.

In a second step □ case b), aggregations by end-use for all the people of the same n-tuple give end-use load curves for each simulated day at the geographical zone level. They are interesting intermediate results that are reused in a following function.

¹⁵ in this case, the inhabited stock represents a population of 1000 n-tuples. 35% of the inhabited stock is constituted by the n-tuple n₁

The daily end-use load curves could be wished for all the people in the geographical zone. That is to say that an aggregation of the end-use load curves for the entire population at the geographical zone level and on the day basis is required. This step is represented in case c).

Finally the end-use load curve for the simulated year and at the geographical zone level could be obtained □ case d) □ thanks to the concatenation of the previous intermediate results.



Insurance of the energy coherence for the typical appliances load curves

The results of the model must be as good as possible in terms of power demand but even in electricity consumption too. Thus we have to ensure the energy coherence of the yearly end-use load curves. This work could only be conducted with comparison data. More precisely it supposes the use of real end-use¹⁶ consumption measurements (data sources could be various¹⁷). That is the reason why this task is only valid for the adjustment year.

¹⁶ for example in the case of the specific electricity end-uses, yearly consumption data are a minima available for the washing, the domestic cold, and the lighting (CEREN)

In order to realize this operation, the consumption corresponding to the modelled load curves¹⁸ has to be calculated. So as to get these values, the corresponding integrals have to be evaluated.

In a second step, the comparison between real end-use measurements data and the previously obtained consumptions have to be conducted in order to know if the model coincides with reality.

Then according to the sign of the differences and their magnitudes by end-use, the input data and more precisely the time-series charts and functioning modes of the concerned typical appliances have to be adapted so as to converge on the predefined consumption target according to preselected **convergence criteria**¹⁹. In fact, we limit for this task the possible modifications on these two input data because of their influence in terms of use intensity and frequency. Moreover it seems complicated to adjust a model when allowing a modification of its whole parameters.

Validation of the results on measured load curves

After having ensured the energy consumption coherence of the model in the previous function, the next step is the validation of the results on measured load curves. Here again this work may only be viable for the adjustment year. The aim of this function is to proceed to a visual comparison between different load curves, comparison which could be formalized with the help of the calculation of load curve specific indicators and other parameters such as:

- the Normalized Variation Factor (*NVF*) [4, 5, 6, 13] :

$$NVF = \frac{1}{n} \cdot \frac{\sum (p_{mea}(t) - p_{mod}(t))^2}{\left(\frac{1}{n} \sum p_{mea}(t) \right)^2}$$

with $p_{mea}(t)$ is the measured power demand at the time step t (n time steps) and $p_{mod}(t)$ is the modeled power demand at the same time step;

- the Mean Absolute Percentage Error (MAPE) [14] :

$$MAPE = \frac{1}{n} \sum \left| \frac{P_{mea}(t) - P_{mod}(t)}{P_{mea}(t)} \right|$$

where $p_{mea}(t)$ and $p_{mod}(t)$ have the same meanings as for the NVF;

- the load factor L_f on the time interval Δt :

$$L_f(\Delta t) = \frac{\bar{P}(\Delta t)}{P_{max}(\Delta t)}$$

with $\bar{P}(\Delta t)$ the mean power demand on the time interval Δt and $P_{max}(\Delta t)$ the maximum power demand on the same time interval;

¹⁷ CEREN, REMODECE, ADEME, Panel □

¹⁸ load curves of the typical appliances

¹⁹ it might be useful to set different precision levels depending on the end-uses

- the diversity factor $K_m(\Delta t)$ ²⁰ for m individual consumers :

$$K_m(\Delta t) = \frac{\sum_{j=1}^m P_{\max,j}(\Delta t)}{P_{\max,m}(\Delta t)}$$

with $P_{\max,j}(\Delta t)$ is the maximum power demand of the individual consumer j on the time interval Δt and $P_{\max,m}(\Delta t)$ is the maximum power demand on the interval Δt of the m consumers together considered;

- descriptive statistics elements: $\bar{P}(\Delta t)$, $P_{\max}(\Delta t)$, $\sigma_P(\Delta t)$ (standard deviation of the power demand on the time interval Δt), distribution of the power demand values.

Calculation of the inevitable energy balance at the territory level

As we previously said, the model precisely considers a restricted series of domestic appliances, the other are not explained. That's the reason why we introduce an additional consumption called inevitable energy balance; this quantity has to be calculated year after year. The adjective inevitable stress the fact that the model systematically forgets certain electricity consumption for each simulated n-tuple.

Because of the geographical availability level of the measured data which play the role of references, the inevitable energy balance could be only calculated at the territory level. Moreover this consumption simply concerns electricity specific equipment whose seasonality is ignored. Concretely the inevitable energy balance is the difference between the total consumption from electricity specific appliances and the consumed energy caused by the typical electricity specific appliances. Yet the calculation of this quantify depends on the considered year. In the first case of the adjustment year, the inevitable energy balance is estimated thanks to the reference data. In the second case when considering a year at the beginning of a period and if the set of explained typical electricity specific appliances has changed²¹, the inevitable energy balance is obtained with removing the corresponding consumption of the new explained device(s). Finally in any other case (non specific year) the inevitable energy balance is estimated with respect of the evolution scenario that has been previously defined.

Repartition of the inevitable energy balance at the geographical zone level

The previously calculated energy balance may be distributed from the territory level to the geographical zone level. This is made possible thanks to the n-tuples participations in the inevitable energy balance that were defined when assembling the typical elements to construct the inhabited stock. With these numbers each n-tuple element is responsible for certain additional energy consumption and because of the knowledge of the n-tuple composition of the inhabited stock at the geographical level, the repartition of the inevitable energy balance at this local scale is obtained. In fact, this is the first task of this function whose final aim is to give a load curve pattern for the inevitable energy balance.

In order to do that, the method uses the following hypothesis: for a simulated day, a specified n-tuple in a geographical zone, the load curve representing its share of inevitable energy balance is the same (modulo the consumption, i.e. its integral) as its electricity specific daily load curve. Moreover the distribution of this energy consumption could be done according to the day-type. That is to say that the inevitable energy balance may be affected day after day with respect to the daily consumption of the typical specific electricity appliances for the n-tuple considered. Thus at the geographical zone level, the end result of the model for an end-use is the aggregation of its modelled power demand

²⁰ or its inverse because of the most interesting variation range [0; 1]

²¹ typically an unexplained end-use or typical appliance becomes explained

(sum of the related typical appliances) and if need be the power demand pattern from the inevitable energy balance.

Aggregation of the load curves for each end-use at the territory level

A last aggregation step could be proceeded in order to get the end-use load curves at the territory level that take into account the inevitable energy balance.

Restitution of the results

Different restitution formats may be wished according to the simulation and the results considered. That is the reason why some post processing functions have been integrated in our methodology.

Selection of the formats for the restitution of the results

In this function the user could specify the aggregation level of the load curves. That is to say that the results may be assembled end-use by end-use, according to the end-use families (consumption items) or even all end-uses considered.

Selection of the restitution's temporal and geographical scales

The temporal and geographical scales of the results' restitution consist in filtering through the load curves. Thus it may be possible to wish results for a unique geographical zone, an aggregation of some zones which doesn't coincide necessarily with the territory or the whole territory itself. Concerning the temporal restitution's scale, the user may be interested in obtaining the load curves at a daily, weekly, monthly, seasonally or yearly basis.

Calculation of some indicators and graphical representation of the results

This last function helps the user so that he could easier visualize the results thanks to graphical representations and some load curve specific indicators. On top of the parameters that were previously defined, this function is notably aimed to calculate the thermic gradient (for heating and cooling) and to represent the power demand monotone (classification of the power demand values according to the magnitude and the duration of the demand).

Application of the methods on different case studies

In this section, we use the load curve reconstitution method for three different end-uses: the fridge, the washing-machine and the lighting. These cases have been chosen because of their significant dissimilarities. Despite this fact, the method is able to adapt the processing according to them. In the following paragraphs we present the main particularities of each end-use and the way the method takes them into account through a detailed case study. For these, we choose a specific n-tuple whose characteristics are given in **Error! Reference source not found.**, **Error! Reference source not found.** and **Error! Reference source not found.** and we apply our method in order to obtain two daily load curves (so two typical days): one for a weekday and another for a weekend day

Modelling of the fridge

Specificities

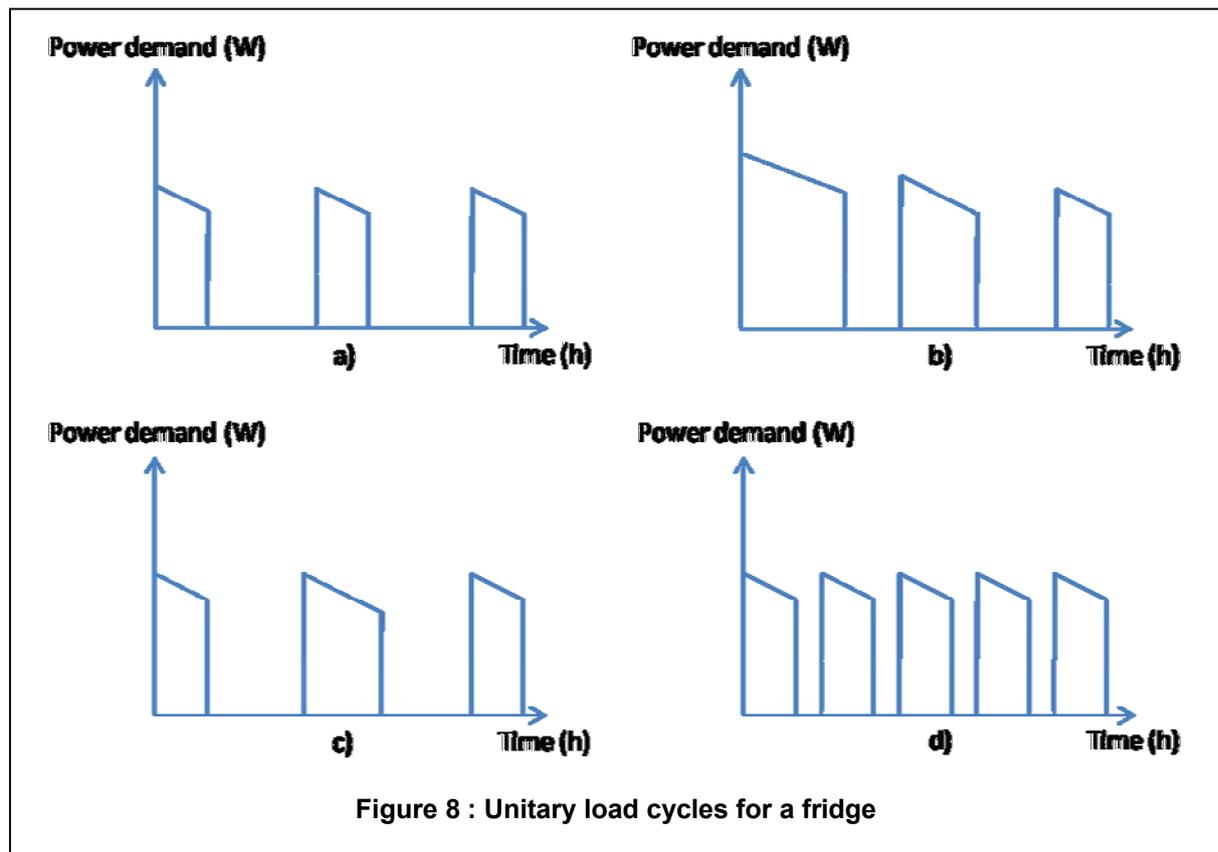
Fridge is characterized by two kinds of functioning particularities. First it works continuously and without any necessary human presence during a simulation because of the needed permanent cold to a preserving aim. Secondly its functioning is typically cyclic; the duration and the power demand magnitude of each of them depend on the use scenarios which include openings and closings of the door (principally at breakfast and mealtimes) and fillings (restocking) after doing shopping.

In Figure 8 we present several unitary load cycles for an illustrative²² purpose. Example a) may correspond to a normal functioning without any disruption (steady state). An ideal cyclic functioning is also notable: each power demand event shows the same duration, shape and magnitude. Case b)

²² these come not from load curve measurements

represents the power demand sequence that could happen just after an opening and a re-filling of the fridge. This causes an increased power demand at direct following cycles which are longer than in steady state too. Load cycles sequence c) only shows a longer power demand for one of them that could be explained by an opening of the fridge door which occurred between the first and the second load cycle. The removing of items out of the fridge theoretically may lead to a reduction of the power demand of this device: magnitude and duration of each unitary load cycle compared with the steady state is normally detectable on appropriate load curve measurements. Finally, case d) could be the power demand for steady state with a lower temperature set than in case a).

With data from a measure campaign another comparisons could be conducted between different fridges. This may probably identify the consequences on the load cycles of non equivalent devices, more precisely in terms of volume, construction year, energetic grade□



In spite of the real impact of the local temperature²³ on the consumption of a fridge and thus on its power demand, our method doesn't model this influence for the moment because of the lack of sufficient detailed data. However it could be implemented as soon as viable data will be available.

Methodological strategy

As we previously said, we decided to make use of our method on a detailed n-tuple. So let's suppose that the simulated n-tuple's fridge is characterized by the elements contained in the second column of **Error! Reference source not found..**

The time-series charts for the fridge are given in Figure 9. In this graph, the rectangles indicate the time slots related to the human activities which cause various fridge functioning modes and the steady

²³ temperature of the room where the fridge is placed in

state periods. The weekday sequence begins with a steady state mode which occurs at the night time underlying that there is no event that breaks the normal functioning. Then a large time slot is noticeable²⁴ as soon as the occupants wake up. Because of their breakfast, there is very chance that the fridge could be opened and closed many times especially if household's members don't wake up simultaneously. Then another steady state starts from 8.30AM up to the middle of the afternoon. Lunch isn't taken at home. The steady state functioning is interrupted at about 4.30PM following the children's afterschool snack. After that another steady state starts which is the piece of evidence that household's members are likely to do domestic activities that don't imply the fridge. Then a long period begins: it is caused by the preparation of the dinner. At the end of the day, another normal functioning occurs.

In the case of the weekend day, the later waking-up of the household's occupants is notable: the corresponding time slot begins at about 8.15PM. Then another longer period in non-steady state functioning mode could be seen around the lunchtime indicating that the occupants eat at home and have to prepare it. This sequence ends at about 2.00PM. Steady state follows this up to about 7.30PM. Here we assume that the children don't take a snack and no interruption occurs during the afternoon. Moreover, it supposes a later dinner time compared with the weekday.

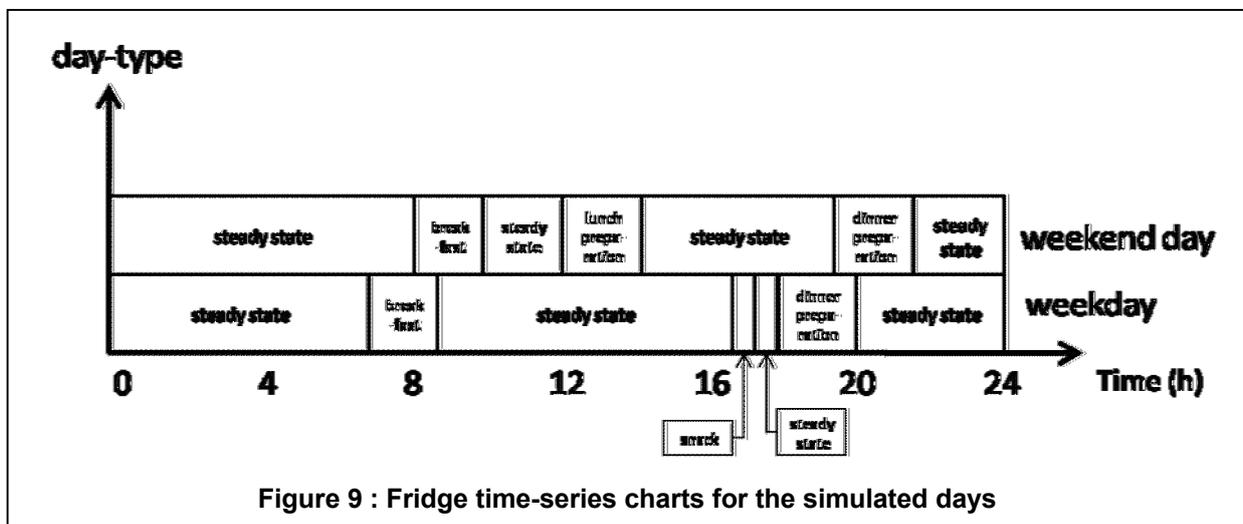


Figure 9 : Fridge time-series charts for the simulated days

Because of the independent functioning of the fridge, the model doesn't need all the switch-on events times throughout the simulated days. Yet according to the previous time-series charts, door openings are distributed in the identified time slots where domestic activities take place. Moreover the model indicates if these events are followed by a restocking (that's not the case here for the two days considered). Thus, the method constructs the Time of Use scenarios which only contain in our case studies the starts times following a door opening. A random delay is added in our model so that each switch-on event after an opening doesn't follow it immediately. The extracted Time of Use scenarios are presented in Table 4.

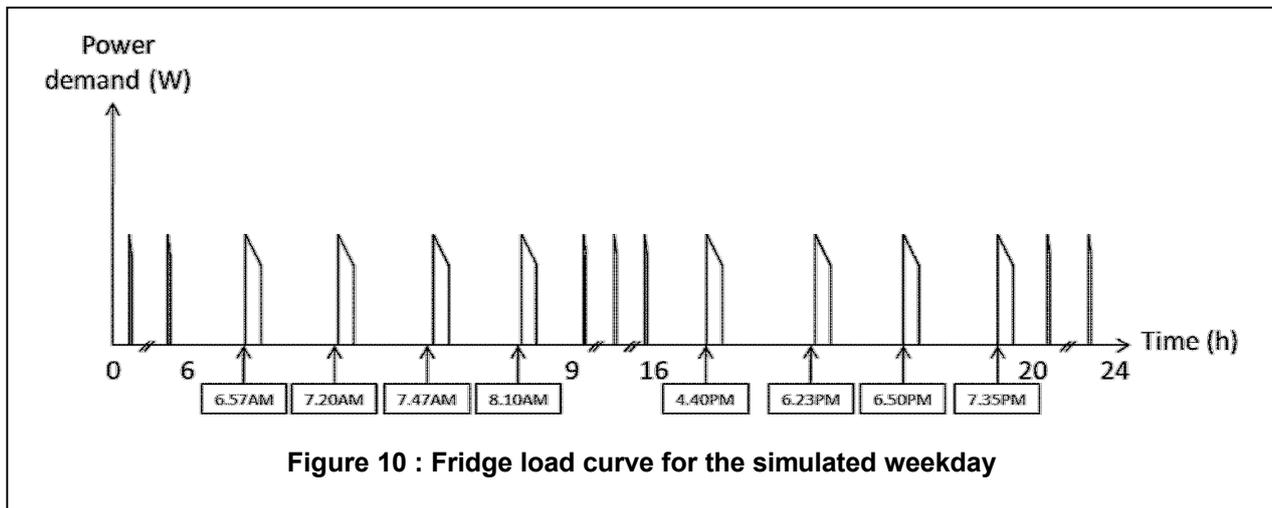
Table 4 : Time of Use scenarios for the fridge and the simulated days

		Time of the day(h)			
Weekday	AM	6.57	7.20	7.47	8.10
	PM	4.40	6.22	6.50	7.35
Weekend day	AM	8.30	8.50	9.14	9.29
	PM	12.10	12.19	12.43	1.18

²⁴ between about 7.00AM and 8.30AM

		1.46	7.35	7.53	8.23
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We suppose that the temperature set of the fridge is 4°C. The corresponding load cycles in steady state and these which follow a door opening are available in the data base. So the model chooses the power demand patterns according to the functioning modes and sets them at the identified starts times. This processing gives the load curves for the weekday and the weekend day. Figure 10 shows the schematic appearance of the weekday fridge load curve.



Modelling of the washing-machine

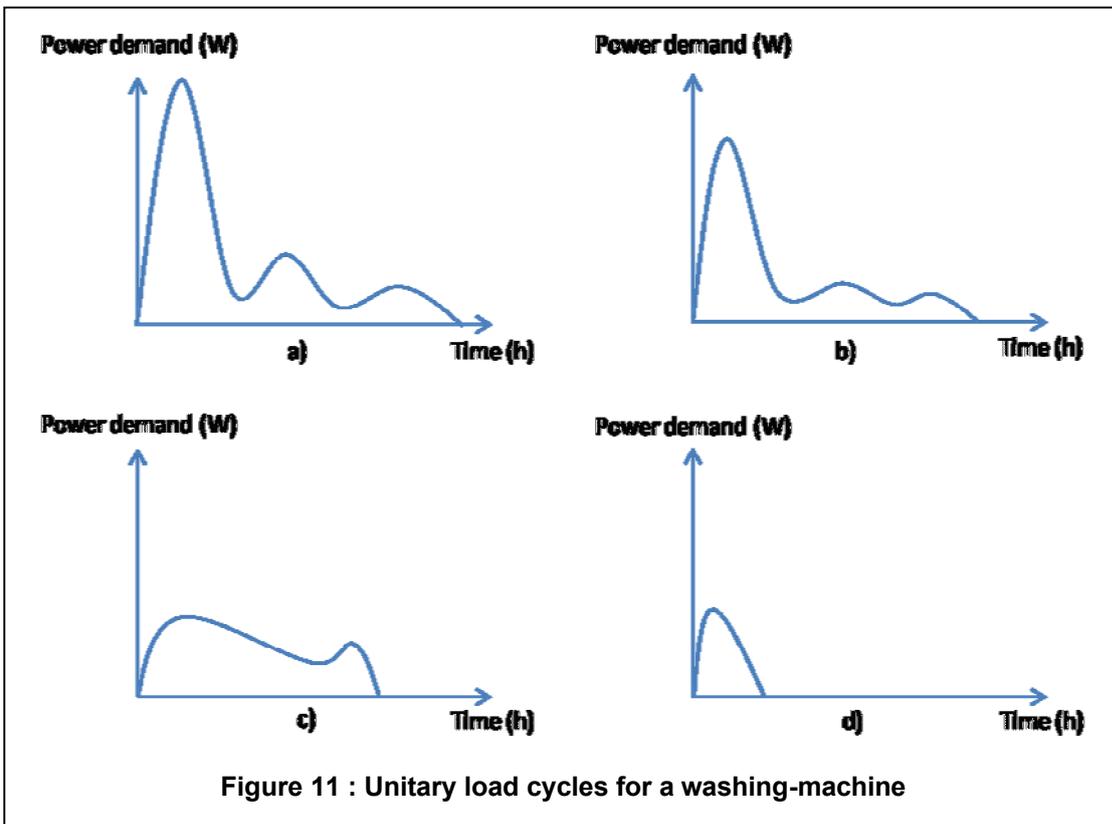
Specificities

Washing-machine is an appliance whose functioning is cyclic too. Contrary to the fridge, its running is partly dependent on the human presence and awareness. However, the switch-on events are distributed in a day according to the habits of the households members. In fact with modern devices, the start of a functioning cycle is programmable so that switch-on at the nighttime is remarkable in certain measure campaigns such as REMODECE²⁵. Moreover depending on the selected functioning mode the corresponding power demand duration and magnitude may be notably different.

In Figure 11 we give some illustrative examples of unitary load cycles for a washing-machine. Here again these don't correspond to real measurements that would quite obviously give less smooth load curves. Case a) may correspond to a 60°C washing cycle. Three peaks could be identified: the first one is the power demand for the water heating. The second peak represents the power demand for rinsing. At the end of the unitary load cycle, a third notable power demand peak is caused by the spin-drying phase. Example b) looks like case a) but the power demand magnitude for each peak is lower and the cycle duration is shorter. This unitary load cycle is likely to be a 30 or 40°C washing cycle with a reduced spin speed compared with case a). In the load cycle c), there is no water heating peak what underlines that this could be a cold washing programme. Finally case d) only shows a short power demand which could be the required load pattern of a high-speed spin-drying phase.

Here again with detailed measurements data, it would be possible to link precisely the unitary load cycles with the characteristics of the corresponding washing-machine.

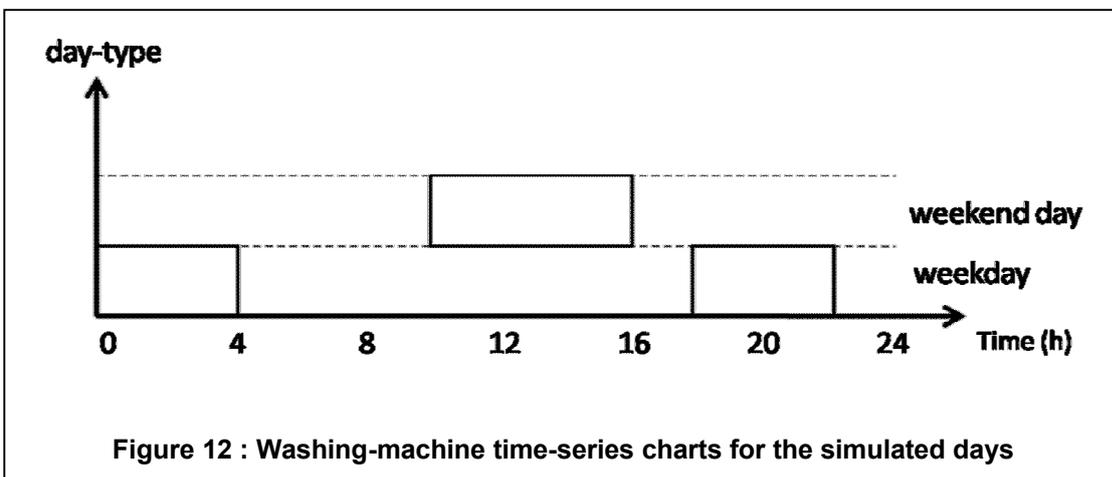
²⁵ RESidential MOnitoring to Decrease Energy use and Carbon emissions in Europe



Methodological strategy

The simulated n-tuples owns a washing-machine whose characteristics are given in the third column of **Error! Reference source not found.**

We pass through the methodology for the two days-types. Corresponding times-series use charts are represented in Figure 12.



We first consider the weekday. Because of the possibility to program this appliance, functioning could happen during the night so that washing could be hung up to dry in the morning. The absence of possible functioning at the beginning of the day indicates that the family isn't prone to let the clothes in a full tub the whole day. A second functioning time slot may occur at the evening as soon as the adults come back home. The switch-on is supposed to happen so that the end of the cycle is attained at 10.00PM (washing must be removed from the device for drying and so requires a human intervention).

The time-series use chart is very different at the weekend because of a more important availability of the household's members which supposes that the occupants stay mainly at home. The functioning time slot only begins at 10.00AM because of a later waking up of the dwelling occupants for this day-type.

We assume that the functioning modes are respectively a 30°C cycle for the weekend and a 60°C at the weekend²⁶. Because of an indifferent household's behaviour towards the specific electricity use, there is little chance that the eco mode is selected.

According to these time-series use charts, random starts times for both typical days have been selected so as to get the following Time of Use scenarios²⁷:

- weekday: start time at 6.11PM;
- weekend day: start time at 2.28PM.

The model then associates the unitary load cycles on the Time of Use scenarios which give the unitary load curves for the simulated days. These results are represented in Figure 13.

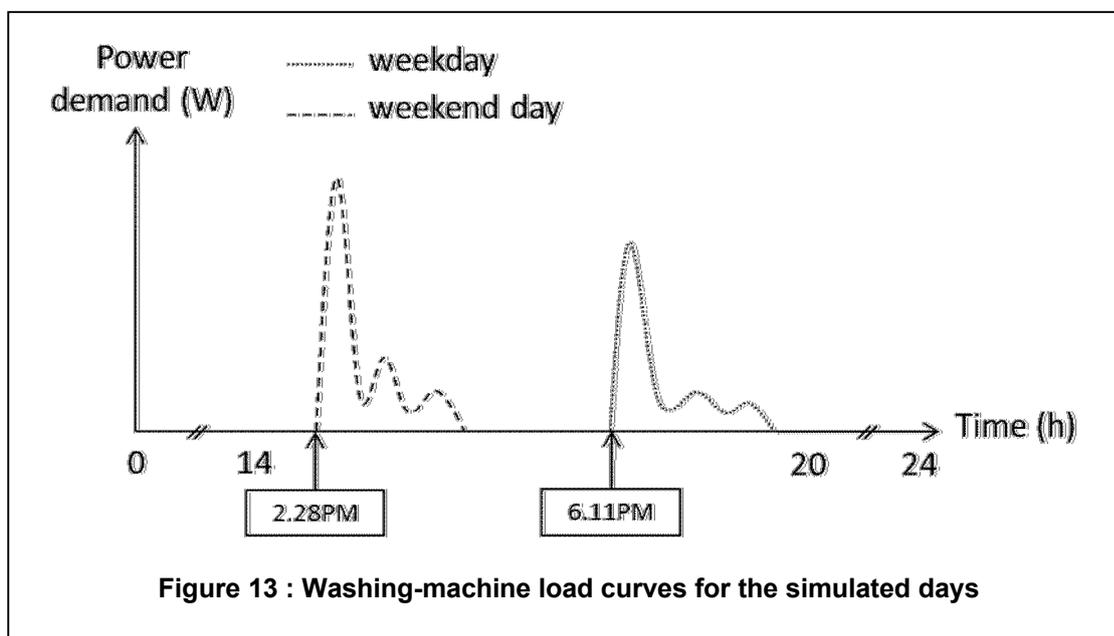


Figure 13 : Washing-machine load curves for the simulated days

Modelling of the lighting

Specificities

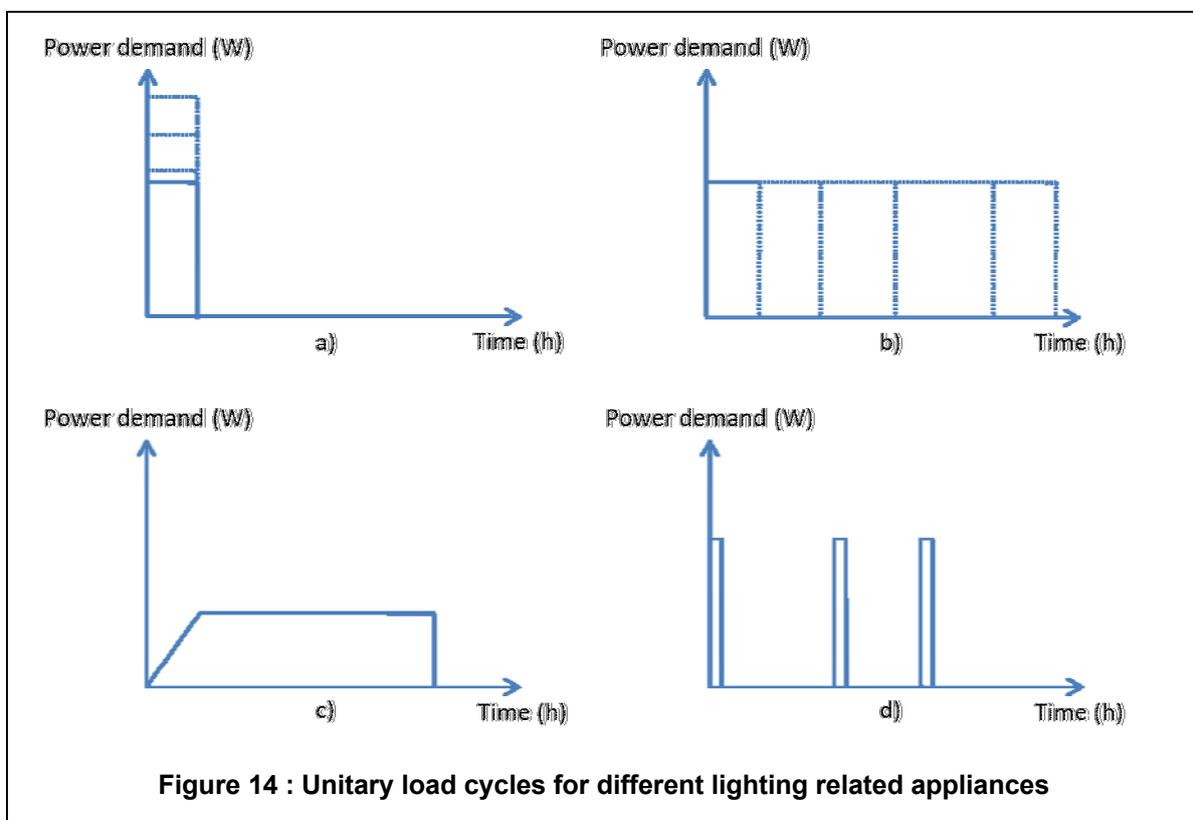
This end-use is a little more complicated to simulate than the previous devices because of its more human dependent functioning characteristics. First it is due to its dependence with the natural light availability. Logically lighting is only used when the occupants of a household are present in their dwelling and when the sunlight isn't available. Yet, some exceptions could happen for specific purposes such as night surveillance or lighting use in rooms where the natural light doesn't satisfy the human comfort or simply isn't available at all. In the whole, this end-use is run preferentially before the sunrise and after the sunset when the occupants are awake but the functioning at other daytimes isn't unlikely at all. Moreover lighting is an end-use which implicates several appliances per dwelling: in

²⁶ the occupants are less constrained at the end of the week in terms of cycle duration □ 60°C is supposed to be longer than a 30°C cycle

²⁷ one cycle is supposed to occur at each of these simulated days according to the weekly number of washing-machine cycles for this n-tuple

fact there are at least so many bulbs and other lighting systems as the number of the rooms in each studied typical building. On top of that, for a selected n-tuple, the set of typical appliances for lighting may be very heterogeneous because of the diversity of these devices which fulfill human and room specific lighting needs.

In Figure 14 we present some schematic unitary load cycles for lighting to an illustrative aim. Case a) shows a short constant power demand whose magnitude could be selected thanks to a regulator. The shape of the power demand may be characteristic of an incandescent light bulb notably with the instantaneous load demand increase. According to the nominal wattage of the light bulb, its power demand is determined and could be significantly more²⁸ (or less) important than the previous described bulb. Case b) underlines the variability of the power demand duration for the same type of device. Case c) may represent the unitary load cycle for a compact fluorescent lamp whose power demand begins linearly up to its maximal lighting capacity. In case d), though a regular power demand magnitude and duration, the representation focus on the irregularity of the switch-on events. This case may be the load curve which corresponds to a controlled lighting of a room depending on the human presence. For instance, the lighting elements in a corridor or a garden spotlight could be turned-on such a way.



Methodological strategy

We assume that the n-tuple is only equipped with two kinds of lighting typical appliances whose properties are contained in the two last columns of **Error! Reference source not found.** According to the lighting needs in each dwelling room that first depends on its surface area, Lb_1 or Lb_2 is chosen by the model.

As lighting use is mainly determined by the human presence and awareness, the model first has to select domestic activities start and stop times (respectively t_{start} and t_{end}) for the considered n-tuple and according to the day-type. These data come from the corresponding density functions included in the definition of the typical days.

²⁸ in our graph

In accordance with the previous case studies, the model selected the following values:

- weekday: $t_{start}=6.55AM$ and $t_{end}=11.23PM$;
- weekend day: $t_{start}=8.17AM$ and $t_{end}=10.35PM$.

We assume that the simulated typical days occur in winter and at these days the natural light when available is systematically too low to satisfy the human lighting needs. These conclusions depend on the position in the year of the regarded days, the corresponding sunrise and sunset times and the geographical zone considered.

The time-series charts for lighting are constructed according to the domestic activities of the n-tuple members and the corresponding rooms they are supposed to occupy to do these. One passing through the method gives the illustrative time-series charts presented in Figure 15.

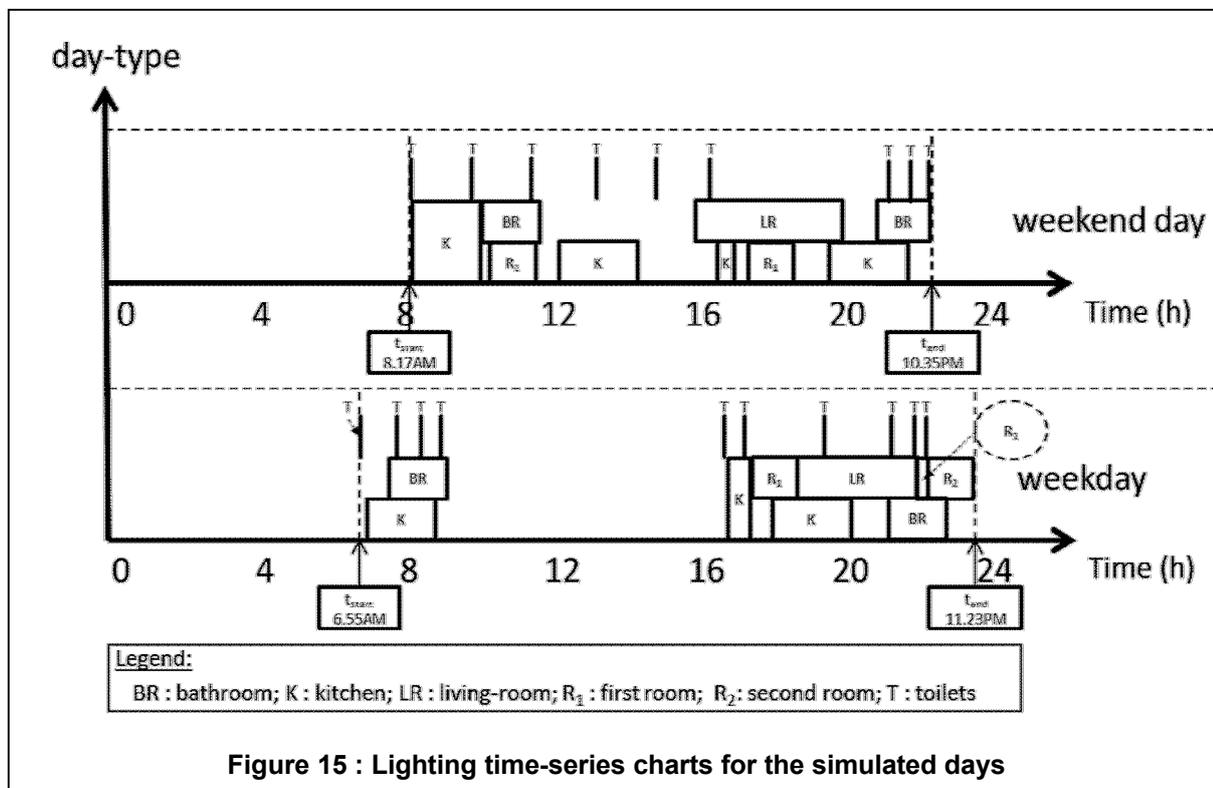
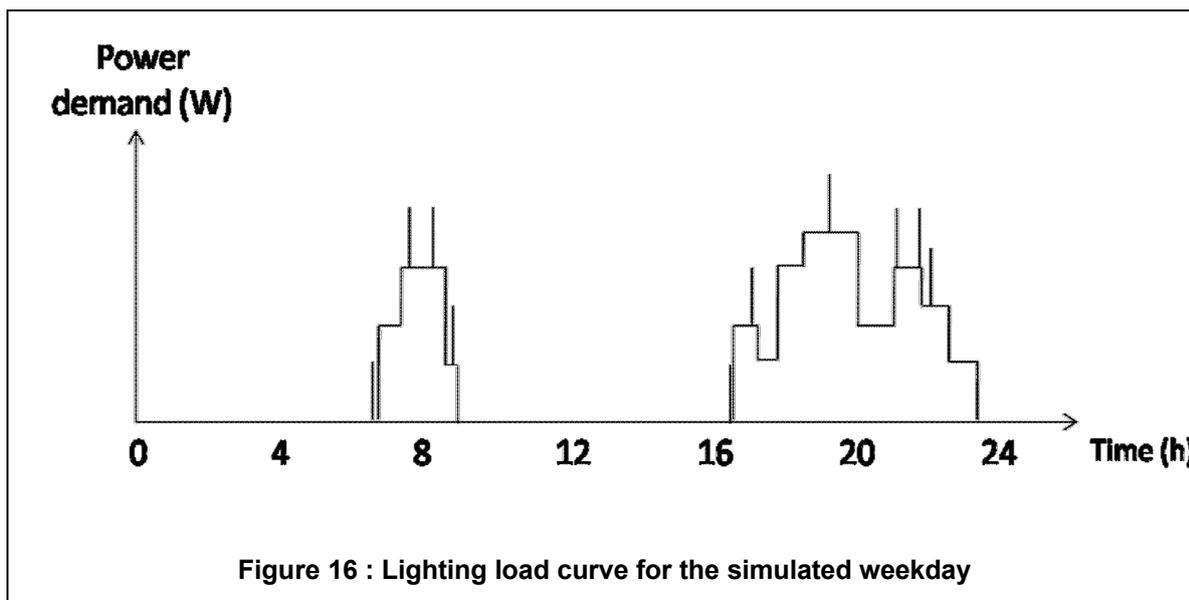


Figure 15 : Lighting time-series charts for the simulated days

We don't comment exhaustively Figure 15 because of its relative simplicity. We only underline the coherence of this data with regard to the two previous case studies. For instance, we could notice at the weekend day that the kitchen is occupied notably from about 12.00PM to about 2.30PM and a short period about 4.30PM. When supposing that the washing-machine is placed in this room, this occupation scenario reveals its whole sense.

Then when first assuming that Lb_1 is only set in the kitchen and in the living-room and Lb_2 is used everywhere else. Secondly we suppose that there is no energy wasting: the n-tuple members turn the light off when leaving a room. Thirdly in **Error! Reference source not found.**, we can notice that the unitary load cycle for both lighting typical appliances have to be parameterized. the model produces the lighting load curves for both simulated days. Figure 16 represents the obtained lighting load curve for the weekly day-type.



Discussion

Our method has been developed so that it could easily evolve according to the simulated inhabited stock and the evolution scenarios that might occur in the future. Concretely it consists in periodic updates which enable a permanent coherent modelling notably in terms of typical elements, affectation laws, input data. The human behaviour modelling plays a great part in our methodology because:

1. it widely influences the domestic electric demand profiles,
2. and deep changes are going to be experienced in a near future concerning the attitude towards energy use.

Thus the capability to take into account a series of representative behaviours and modifications of them seems to us essential to estimate the residential electric power demand.

Yet the model has to be improved in order to take into account influences that are not implemented in this first version (for instance the impact of electricity tariffs on the power demand). That is the reason why we choose to build-up a modular tool. Thus any additional or remote element doesn't change the general architecture of the model. However all the constitutive model parts²⁹ are standardized: for instance the in- and output data formats of an n-tuple are the same independently of the modalities taking by the considered n-tuple. Scalability, modularity, adaptability³⁰ and human behaviour modelling are the main strengths of our model. On the opposite, frequently updated extensive input data, detailed knowledge of the residential sector are required. This represents a noticeable weakness and/or difficulty of the exposed methodology.

²⁹ each one could be seen as a box

³⁰ our method is non specific of a particular inhabited stock

In the case of the electricity specific end-uses, load curves are obtained thanks to various iterative, selection, affectation steps which work with very specific elements³¹ and that are precisely arranged in order to take into consideration all the influences affecting the domestic power demand. For the thermic end-uses, the generation of the load curves is a little different because of the required building-simulation software which calculates the heating and cooling needs that depend on the geographical zone considered and thus the corresponding weather data.

So as to build up the required database for the establishment of our model, we make use of various sources of information:

- typical buildings and households are defined notably thanks to dwellings statistical survey on the one hand, population general census on the other hand. In France, both are carried out by the INSEE (Institut National de la Statistique et des Études Économiques);
- data about the inhabited stock in the whole (inclusive energy consumption) are provided by the CEREN (Centre d'Études et de Recherches Économiques sur l'Énergie);
- typical appliances are implemented with help of manufacturers and on-site measurement campaign data such as REMODECE or our own;
- weather data come from hourly readings conducted in stations distributed on the territory. In France the institute is METEO FRANCE.

Conclusion

In this paper, we exposed the domestic end-uses reconstitution load curve model that we established. We first described our method in a global way so as to introduce and define the different elements of the modelling. Then, we chose three electricity specific end-uses (fridge, washing-machine and lighting) and we discussed their main particularities which are the most relevant properties that influence their individual power demand. After that we selected a specified n-tuple and we made use of our method to get daily end-use load curves. We presented some input data as illustrative figures and we graphically plotted the results of our model. At the end of the article, we discuss the improvement possibilities of our method and we shortly underline the load curve calculation procedure in the case of the thermic end-uses.

³¹ unitary load cycle, time-series charts, density functions

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