Novel procedure to formulate load profiles for off-grid rural areas

Stefano Mandelli *, Marco Merlo, Emanuela Colombo

Department of Energy, Politecnico di Milano, via Lambruschini 4, Milano 20156, Italy

In this paper, we describe the development, implementation and application of a novel mathematical procedure devoted to formulating the daily load profiles of off-grid consumers in rural areas. The procedure aims at provid-ing such profiles as input data for the design process of off-grid systems for rural electrification. Indeed, daily load profiles represent an essential input for off-grid systems capacity planning methods based on steady-state energy simulation and lifetime techno-economic analyses, and for the analysis of the logics to control the energy fluxes among the different system components. Nevertheless, no particular attention has been devoted so far in the scientific literature as regards specific approaches for daily load profiles estimates for rural consumers. In order to contribute to covering this gap, we developed a new mathematical procedure taking into consideration the specific features of rural areas. The procedure is based on a set of data that can be surveyed and/or assumed in rural areas, and it relies on a stochastic bottom-up approach with correlations between the different load profile parameters (i.e. load factor, coincidence factor and number of consumers) in order to build up the coincidence behavior of the electrical appliances. We have implemented the procedure in a software tool (LoadProGen) which can eventually support the off-grid systems design process for rural electrification. Finally, we have applied the procedure to a case study in order to clarify the proposed approach.

Keywords: Renewables, Rural electrification, Electric consumptions, Load model, Stochastic model, Off-grid energy systems

Design process of off-grid systems for rural electrification and users' electric consumptions

At the world level, about 1.3 billion people live without access to electricity and nearly 82% of these people live in rural areas of developing countries. This number is not expected to significantly change in the next decades. Indeed, according to the WEO 2014, 0.5 billion people are expected to remain without access to electricity in the New Policy Scenario (IEA, 2014). Moreover, by comparing this scenario with the Universal Access Scenario proposed by the IEA in 2012 (IEA, 2012), it clearly emerges that in order to provide electricity to these people, it is required to consider other options besides the traditional centralized electrification approach. In particular, off-grid systems (i.e. stand-alone and micro-grid systems), mainly based on renewable sources of energy and integrating storage, are often the only feasible solution for the supply of electricity in rural areas. The design process of such systems requires special attention since it deals with unpredictable energy sources, unknown or uncertain electric consumptions and it is a joint matter of cost-saving (affordability), appropriate sizing (reliability) and long-term duration (sustainability). Moreover, the scenario for rural areas of developing countries is complicated by the well-known lack of information about both users' electric consumptions and energy sources' availability. Indeed, in most rural electrification actions, precedent experiences are not available to base the system design on.

Article history:
Received 3 September 2015
Revised 12 October 2015
Accepted 20 January 2016
Available online 12 February 2016

* Corresponding author. Tel.: +39 02 2399 3816.
E-mail address: stefano.mandelli@polimi.it (S. Mandelli).

Users' electric consumption is a key element in the design process of off-grid systems especially when dealing with unpredictable renewable sources, when integrating multiple sources and when including energy storage. In fact, such information is necessary in the different phases of the design process; e.g. to appropriately perform the sizing of power sources and storage capacities, to analyze and optimize the logics to control the energy fluxes among the different components and to study the real-time power control of the system (i.e. voltage and current regulation).

In the scientific literature, depending on the design phase undertaken and the method employed, information about users' electric consumptions has different degrees of detail:

- Intuitive sizing methods, based on simple algebraic relationships between power requirements and energy sources availability, typically rely on average daily electric consumptions of the targeted group of users (Elhadidy and Shaahid, 2000; Ahmad, 2002; Bhuiyan and Ali Asgar, 2003; Mandelli et al., 2014).
- Capacity planning methods, based on steady-state energy simulation, heuristic or analytical optimization and analyses of the logics to control the energy fluxes among the different system components, typically rely on *daily load profiles* (Barley and Winn, 1996; Shen, 2009; Belfkira et al., 2011; Bekele and Tadesse, 2012). In these cases, load profiles are a numerical series, the values of which define the average constant power load required by the users within a given time-step. Usually, 24 values represent the hourly average powers load which define the daily profile.

Published Journal Article available at: http://dx.doi.org/10.1016/j.esd.2016.01.005

- Real-time power control analyses, based on circuital or block-set models comprising power electronics and system control components, typically rely on short-term load profiles (Ozaki et al., 2010; Chen et al., 2012). In these cases, load profiles are continuous functions which represent the power loads required by the users for a few seconds/min.

It is worthwhile to highlight that in all these methods, besides input data concerning users' electric consumptions, data about the availability of unpredictable renewable sources (i.e. mainly solar and wind) are also required. Obviously, when they are not available, they have to be estimated, and this is typically what occurs in rural areas of developing countries. Nevertheless, for renewable sources, data can be retrieved from weather stations usually located in the main nearby cities, several databases are available (see for example GeoModel Solar; IRENA; NASA; SANEDI), and a number of models have been developed (see for example Graham and Hollands (1990); Oliva (2008); Huld et al. (2012). As regards users' electric consumptions, it can be noticed that no particular attention has been devoted to introducing proper modeling or methods for their estimate.

In this paper, we address this issue and we describe the development, implementation and application of a novel mathematical procedure to formulate daily load profiles. The procedure is based on microscopic data about users' classes, electrical devices and usage habits, and employs a bottom-up stochastic approach to build up a realistic coincidence behavior. Its application addresses the design process of off-grid systems for rural electrification, and in particular capacity planning methods as well as analysis of energy fluxes control.

In Brief literature overview of user's electric consumptions modeling, we provide a brief overview of the literature dealing with the user's electric consumptions modelings and we highlight the lack of a dedicated area of interest in daily load profiles formulation for rural off-grid systems. In Formalization of literature-based approaches to formulate daily load profiles for rural areas, we formalize two approaches to formulate daily load profiles for rural areas on the basis of the unstructured methods sometimes employed in the literature. In New mathematical procedure proposed, we describe the development of the new procedure by introducing the targeted general features, the required input data and we present its mathematical formulation. In Implementation of the new procedure: the software *LoadProGen*, we introduce the algorithm that implements the procedure in a software tool—*LoadProGen*—which supports the formulation of daily load profiles. Finally, in Application of the new procedure in a case study, we present the application of the new procedure for a college in a small town in Cameroon comparing the profiles formulated via *LoadProGen* with the real ones we metered in-field. The detailed input data for this application are reported in the Appendix. They were collected during in-field missions via local observations, surveys and questionnaires as regards people's habits and electrical appliances.

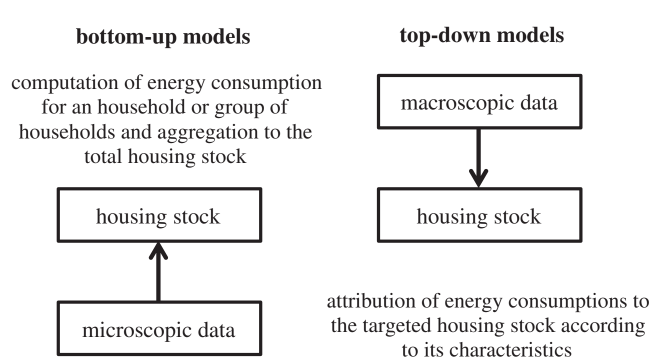

Fig. 1. Bottom-up and top-down model approaches (Swan and Ugursal, 2009).

Table 1
Description of input data required by literature-based approaches.

1.	i	Type of electrical appliances (e.g. light, mobile charger, radio, TV)
2.	j	Specific user class (e.g. household, school, stand shop, clinics)
3.	N_j	Number of users within class j
4.	n_{ij}	Number of appliances i within class j
5.	P_{ij}	Nominal power rate [W] of appliance i within class j
6.	h_{ij}	Overall time each appliance i within class j is on during a day [h]: *functioning time*
7.	$w_{F,ij}$	Period(s) during the day when each appliance i within class j can be on: *functioning windows*

Brief literature overview of user's electric consumptions modeling

The study of user's electric consumptions has been widely addressed within different research themes and with different purposes. These can be grouped into two main areas:

- Power system engineering refers to *load forecasting* as the domain of models able to provide data for setting the best planning and operating of grids. Load forecasting can be divided into three categories: (a) *short term*, which is used to predict loads from 1 h to a week ahead and is required to solve unit commitment and economic load dispatch problems; (b) *medium term*, which is used to predict weekly, monthly and yearly peak loads up to 10 years ahead and is required for efficient grid operational planning; and (c) *long term*, which is used to predict loads up to 50 years ahead and is required for grid expansion planning. Examples are shown in Jia et al. (2001); Al-Hamadi and Soliman (2005); Carpinteiro et al. (2007); Li and Meng (2008); Javed et al. (2012); Liu et al. (2014); and Lee and Hong (2015).
- Energy planning research refers to *energy consumption modeling* as the domain of models able to support energy-related policy decisions. Energy consumption modeling deals with energy consumptions for a country, a region or a sector and they can be grouped into two categories: (a) *top-down*, which is used to determine the effect on consumptions due to ongoing long-term changes in order to assess future supply requirements, and is based on econometric or technological models; (b) *bottom-up*, which is used to model consumptions of each end-use and hence to identify areas for efficiency improvements at user level, and is based on statistical or engineering models (Fig. 1). Examples are shown in Howells et al. (2005); Swan and Ugursal (2009); Song et al. (2011); Zhang and Zhong (2011); Lü et al. (2015); and Xu et al. (2015).

Despite the large number of scientific papers that have addressed these themes, only a few of them specifically focus on the estimate of *daily load profiles* for off-grid systems. Moreover, most of them deal with the particular case of domestic electric consumptions in developed countries and they are mainly devoted to support decisions as regards distributed generation integration in power systems, analysis of

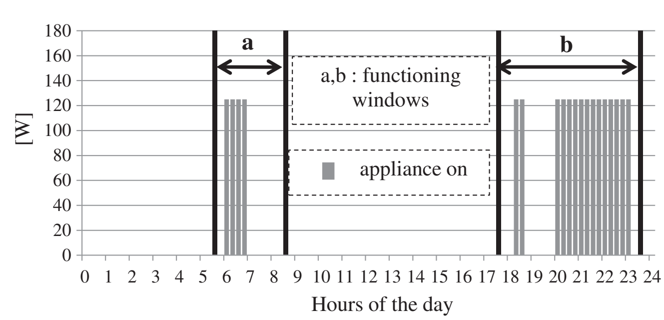

Fig. 2. Graphical representation of functioning windows for a single appliance.

Table 2
Input data required by the new procedure.

1.	i	Type of electrical appliances (e.g. light, mobile charger, radio, TV)
2.	j	Specific user class (e.g. household, school, stand shop, clinics)
3.	N_j	Number of users within class j
4.	n_{ij}	Number of appliances i within class j
5.	P_{ij}	Nominal power rate [W] of appliance i within class j
6.	h_{ij}	Overall time each appliance i within class j is on during a day [min]: *functioning time*
7.	$w_{F,ij}$	Period(s) during the day when each appliance i within class j can be on: *functioning windows*
8.	d_{ij}	*functioning cycle* [min], i.e. *minimum* continuous functioning time once appliance ij is on
9.	Rh_{ij}	% random variation of functioning time appliance ij
10.	Rw_{ij}	% random variation of functioning window appliance ij

demand side management measures, impacts of various scenarios on local power demand, etc. In this regards, Grandjean et al. (2012) have recently revised and described 12 models for daily load profiles formulation within the residential sector. They classified these models into three main categories: bottom-up, top-down and hybrid. Then, a further five sub-divisions were proposed according to the way the coincidence behavior, which is the key parameter in load profile formulation, was modeled: deterministic statistical disaggregation models, statistical random models, probabilistic empirical models, time of use-based models and statistical engineering models.

In the light of the mentioned literature and to the authors' knowledge, it is worthwhile to highlight that no structured and formalized models have been developed so far to formulate daily load profiles to support the design process of off-grid systems. Moreover, in the specific research field of off-grid rural electrification, this is true not only when looking at the literature which focuses on developments of new sizing methods and models but also when looking at their applications or systems feasibility analyses. Only Celik (2007) brought about the issue of load profiles and system sizing for stand-alone PV systems.

In practice, researchers in this field generally introduce daily load profiles in three manners:

- Profiles are defined without any explanations about their origin (Bala and Siddique, 2009; Nandi and Ghosh, 2010; Kanase-Patil et al., 2011).
- Profiles are derived by employing other ones from similar contexts (Nfah and Ngundam, 2009, 2012; Phrakonkham et al., 2012; Semaoui et al., 2013; Sen and Bhattacharyya, 2014).
- Profiles are formulated without any defined procedure, but by employing assumptions on electric appliances functioning periods and/or load factors, in order to build up a coincidence behavior (Al-Karaghouli and Kazmerski, 2010; Gupta et al., 2010; Bekele and Tadesse, 2012).

In our opinion, these approaches cope without the appropriate attention with the theme of daily load profiles formulation. In particular, none of them are based on a structured procedure which is recognized as appropriate for application in capacity planning methods and analysis of energy fluxes control for off-grid systems in rural areas. In the following sections, we contribute to filling this gap by proposing the formalization of two approaches based on the literature and by introducing a novel new mathematical procedure.

Formalization of literature-based approaches to formulate daily load profiles for rural areas

Despite no structured procedures being reported in the literature, we formalize two possible approaches that can be considered as references for state-of-the-art in daily load profile formulation for rural areas. We consider them as *literature-based approaches* and refer to them as *Lit_Appr1* and *Lit_Appr2*. They are described in the following.

The purpose of both approaches is to compute a daily load profile of a number of rural consumers who are grouped according to different user classes j having different electrical appliances i. Table 1 reports the list of input data required by the two approaches. Specific features of *Lit_Appr1* and *Lit_Appr2* are:

- They require a classification of user classes and electrical appliances together with data about the number of users and appliances, i.e. they are bottom-up approaches.
- They assume that each appliance is modeled with its nominal power (i.e. no power cycles are considered).
- They require data about the daily overall time each appliance is in use, i.e. the functioning time.
- They require defined period(s) during the day when each appliance can be in use, i.e. the functioning window(s) (Fig. 2).
- Both the functioning times and the functioning windows are typically defined according to a minimum time-step of one hour.

These data are the necessary minima required to formulate a daily load profile of a given group of consumers in rural areas. They can be easily assumed based on practical experience on similar context conditions or by mean of local surveys. Appliances' functioning times and functioning windows are the most significant data since they determine the daily electric energy consumption and the coincidence behavior of the appliances, respectively. Given the same group of users and appliances, different sets of functioning times and functioning windows define different load profiles. This can be employed to formulate different load profiles for the same targeted group of users according to seasonal change, working days/weekends, etc.

It can be noticed that given the types of appliances, the user classes, the number of users, the number of appliances, the appliance rate powers and the functioning times, the daily electric energy consumption E_C is set and can be computed as follows:

$$E_C = \sum_{j}^{User\ Class} N_j * \sum_{i}^{Appliance} n_{ij} * P_{ij} * \mathtt{h}_{\mathtt{ij}} \Bigg) \quad [\mathtt{Wh/day}] \tag{1}$$

This is the same for the two literature-based approaches which, on the contrary, differ because of the relationship between functioning times and functioning windows, i.e. because of the method, the daily electric energy consumption (related to the functioning times) is distributed throughout the day (related to the functioning windows) defining the coincidence behavior of the appliances.

Table 3
Example of input data for a user class.

Class type j	N_j	App. name i	P_{ij} [W]	N_{ij}	d_{ij} [min]	h_{ij} [h]	$w_{F,ij}$_1 h_{start} h_{stop}		$w_{F,ij}$_2		$w_{F,ij}$_3	
Household	55	Lights	10	4	10	6	17	24	–	–	–	–
		Phone charger	5	2	30	3	0	9	13	15	21	24
		Security lights	20	1	30	12	0	7	19	24	–	–

Lit_Appr1 is characterized by the following condition in the relationship between functioning times and functioning windows:

$$\sum duration(w_{F,ij}) = h_{ij} \qquad \forall ij \tag{2}$$

i.e. the functioning windows of each appliance *ij* is set in order that the sum of their durations is equal to the functioning time h_{ij}. Accordingly, all the n_{ij} appliances are on at the same time and the coincidence factor is equal to 1 for each appliance *ij*. *Lit_Appr1* requires defining how long and when the appliances are on without considering any coincidence behavior. Thus, the peak power is overestimated, and in general, the profiles are not flat, but have high or low values.

Lit_Appr2 is based on the following condition on the relationship between functioning times and functioning windows:

$$\sum duration(w_{F,ij}) > h_{ij} \qquad \forall ij \tag{3}$$

in addition, the contribution of each appliance in formulating the load profile is computed as follows: first, the electric energy consumption $E_{L,ij}$ associated with each appliance *ij* is computed (Eq. (4)); then, an average power $P_{av,ij}$ associated with each appliance *ij* within its functioning window is calculated (Eq. (5)). The values $P_{av,ij}$ are those which contribute to building up the load profile.

$$E_{L,ij} = P_{ij} * h_{ij} \tag{4}$$

$$P_{av,ij} = \frac{E_{L,ij}}{\sum duration(w_{F,ij})} \tag{5}$$

In *Lit_Appr2*, the power contribution of each appliance *ij* to the load profile refers to the average power computed by "spreading" the consumed energy on the total duration of the functioning windows. In this way, the coincidence factor assumes the minimum value possible given by the functioning times and functioning windows. Hence, the power peaks are underestimated, and in general the profiles are flat.

Having in mind the two literature-based approaches, some considerations can be made:

- Both approaches formulate load profiles which are subjected to a certain degree of subjectivity, mainly in setting the functioning windows, owing to the operator that defines the input data. This is typical of the conditions in rural areas which does not allow for the collection of detailed information. This aspect highlights the issue of uncertainty in the input data and hence that given a certain set of data, formulating a single profile cannot represent a realistic situation.
- A hybrid method, which provides for properly selecting and applying for some appliances *Lit_Appr1* and for others *Lit_Appr2* according to their typology, can compensate for the limitations of the two approaches. Nevertheless, this requires further specific information about each appliance thus leading to the introduction of further subjectivity in the input data and hence further uncertainty.
- Embracing uncertainty in order to differentiate a number of realistic load profiles given the same set of input data can be performed by introducing a random noise on the formulated profile. This is the solution adopted in the HOMER Energy software (HOMER Energy LLC, 2014) which is a well-known tool in the field of off-grid systems design. Nevertheless, uncertainty is considered ex-post the load profile formulation by means of literature-based approaches.

Lit_Appr1 and *Lit_Appr2* represent simple, engineering-based, structured procedures that can be applied to formulate daily load profiles for rural areas. Nevertheless, as highlighted by the previous considerations, they have some limitations. In this regard, we describe in the following a novel mathematical procedure taken from these literature-based approaches, but it embraces elements of advanced electric consumption

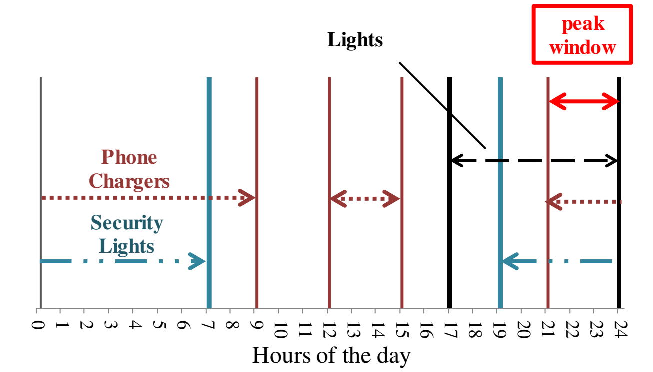

Fig. 3. Peak window definition, example based on data from Table 3. In this case, all the appliances contribute to the power peak definition.

modeling techniques in order to properly formulate daily load profiles for rural consumers.

New mathematical procedure proposed

In setting the framework to develop the new procedure, the characteristics of an ideal method for load profiles formulation have been taken as a reference. An ideal model should present the following features (Grandjean et al., 2012):

- It has to be parametric in order to simulate various scenarios.
- It has to be technically explicit, i.e. the different specificities of the simulated appliances must impact the load profile results.
- It has to be evolutive, i.e. new elements can be introduced so as to be simulated.
- It has to be aggregative so that results can be obtained at different levels (household, city, region, etc.).
- All end-uses can be considered in the load profile calculations.

In the light of this reference, a new procedure has been developed in order to embrace the following features:

- It has to be based on input data that can be easily assumed based on practical experience on similar context conditions or by mean of local surveys.
- It has to be based on a rigorous mathematical formulation which allows generating the load profile, i.e. apart input data, the designer judgments should not affect the profile shape.
- It has to be bottom-up, i.e. the load profile formulation has to rely on microscopic input data referring to each appliance's features within a specific type of user class.

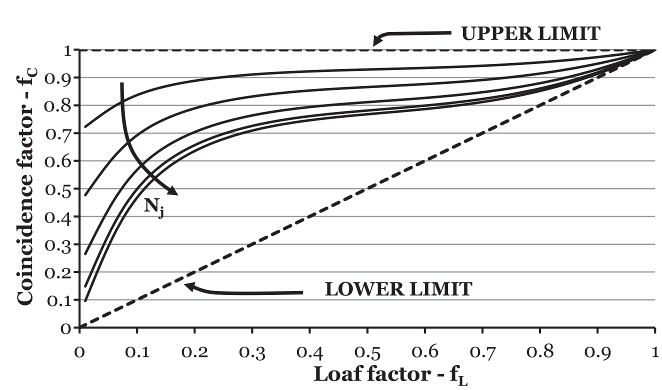

Fig. 4. Relationship between coincidence factor, load factor and number of consumers in a class.

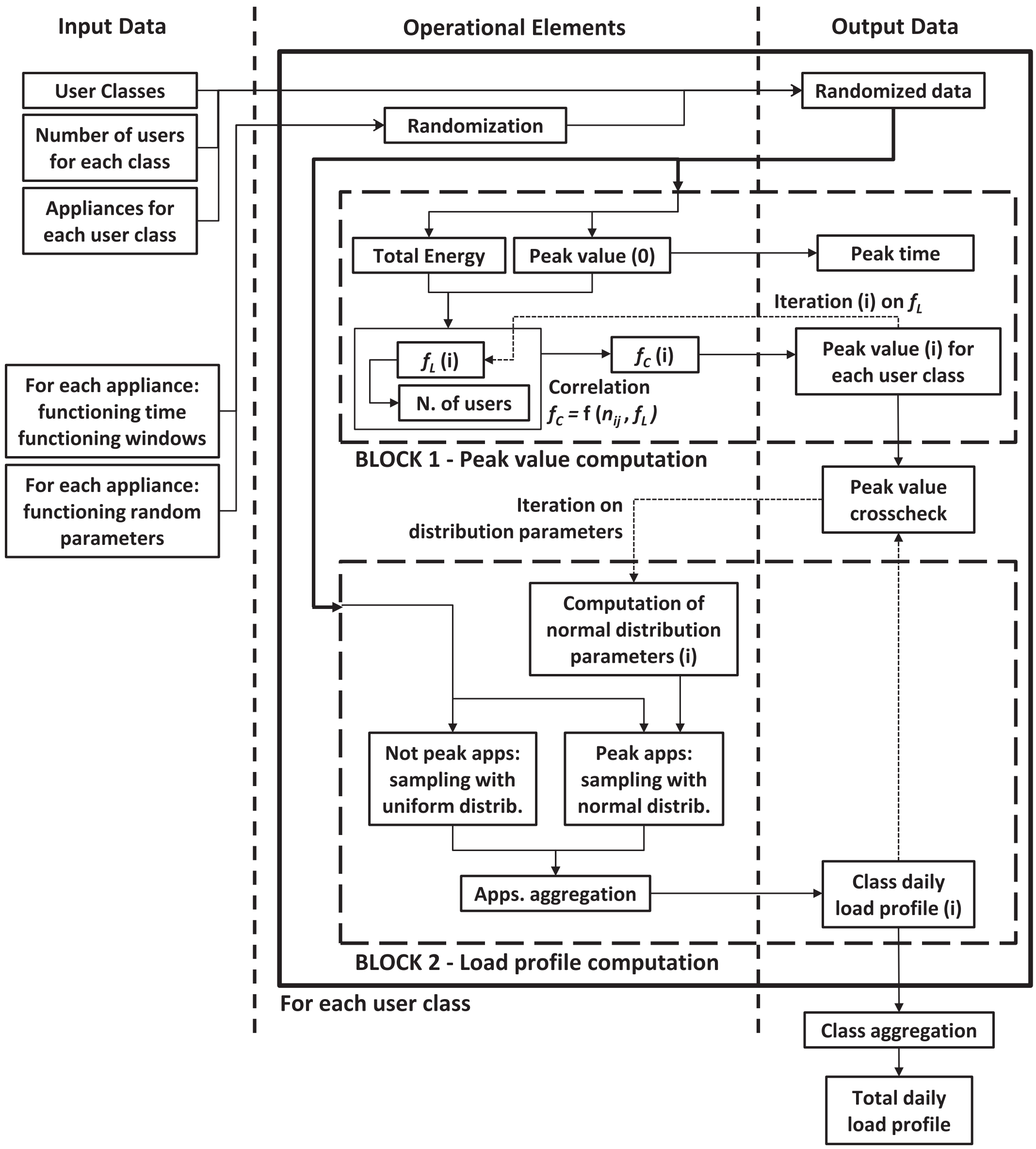

Fig. 5. Block representation of the algorithm for load profile formulation.

- It has to build up the coincidence behavior of the appliances and the power peak value with regards to the existing empirical correlation between number of users, load factor and coincidence factor.
- It has to be stochastic in order to embrace uncertainty, i.e. given the input data, the procedure output should allow formulating a number of realistic profiles within the given input data.

Moreover, it is relevant to point out that the main purpose of this procedure is not to *forecast* load profiles, but rather to *formulate* load profiles. Specifically, we refer to forecasting load profiles as the process of evaluating the future consumptions trend of a group of *consolidated* electric users. This is the typical issue addressed with different purposes in the literature. Our aim is different though; indeed, we refer to formulating as the process of evaluating the consumptions trend of *expected new consumers in an off-grid rural area without access to electricity*. In this perspective, the main objective of the new procedure is to support capacity planning methods and analyses of energy fluxes control for off-grid systems for a rural electrification system by computing *possible realistic* daily load profiles according to a formalized method which considers elements of the advanced techniques developed within the user's electric consumptions modeling research field.

Table 4
Summary of energy consumptions for household user classes.

Class type	N_{US}	$E_{class,day}$ [kWh/day]	$E_{user,day}$ [kWh/day]	$E_{pc,year}$* [kWh/year/pc]
Household_1	18	36.5	2.0	176.1
Household _2	14	30.1	2.1	186.7
Household _3	11	8.1	0.7	64.3

* on average 4.2 people per households.

Table 5
Summary of energy consumptions for college facilities user classes.

Class type	N_{US}	$E_{class,day}$ [kWh/day]
Students' dormitories	1	12.2
Classrooms	1	13.0
Kitchen	1	2.9
Bakery	1	1.0
Dining hall	1	0.9
Canteen	1	0.9
Workshop	1	0.7
Dispensary	1	0.4
Church	1	2.0
Administration office	1	7.9
Library	1	3.5
ICT college	1	20.1

With respect to the hypotheses and the aforementioned features, a novel procedure has been developed; in particular, Table 2 shows the adopted input data structure while Table 3 reports an example of such a structure for a generic rural user class.

Besides the input data already managed in the literature-based approaches (Table 2, 1–7), new ones are requested: the functioning cycle (d_{ij}), and the parameters of random variation of functioning time (Rh_{ij}) and windows ($Rw_{F,ij}$). Moreover, the functioning times, the functioning windows and the functioning cycles are defined according to a minimum time-step of one minute.

Having in mind these input data, some considerations can be made:

- The new procedure follows a bottom-up approach.
- All the appliances are modeled with an on–off functioning mode and considering a minimum continuous functioning cycle (d_{ij}). For example, a functioning cycle of 45 min may be suitable for an oven while a functioning cycle of only 2/3 min may be suitable for a blender.
- In order to consider a degree of uncertainty in the values of h_{ij} and $w_{F,ij}$, random parameters Rh_{ij} and $Rw_{F,ij}$ are introduced, respectively. They set the maximum percentage of h_{ij} and $w_{F,ij}$ subjected to random variation.
- Given all the input data and apart from considering the effect of Rh_{ij}, the total required daily electric energy of each user class is defined (Eq. (1)).
- Given all the input data, a possible theoretical maximum power peak for each user class is defined. Indeed, overlapping the functioning windows for the different appliances within a class, a window (*peak window*) will result to be embraced by a number of appliances hence defining a possible maximum power peak considering a coincidence factor equal to 1 (Fig. 3). For the example shown in Table 3, the class peak can occur from 21:00 to 24:00, and the maximum value can be 3.85 kW.
- According to previous considerations, a load factor for each user class relating to the maximum possible peak power and the total required daily electric energy can be computed.

In the following, we provide a mathematical formulation of the new procedure according to an objective function and constraints.

Objective function

The load profile of each appliances *ij* is computed by defining, in a stochastic manner, the times t_{ij} the appliance *ij* is switched on within the vector of the daily minutes [1:1440]. Hence, having the switching on times t_{ij} and the functioning cycles d_{ij}, the load profile of each appliance is defined. Then, the daily load profile of the user class *j* results from the aggregation of single appliance profiles *ij*. Accordingly, the overall daily load profile results from the aggregation of the user classes' profiles *j*.

Constraints

- The functioning cycles must be shorter than functioning times:

$$d_{ij} \leq h_{ij} \qquad \forall \text{ij} \tag{6}$$

- The functioning times must be shorter or equal to the total duration of functioning windows:

$$\sum duration(w_{F,ij}) \geq h_{ij} \qquad \forall \text{ij} \tag{7}$$

where equality applies only when $w_{F,ij}$ are exactly well-known.

- The amount of functioning cycles ($n_{t,ij}$) occur in a day for each appliance *ij* is defined as follows:

$$n_{t,ij} = \frac{h_{ij} + random(h_{ij} * Rh_{ij})}{d_{ij}} \tag{8}$$

where $random(h_{ij}*Rh_{ij})$ refers to the computation of a random value defined in $[-(h_{ij}*Rh_{ij}), +(h_{ij}*Rh_{ij})]$. $n_{t,ij}$ also coincides with the amount of times each appliance is switched on.

- The functioning window(s) $w_{F,ij}$, which define the periods when t_{ij} can occur, is defined as follows:

$$w_{F,ij} = w_{F,ij} + random(w_{F,ij} * Rw_{F,ij}) \tag{9}$$

where *random* ($w_{F,ij}*Rw_{F,ij}$) refers to the computation of random values for the starting and ending times of the functioning window(s) *ij*.

- *Power peak time* ($t_{P,J}$) (i.e. the time power peak occurs) of each user class *j* is randomly chosen with uniform probability distribution within the *peak window* of the class (Fig. 3).
- t_{ij} are defined by random sampling within the respective functioning windows with two probability distributions: (i) for appliances

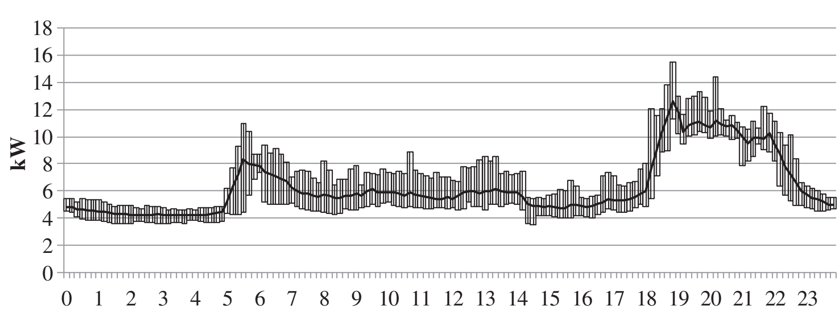

Fig. 6. Box plot for the metered load profiles of Presbyterian College in Bali. For each time-step (10 min) max, min and average values are reported.

which do not contribute to the peak, sampling is carried out with uniform probability distribution; (ii) for appliances which contribute to the peak (e.g. all the appliances in Fig. 3), sampling is carried out with normal probability distribution having mean value on $t_{P,J}$.
- Starting from each t_{ij}, the appliance ij is on for the following d_{ij} minutes.
- Standard deviation of the normal probability distribution for appliances contributing to the peak is defined in order to obtain, within each user class j, a power peak value which complies with the peak power obtained via the correlation between coincidence factor (Eq. (10)), load factor (Eq. (11)) and number of users N_j.

$$f_{C,j} = \frac{p_{L,j}}{p_{MAX,J}} \tag{10}$$

$$f_{L,j} = \frac{E_{C,j}}{24h \; x \; p_{L,j}} \tag{11}$$

where $p_{L,j}$ represents the actual power peak; $p_{MAX,j}$ represents the possible theoretical maximum power peak and $E_{C,j}$ represents the daily electric energy consumption.

The appearance of this empirical correlation has been reported by recent reviews (Grandjean et al., 2012) as well as analyses of distribution grid expansion (Willis and Northcote-Green, 1983; Gaunt, 1996). The general formulation of this correlation results as follows:

$$f_{c,j} = a * f_{L,j} + \left(1 - a * f_{L,j}\right) * N_j^{-1/\alpha} \tag{12}$$

where a is the ratio between the coincidence factor for infinite consumers $f_{C,j}(\infty)$ and $f_{L,j}$, and it is expressed as regards the probability p that single consumers' peaks occur at the same time:

$$a = \frac{1}{p}\left[1 - (1-p)^{1/f_{L,j}}\right] \tag{13}$$

$$p = b + c * e^{-h^2 * g\left(f_{L,j}\right)^2} \tag{14}$$

p is formulated to conform to Gauss' normal probability distribution. The proposed parameters of Eq. (15) have been empirically calculated providing the following formulation:

$$p = 0.187 + 0.813e^{-4\left[\left(1-f_{L,i}\right)^2 + \left(1-f_{L,i}\right)^{16}\right]} \tag{15}$$

Eq. (12) is quite important since it allows embracing in the new procedure information about the user classes power peaks and it also determines the probability distribution which affects the simulation of switching on time of the appliances. In Fig. 4, we report a graphical representation of this correlation according to the empirical parameters of

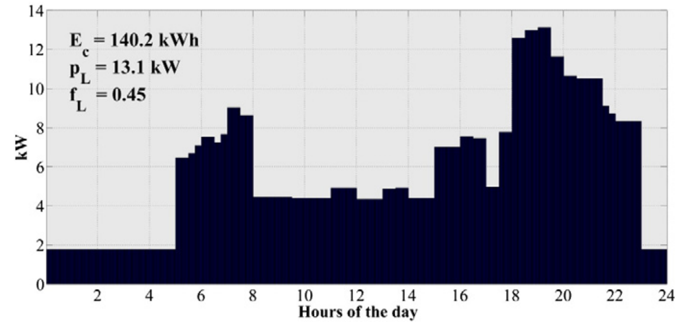

Fig. 8. Load profile resulting from *Lit_Appr2*.

Eq. (15). These trends can be explained by analyzing the relation between coincidence factor and load factor for a given number of consumers and then considering the effect of a different number of consumers.

Implementation of the new procedure: the software *LoadProGen*

We developed an algorithm which implements the mathematical procedure. It is based on MATLAB and we call it *LoadProGen* (i.e. Load Profile Generator). Given a set of input data, it can formulate n load profiles all complying with the given inputs. It can work as a support tool to formulate load profiles to be employed in the design process of off-grid systems for rural electrification. In Fig. 5, a block representation of the algorithm is presented. In particular:

- The algorithm develops the profiles of each single user class defined by the designer with a bottom-up approach. Then, the final load profile is given by aggregating each user class load profile.
- The algorithm is divided into three sections: (i) *input data*, which highlights different groups of required inputs; (ii) *operational elements*, which considers the different computational steps, and (iii) *output data*, which highlights different groups of computed outputs.

A description of the algorithm sections is presented hereafter.

Input data

These can be divided between those which are not subjected to a first randomization and those which can be randomly modified according to parameters Rh_{ij} and Rw_{ij}.

Operational elements and output data

1. The algorithm elaborates the input data in order to obtain them in the proper form to compute the load profile: functioning times and

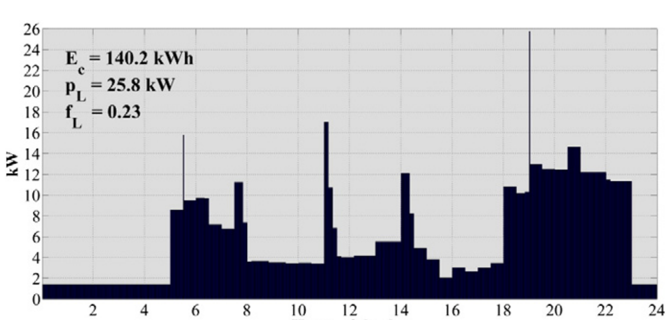

Fig. 7. Load profile resulting from *Lit_Appr1*.

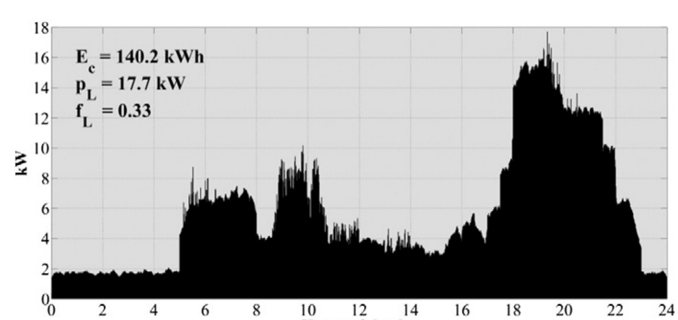

Fig. 9. Load profile resulting from the new procedure based on case *LoadProGen_0*.

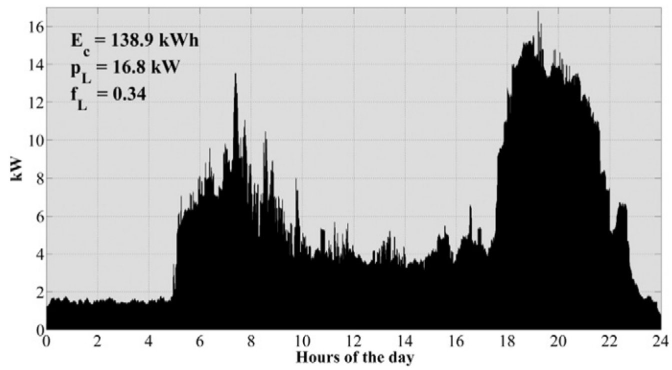

Fig. 10. Load profile resulting from the new procedure based on case *LoadProGen_30*.

functioning windows are randomized and then aggregated with the other inputs.

2. *Peak value computation*. In this block, the total required energy, the peak window(s), the possible theoretical maximum power peak (i.e. *peak value*(0)), and the peak time t_{PJ} are first computed. Then, with an iterative process, the load factor and the coincidence factor are computed according to Eq. (12) until convergence is reached for their values. Hence, the reference value of the power peak for the considered user class can be computed.
3. *Load curve computation*. In this block, for each appliance, the switching on times t_{ij} are randomly selected according to the specific probability distributions (i.e. uniform distribution if the appliance does not contribute to the peak, normal distribution if the appliances contribute to the peak). Accordingly, the load profile for the user class can be computed. Nevertheless, the resulting peak may not comply with the estimated one (previous step). Therefore, iterations are performed by relaxing the standard deviation of the normal probability distribution which guides the random sampling of t_{ij} of the peak appliances.
4. Once the resulting peak value matches, with an error defined by the designer, the computed power peak via Eq. (12), the iterations are stopped and the final load profile is identified.
5. Repeating steps 2, 3 and 4 for each user class and aggregating the different user class load profiles allows computing the final profile.

The algorithm implements the new procedure and complies with the proposed features introduced in Paragraph 4. In particular, it is worthwhile to highlight that by developing the load profile of each single appliance and then by aggregating them, the coincidence behavior within a user class is achieved in a similar way as it occurs in real power systems. Moreover, due to the stochastic approach in defining the peak time t_{PJ} and the switching-on times t_{ij}, the algorithm computes a different load profile each time it is run.

Application of the new procedure in a case study

As already highlighted, the new procedure aims at *formulating* the load profiles of expected new consumers in an off-grid area without access to electricity. Nevertheless, in the following, we propose an analysis based on the electric consumptions of an already electrified college in a small town of Cameroon in order to assess the applicability of the new procedure to a real context and to analyze the results (in a real-life application of the procedure the real energy consumptions are unavailable; consequently, in the case study we performed, the energy figure has been assumed as the theoretical energy need ex-post the electrification of the area, i.e. a benchmark). Specifically, we carried out the application of the new procedure in two steps: (i) we formulate the load profiles for the college by means of the two literature-based approaches (*Lit_Appr1* and *Lit_Appr2*) and the new procedure in order to highlight their specific features; and (ii) we compare the formulated profiles with those we metered in-field.

Description of the case study

The case study adopted for the new procedure is the Presbyterian College of Bali, Cameroon (5.53 N/10.01E). All the available information is the result of activities carried out during a two-month in-field mission addressing the energy assessment of the college.

Currently, the college has about 1000 students and about 180 staff/personnel who dwell in the campus day and night all week long. Therefore, besides classrooms and offices, within the campus there are also buildings and facilities with the everyday life needs (e.g. dormitories, staff houses, small shops, canteen). The college is already supplied by electricity which is provided by a three-phase 380 V connection with the national grid managed by AES-SONEL. Nevertheless, a 24 kVA diesel generator is available in order to make up for the frequent grid outages.

The input datasets for load profile formulation have been devised by collecting information about available electrical appliances and usage habits of people via questionnaires and surveys with the college staff and students. Accordingly, the input data for the load profile formulation were defined. In Tables 4 and 5, we list the defined user classes together with a summary of energy related features, while in the Appendix, we report the detailed input datasets. Globally, the collected information provide for a daily total consumption of the college of 140.2 kWh, which amounts to 43.4 kWh/year/per capita considering students and staff.

Moreover, we also collected data as regards the actual consumption of the school. Similar to the typical situation in developing countries, metering of college power loads was a challenging task. Frequent outages of the grid, switching on the back-up diesel generator, instability of the power supply (frequency and voltages vary within very wider ranges when compared with industrialized countries grids) and lack of data as regards electrical distribution system, connections and switches are all

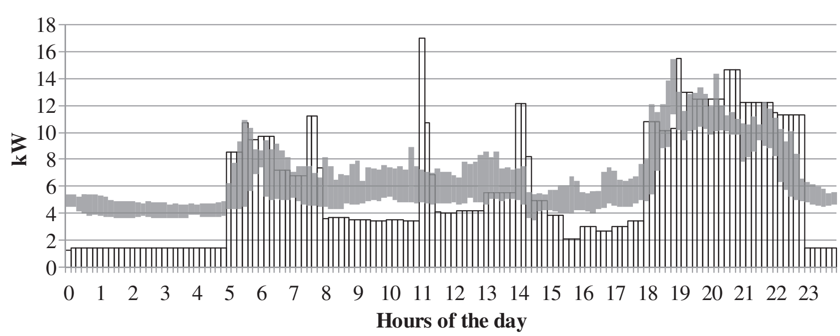

Fig. 11. Comparison between *Lit_Appr1* (bar profile) and the metered data (gray band).

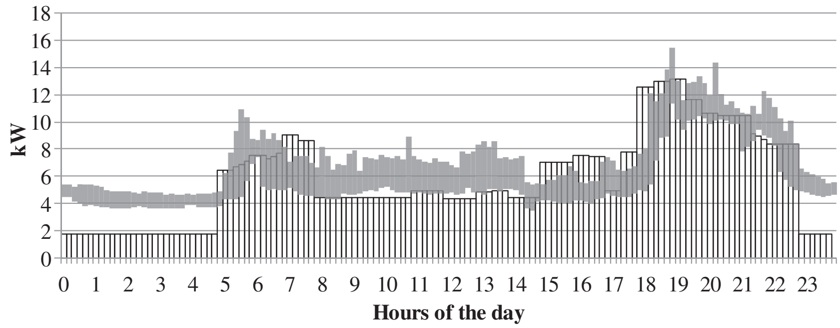

Fig. 12. Comparison between *Lit_Appr2* (bar profile) and the metered data (gray band).

typical elements of power systems in developing countries that can hinder a metering campaign. In our case, we carried out a metering campaign by monitoring the meter at the connection of the school electric system with the AES-SONEL distribution grid and we collected the complete load profiles for 8 days with a 10 min time-step resolution.

The metered profiles are shown by Fig. 6, which reports, for each time-step, the minimum, maximum and average values recorded. In the metered days, the power peak ranges between 11.5 and 15.4 kW, while the daily energy consumed ranges between 139.5 and 161.2 kWh.

Literature-based approaches vis-à-vis LoadProGen

As a first analysis, we formulated load profiles for the college by means of the two literature-based approaches (*Lit_Appr1* and *Lit_Appr2*); while in a second step, we adopted the new procedure and compared the results. It is worthwhile to mention that the input data (Appendix) had been defined in order to embrace the uncertainty of the collected information and hence all functioning windows and functioning times comply with the condition of Ineq. 3. In applying *Lit_Appr1*, each functioning window width has been reduced in order to comply with Eq. (2) and hence the daily electric energy consumption has not changed.

The resulting load profiles are reported in Figs. 7, 8, 9 and 10 together with key load profile parameters: daily electric energy consumption E_C, power peak p_L and load factor f_L. Specifically, Fig. 7 shows the load profile formulated with *Lit_Appr1*, Fig. 8 shows the load profile formulated with *Lit_Appr2*, Figs. 9 and 10 show two examples of load profiles formulated with *LoadProGen* with parameters Rh_{ij}, Rw_{ij} equal to 0% and 30%, respectively (from here, we refer to them as *LoadProGen_0* and *LoadProGen_30*).

Looking at the formulated load profiles,, some considerations can be made. As regards *Lit_Appr1* (Fig. 7), Eq. (2) leads to comply with the power contribution of each appliance to the load profiles (i.e. each and every appliance contributes with its own rate power P_{ij}). Nevertheless, when n_{ij} appliances are available, they all result to be on at the same time without considering any coincidence behavior. Moreover, for appliances such as fridges, chiller and heaters, it is quite difficult to set the functioning windows given their cyclical on–off functioning. This approach suits users with different single appliances or when functioning windows are exactly known. Outside these conditions, such as in the case under study, the resulting profile often has a number of marked peaks (related to high power rated appliances which work for short periods) together with periods with constant power (related to low–medium power-rated appliances which work for long periods).

As regards *Lit_Appr2* (Fig. 8), Ineq. 3 leads to comply with the energy contribution of each appliance. Nevertheless, the relating contribution in term of power does not refer to the rate power of the appliance, but it is reduced according to the ratio between functioning time and duration of functioning window(s). To put it in another way, each appliance contributes to the profile not with its rate power, but with an average (lower) one. This approach suits for users with a number of appliances of the same type which work over wide functioning window(s) with respect to the functioning time. The resulting profile, such as in the case under study, often has lower power peaks and highest load factor (i.e. the profile tends to be flat).

As regards the new procedure (Figs. 9 and 10), each and every appliance contributes to the load profile with its own rate power. However, the stochastic approach for defining the switching-on times allows to simulate a realistic functioning of the appliances and hence to simulate a realistic coincidence behavior. Moreover, the implementation of the relationship between load factor, coincidence factor and number of users has the objective to lead to proper user class peaks. This results in profiles with continuous smaller and larger spikes, which follow from the stochastic switching on of appliances; that is, the spikes values are not random, but results from the features of the considered appliances. Therefore, the model, considering the feature of having a minute time-step, allows performing analyses of the logic to control the energy fluxes among the different system components of an off-grid system. Indeed, the extent of the variations of load between sequent time-steps are a significant element that affects the control capacity of the system.

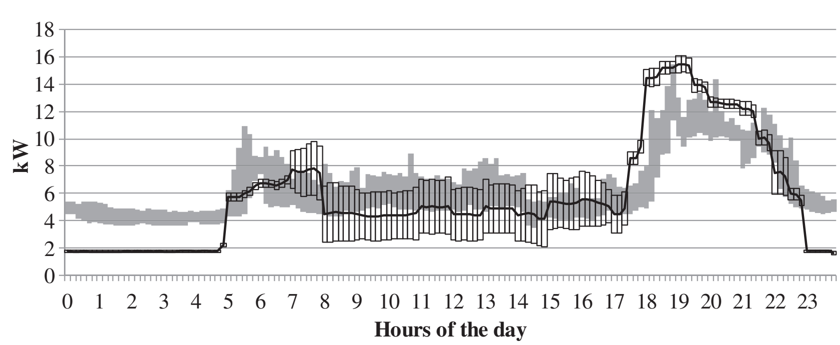

Fig. 13. Comparison between *LoadProGen_0* and the metered data (gray band).

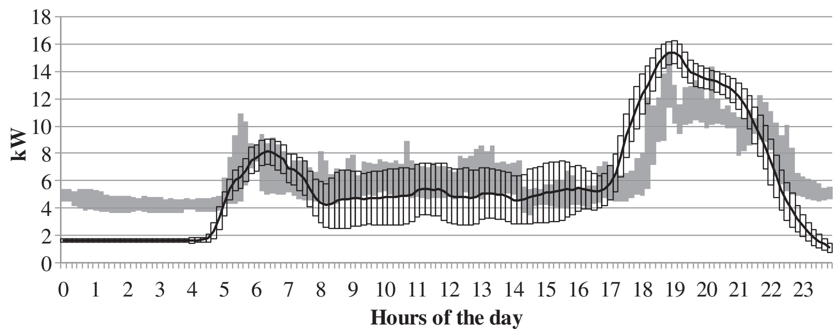

Fig. 14. Comparison between *LoadProGen_30* and the metered data (gray band).

Comparing the resulting profiles of the new procedure, computed with Rh_{ij}, Rw_{ij} equal to 0% and 30%, respectively, it can be noticed that for the second case (Fig. 10): (i) the profile shape is smoother and less blocky due to the random effect on functioning windows, (ii) the daily electric energy consumption E_C is slightly smaller due to the random effect on functioning times and (iii) the power peak is smaller, but a new secondary peak has appeared in the morning. It is worthwhile to mention that while what is mentioned in point (i) always occurs when considering Rw_{ij} different from zero, as regards points (ii) and (iii), the resulting features of the profiles are peculiar to these specific profiles. Indeed, the stochastic approach implemented in the new procedure provides for the capability to formulate a number of realistic load profiles complying with the given in input dataset. This is not possible with the two literature-based approaches which allow formulating only one profile given a set of input data.

Metered profiles vis-à-vis literature-based approaches and LoadProGen

In order to quantify the performance of the proposed procedure, we elaborated the box plot of Fig. 6 which reports, for each time-step, the minimum, maximum and average values recorded. This representation of the metered data is taken for comparison with the profiles formulated via the literature-based approaches and the new procedure. In particular, we report the comparison between the box plot of the metered data and the profiles formulated via the two literature-based approaches in Figs. 11 and 12. It is worthwhile to stress again that the two literature-based approaches each allow formulating a single load profile; hence, the bar profiles reported in Figs. 11 and 12 represent a single profile.

When considering the new procedure, owing to its stochastic nature, employing only a single estimated load profile is not appropriate. In this case, we carry out the comparison of the metered data with the output of n profiles formulated via *LoadProGen* where n is the number of profiles to be formulated in order that the relating average profile represents the profile to which the procedure converges. In particular, we defined the following conditions to identify n:

$$\frac{\overline{y}(k)_n-\overline{y}(k)_{n+1}}{\overline{y}(k)_n} \le 0.25\% \quad for\ k \ge 95\% \text{of time steps}$$
$$\text{and} \tag{16}$$
$$\frac{\overline{std}[y(k)_n]-\overline{std}[y(k)_{n+1}]}{\overline{std}[y(k)_n]} \le 0.25\% \quad for\ k \ge 95\% \text{of time steps}$$

where

- k refers to the profile time-steps, in this case, the considered load profiles are constituted by averaged values over 10 min time-steps in accord with the metered ones
- $\boldsymbol{y}(\boldsymbol{k})_{\boldsymbol{N}}$ refers to the average load profile value of n generated profiles at the time-step k
- $\boldsymbol{std}[\boldsymbol{y}(\boldsymbol{k})_{\boldsymbol{N}}]$ refers to the average standard deviation of the load profile value of n generated profiles at the time-step k

According to this approach, we evaluated load profiles to convergence computed with Rh_{ij}, Rw_{ij} equal to 0% and 30%, respectively (i.e. case *LoadProGen_0* and *LoadProGen_30*). Key parameters of the load profiles generated with *LoadProGen* to reach convergence are reported in Table 6.

In Figs. 13 and 14, we compare the metered data with the box plots resulting from the n profiles generated to convergence for the cases *LoadProGen_0* and *LoadProGen_30*. The box plots report, for each time-step, the average values with standard deviation band obtained from the n profiles.

Looking at the comparisons between metered and formulated profiles via the literature-based approaches and *LoadProGen*, some consideration can be made.

Lit_Appr1 has led to a profile that fits well with the metered data only at the high load power periods of the morning and evening (5–7 and 18–22). Nevertheless, it has lower values in the central part of the day (7–18) as well as at night (22–5). Moreover, at least three peaks occur which are clearly the effect of the inappropriate modeling of the coincidence behavior of this approach. These peaks do not fit at all with the figures of the metered profiles. *Lit_Appr2* led to a profile that fits well with the metered profiles from 5 to 22 despite its having slightly lower values in the central part of the day (8–18). On the contrary, it shows lower values in the night hours (22–5).

Clearly, when looking at the literature-based approaches, *Lit_Appr2* is better suited for application in the design process of off-grid systems for rural electrification. Indeed, despite safety parameters being considered as regards the resulting peak power (which may be underestimated), it avoids large overestimations of the power peaks if compared with *Lit_Appr1* and it better distributes the energy throughout the day (i.e. less blocky profile). Nevertheless, both *Lit_Appr1* and *Lit_Appr2* are deterministic approaches which are not capable of taking

Table 6
Key parameters for the set of profiles generated to convergence of the new procedure.

	n profiles to convergence	E_C [kWh/day]			p_L [kW]			f_L		
		min	av.	max	min	av.	max	min	av.	max
LoadProGen_0	231	“	140.2	“	14.4	15.7	17.5	0.33	0.37	0.41
LoadProGen_30	253	128.7	140.6	151.4	13.6	15.7	17.6	0.33	0.37	0.43

into account uncertainty about the input data and hence are not capable of embracing the high uncertainty of users' electric consumptions in rural areas.

LoadProGen, which is based on a stochastic mathematical procedure, allows formulating a number of realistic load profiles within a given set of input data. The analysis to convergence that was carried out with *LoadProGen* has led to the consideration of a number of profiles that are representative of their stochastic nature. In both cases, results fit quite well with the on-field data: formulated samples properly reflect the metered ones from 8 to 17, in the *LoadProGen_0* case, the morning peak occurs later; in both cases, there is a tendency to slightly overestimate the peak bell in the evening, but the peak power is well represented.

Besides, it is worthwhile to highlight that both *LoadProGen* and *Lit_Appr1* and *Lit_Appr2*, being based on input data coming from local questionnaires and surveys, are strongly influenced by these input data. That is, in the application case of load profile formulation, mistakes in data collection provide for errors in the computed profile. This is clearly the case of our applications during the night hours (22–5). Most of the interviewed people probably forgot or have a wrong idea of the functioning of some devices or wrongly translate their perception as regards some devices into answers to the survey. Another option could also be related to some illegal load connections or night loads which were not reported by local people. This issue is also the main cause for the amount of meted sampled data which do not fall in the band provided by *LoadProGen* during night hours.

Comparing *LoadProGen_0* and *LoadProGen_30* cases on the basis of the number of metered samples that fall within the standard deviation band of the *LoadProGen* profiles from 5 to 22 show that 51.7% and 60.3% of the metered samples were, respectively, within the standard deviation band. In our opinion, this is a fair result for the new mathematical procedure; indeed, when analyzing the accuracy of the results, one has to consider the specific features of the context under analysis. The formulated profiles are the results of input data that have been collected on the field by means of simple questionnaires and surveys in a college campus from a rural town of Africa where people do not have the same perception of the electric supply service that people of high-income countries are used to. The local distribution grid suffers continuous outages, the local back-up system is sometimes not available, and hence, local users do not have constant typical habits in electrical appliances usage.

Conclusions

In this paper, we have described a new mathematical procedure devoted to formulating daily load profiles for off-grid consumers in rural areas of developing countries. We have implemented the new procedure in a software tool (*LoadProGen*), which contributes to compensating for the lack of formalized methodologies to formulate load profiles to be employed as input data in the capacity planning methods and energy fluxes control for off-grid systems for rural electrification. The new procedure is based on input data that can be reasonably surveyed and/or assumed in rural areas, and it is based on a stochastic bottom-up approach with correlations between load profile parameters in order to build up the coincidence behavior of electrical appliances. We have presented the application of the procedure in the formulation of load profiles for a college in a small town in Cameroon and we have also compared the resulting profiles with on-field metered data. Actually, it is relevant to point out that the main purpose of this procedure was not to forecast load profiles, but rather to properly formulate load profiles to support electrification studies in rural areas. Indeed, further work based on this procedure should analyze the effects of load profile uncertainty on the sizing of off-grid systems and should address optimum stochastic sizing with regard to load profiles.

Acknowledgments

We would like to thank Dario Accorona, Leonardo Bandiera and Jerome N. Mungwe (Politecnico di Milano) for data collection during the mission in Cameroon (October–December 2014), Simone Losa for the optimization of the *LoadProGen* MATLAB code and Davide Mandelli (SISSA Trieste) for the comments and suggestions on the algorithm for weighted random sampling.

Appendix

Table A1
Load data assumptions for the Presbyterian College in Bali.

Class type j	N_j	App. name i	P_{ij} [W]	N_{ij}	d_{ij} [min]	h_{ij} [min]	w_{F,ij_1} h_{start} h_{stop}		W_{F,ij_2}	
Household _1	18	TV	80	1	30	300	15:00	23:00	–	–
		Stereo set	36	1	30	300	6:00	20:00	–	–
		Ph. Chargers	5	3	30	180	0:00	24:00	–	–
		Indoor bulb	26	5	30	300	5:00	8:00	18:00	23:00
		Outdoor bulb	26	1	30	180	18:00	23:00	–	–
		Security light	5	1	60	720	0:00	6:00	18:00	24:00
		Fridge	40	1	10	480	0:00	24:00	–	–
		PC	50	1	60	180	15:00	22:00	–	–
		Iron	800	1	1	2	5:00	6:30	19:00	20:30
		DVD	15	1	60	240	15:00	23:00	–	–
		Flask	700	1	2	2	5:00	6:30	–	–
		Blender	350	1	2	10	11:00	12:00	13:00	14:00
		TV	80	2	30	300	15:00	23:00	–	23:00
		Radio	5	1	30	300	6:00	20:00	–	–
		Stereo set	50	1	30	300	6:00	20:00	–	–
		Ph. charger	5	2	30	180	0:00	24:00	–	–
Household _2	14	Indoor bulb	26	4	30	300	5:00	8:00	18:00	23:00
		Outdoor bulb	26	1	30	180	18:00	23:00	–	–
		Security light	26	1	60	720	0:00	6:00	18:00	24:00
		Iron	800	1	1	2	5:00	6:30	19:00	20:30
		DVD	15	1	60	240	15:00	23:00	–	–
		Ph. charger	5	2	30	180	0:00	24:00	–	–
Household _3	11	TV	85	1	30	240	16:00	23:00	–	–
		Indoor bulb	26	3	30	300	5:00	8:00	18:00	23:00
Dormitories	4	Lights	26	8	30	180	5:00	7:00	17:30	19:30
		Tubes	36	8	30	180	5:00	7:00	17:30	19:30

Table A1 (*continued*)

Class type j	N_j	App. name i	P_{ij} [W]	N_{ij}	d_{ij} [min]	h_{ij} [min]	w_{F,ij_1} h_{start}	h_{stop}	w_{F,ij_2}	
		Safety lights	26	5	60	720	0:00	6:00	18:00	24:00
		Bulbs	26	3	30	300	6:00	8:00	17:30	21:30
		Tubes	36	1	30	300	6:00	8:00	17:30	21:30
Classrooms	14	Safety lights	30	1	60	720	0:00	6:00	18:00	24:00
		Lights	26	6	30	690	5:30	20:00	–	–
		Radio	5	1	30	690	5:30	20:00	–	–
		Sharpener	50	1	2	20	5:30	11:00	–	–
Kitchen	1	Fridge	53	2	10	600	0:00	24:00	–	–
Bakery	1	Lights	26	4	60	600	5:30	16:30	–	–
		Bulbs	26	5	30	120	17:00	20:00	–	–
Refectory	1	Tubes	36	9	30	120	17:00	20:00	–	–
		Bulbs	26	1	30	360	7:00	9:30	13:30	20:00
		Tubes	10	1	30	360	7:00	9:30	13:30	20:00
		Bulb	40	1	30	360	7:00	9:30	13:30	20:00
Canteen	1	Fridge	40	1	10	600	0:00	24:00	–	–
		Lights	26	1	60	1440	0:00	24:00	–	–
Workshop	1	Radio	5	1	60	480	7:00	20:00	–	–
		Bulbs	26	1	30	420	8:00	12:00	16:00	21:30
Dispensary	1	Tubes	36	1	30	420	8:00	12:00	16:00	21:30
		Bulbs	26	8	30	240	5:45	7:30	18:30	21:45
Church	1	Tubes	36	8	30	240	5:45	7:30	18:30	21:45
		Bulbs	26	4	30	540	7:00	17:00	–	–
		Tubes	40	7	30	540	7:00	17:00	–	–
		Mini–tube	18	1	30	540	7:00	17:00	–	–
Admin. Off.	1	Electronics	32	19	30	420	7:00	17:00	–	–
		Tubes	40	12	30	420	6:45	15:00	–	–
Library	1	Photocopier	32	1	10	180	6:45	15:00	–	–
ICT college	1	Bulbs	26	4	60	480	7:00	17:00	–	–
		Tubes	36	11	60	480	7:00	17:00	–	–
		Laptop	55	18	60	480	7:00	17:00	–	–
		Printer_1	550	4	5	90	7:00	17:00	–	–
		Printer_2	510	1	5	90	7:00	17:00	–	–
		Photocopy_1	1280	1	10	60	7:00	17:00	–	–
		Photocopy_2	1300	2	10	60	7:00	17:00	–	–
		Standby	35	1	480	480	7:00	17:00	–	–

References

Ahmad GE. Photovoltaic-powdered rural zone family house in Egypt. Renew Energy 2002;26(3):379–90.

Al-Hamadi HM, Soliman Sa. Long-term/mid-term electric load forecasting based on short-term correlation and annual growth. Electr Power Syst Res 2005;74:353–61.

Al-Karaghouli A, Kazmerski LL. Optimization and life-cycle cost of health clinic PV system for a rural area in Southern Iraq using HOMER software. Sol Energy, 84(4). Elsevier Ltd; 2010. p. 710–4.

Bala B, Siddique SA. Optimal design of a PV-diesel hybrid system for electrification of an isolated island—Sandwip in Bangladesh using genetic algorithm. Energy Sustain Dev Int Energy Initiat 2009;13(3):137–42.

Barley CD, Winn CB. Optimal dispatch strategy in remote hybrid power systems. Sol Energy 1996;58(4):165–79.

Bekele G, Tadesse G. Feasibility study of small hydro/PV/wind hybrid system for off-grid rural electrification in Ethiopia. Appl Energy, 97. Elsevier Ltd; 2012. p. 5–15. [Sep].

Belfkira R, Zhang L, Barakat G. Optimal sizing study of hybrid wind/PV/diesel power generation unit. Sol Energy, 85(1). Elsevier Ltd; 2011. p. 100–10.

Bhuiyan MMH, Ali Asgar M. Sizing of a stand-alone photovoltaic power system at Dhaka. Renew Energy 2003;28(6):929–38.

Carpinteiro OaS, Leme RC, de Souza ACZ, Pinheiro CaM, Moreira EM. Long-term load forecasting via a hierarchical neural model with time integrators. Electr Power Syst Res 2007;77:371–8.

Celik AN. Effect of different load profiles on the loss-of-load probability of stand-alone photovoltaic systems. Renew Energy 2007;32(12):2096–115. [Oct].

Chen J, Chen J, Gong C, Deng X. Energy management and power control for a stand-alone wind energy conversion system. IECON 2012—38th Annu Conf IEEE Ind Electron Soc; 2012. p. 989–94.

Elhadidy Ma, Shaahid SM. Parametric study of hybrid (wind + solar + diesel) power generating systems. Renew Energy 2000;21(2):129–39.

Gaunt CT. Scope for research and development in low voltage distribution design. Proc IEEE AFRICON 4th; 1996. p. 5.

GeoModel Solar. Solargis [Internet]. [cited 2015 Jun 5]. Available from: http://geomodelsolar.eu/

Graham VA, Hollands KGT. A method to generate synthetic hourly solar radiation globally. Sol Energy. 1990;44(6):333–41.

Grandjean a, Adnot J, Binet G. A review and an analysis of the residential electric load curve models. Renew Sustain Energy Rev, 16(9). Elsevier; 2012. p. 6539–65.

Gupta A, Saini RP, Sharma MP. Steady-state modelling of hybrid energy system for off grid electrification of cluster of villages. Renew Energy, 35(2). Elsevier Ltd; 2010. p. 520–35.

HOMER Energy LLC. Homer Energy [Internet]. 2014. Available from: http://www.homerenergy.com/index.html.

Howells MI, Alfstad T, Victor DG, Goldstein G, Remme U. A model of household energy services in a low-income rural African village. Energy Policy 2005;33(14):1833–51.

Huld T, Müller R, Gambardella A. A new solar radiation database for estimating PV performance in Europe and Africa. Sol Energy 2012;86(6):1803–15.

IEA. World Energy Outlook 2012. OECD Publishing; 2012.

IEA. World Energy Outlook 2014. OECD Publishing; 2014.

IRENA. Global Atlas for Renewable Energy—Wind [Internet]. [cited 2015 Mar 10]. Available from: http://irena.masdar.ac.ae/?map=180

Javed F, Arshad N, Wallin F, Vassileva I, Dahlquist E. Forecasting for demand response in smart grids: an analysis on use of anthropologic and structural data and short term multiple loads forecasting. Appl Energy, 96. Elsevier Ltd; 2012. p. 150–60.

Jia N, Yokoyama R, Zhou Y, Gao ZY. A flexible long-term load forecasting approach based on new dynamic simulation theory—GSIM. Electr Power Energy Syst 2001;23.

Kanase-Patil aB, Saini RP, Sharma MP. Sizing of integrated renewable energy system based on load profiles and reliability index for the state of Uttarakhand in India. Renew Energy, 36(11). Elsevier Inc.; 2011. p. 2809–21.

Lee W-J, Hong J. A hybrid dynamic and fuzzy time series model for mid-term power load forecasting. Int J Electr Power Energy Syst, 64. Elsevier Ltd; 2015. p. 1057–62.

Li CX, Meng LM. Comprehensive model for mid-long term load forecasting basing three-target quantities and RBFNN. Proc. 4th Int Conf Nat Comput ICNC 2008, 4. ; 2008. p. 486–91.

Liu N, Tang Q, Zhang J, Fan W, Liu J. A hybrid forecasting model with parameter optimization for short-term load forecasting of micro-grids. Appl Energy, 129. Elsevier Ltd; 2014. p. 336–45.

Lü X, Lu T, Kibert CJ, Viljanen M. Modeling and forecasting energy consumption for heterogeneous buildings using a physical–statistical approach. Appl Energy. Elsevier Ltd; 2015.

Mandelli S, Colombo E, Merlo M, Brivio C. A methodology to develop design support tools for stand-alone photovoltaic systems in developing countries. Res J Appl Sci Eng Technol 2014;8(6):778–88.

Nandi SK, Ghosh HR. Prospect of wind-PV-battery hybrid power system as an alternative to grid extension in Bangladesh. Energy, 35(7). Elsevier Ltd; 2010. p. 3040–7.

NASA. Surface meteorology and solar energy [Internet]. [cited 2014 May 6]. Available from: https://eosweb.larc.nasa.gov/sse/

Nfah EM, Ngundam JM. Feasibility of pico-hydro and photovoltaic hybrid power systems for remote villages in Cameroon. Renew Energy, 34(6). Elsevier Ltd; 2009. p. 1445–50. [Jun].

Nfah EM, Ngundam JM. Evaluation of optimal power options for base transceiver stations of Mobile Telephone Networks Cameroon. Sol Energy, 86(10). Elsevier Ltd; 2012. p. 2935–49. [Oct].

Oliva RB. Simulation and measurement procedures for effective isolated wind and hybrid system development in South Patagonia. Energy Sustain Dev, 12(2). International Energy Initiative, Inc.; 2008. p. 17–26. [Jun].

Ozaki Y, Miyatake M, Iwaki D. Power control of a stand-alone photovoltaic/wind/energy storage hybrid generation system with Maximum Power Point Tracker. In: IEEE, editor. Electr Mach Syst (ICEMS), 2010 Int Conf. Incheon; 2010. p. 607–11.

Phrakonkham S, Remy G, Diallo D, Marchand C. Pico vs micro hydro based optimized sizing of a centralized AC coupled hybrid source for villages in Laos. Energy Procedia 2012;14(0):1.

SANEDI. Wind Atlas for South Africa [Internet]. [cited 2015 Jun 5]. Available from: http://www.wasaproject.info/index.html

Semaoui S, Arab AH, Bacha S, Azoui B. Optimal sizing of a stand-alone photovoltaic system with energy management in isolated areas. Energy Procedia 2013;36:358–68.

Sen R, Bhattacharyya SC. Off-grid electricity generation with renewable energy technologies in India: an application of HOMER. Renew Energy, 62. Elsevier Ltd; 2014. p. 388–98.

Shen WX. Optimally sizing of solar array and battery in a standalone photovoltaic system in Malaysia. Renew Energy 2009;34(1):348–52. [Jan].

Song H, Zhang R, Zhang Y, Xia F, Miao Q. Energy consumption combination forecast of Hebei Province based on the IOWA operator. Energy Procedia 2011;5:2224–9.

Swan LG, Ugursal VI. Modeling of end-use energy consumption in the residential sector: a review of modeling techniques. Renew Sustain Energy Rev 2009;13:1819–35.

Willis HL, Northcote-Green JED. Spatial electric load forecasting: a tutorial review. Proc IEEE 1983;71(2):232–53.

Xu W, Gu R, Liu Y, Dai Y. Forecasting energy consumption using a new GM-ARMA model based on HP filter: the case of Guangdong Province of China. Econ Model, 45. Elsevier B.V.; 2015. p. 127–35.

Zhang H, Zhong N. Forecast of energy demand in the next decade. Energy Procedia 2011; 5:2536–9.