Effect of load profile uncertainty on the optimum sizing of off-grid PV systems for rural electrification

Stefano Mandelli *, Claudio Brivio, Emanuela Colombo, Marco Merlo

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

Off-grid systems based on PV and batteries are becoming a solution of great interest for rural electrifica-tion. Nevertheless, sizing these systems is not straightforward since it means matching unpredictable energy sources with uncertain demands while providing the best reliability and costs. In our opinion, the effect of users' energy consumptions uncertainty on the sizing of these systems has not been appro-priately investigated. This paper addresses this issue and analyzes the effect of load profile uncertainty on the off-grid PV systems optimum design. Specifically a novel sizing methodology has been introduced based on: (i) an effective approach of modelling rural energy needs; (ii) an innovative stochastic method which formulates different possible realistic daily load profiles for un-electrified rural areas; (iii) a PV-battery techno-economic analysis via steady-state simulation; (iv) the evaluation of the optimum system sizing via a numerical method based on net present cost and loss of load probability. Finally, the proposed methodology has been applied to find the optimum size of an off-grid PV system for a peri-urban area of Uganda. The results show that the optimum system configurations are significantly affected by load pro-files; consequently an approach to identify the robust solution with regards the assumed uncertainty is proposed.

Keywords: Renewables, Electric consumptions, Stochastic model, Simulation, Optimization

Introduction

The application of PV systems as renewable source of energy in transmission and distribution grids [1] or as source of power for dedicated loads [2] is well-known. Nevertheless, in emerging countries there is a growing demand for off-grid PV systems eventually coupled with electro-chemical storage [3]. These systems are recognized as a reliable and cost-effective solution which can supply electricity in un-electrified areas, which can substitute or retrofit conventional diesel/petrol generators or which can act as back-up of weak national grids. The costs reduction, the increase of products suppliers, the growing popularity, the integration in governmental programs and the wide range of systems configurations (i.e. solar lanterns, home-based systems and micro-grids [4]) are fostering the implementation of these systems to provide electricity in rural and remote areas in particular [5–8].

The study of the optimum sizing is one among the technical issues about off-grid PV systems [9]. Indeed, sizing the main components of these systems (i.e. PV array, battery bank, inverter, etc.), is not straightforward since it means matching unpredictable energy sources with unknown or uncertain load demands and, at the end, providing the most favorable conditions in terms of reliability and costs [10,11]. Within this issue, in our opinion, the analysis of the effect of users' energy consumptions uncertainty on the selection of the main systems components sizes (i.e. PV array peak power and capacity of the battery banks) has not been appropriately investigated. As a matter of fact, when dealing with analyses of electrification of rural and remote areas, information about users' electric consumptions are typically not available owing to the fact that electric consumptions do not exist or are limited to small sources apparatus for portable devices (e.g. mobile phones, radios). Therefore, consumptions have to be properly estimated being one of the main input data in the design process of off-grid PV systems. Clearly, such estimates are prone to a significant degree of uncertainty since they have to represent the expected consumptions of people with their own habits, needs, and who often do not have electricity access yet. Focusing on the advanced methods for the optimum sizing of off-grid PV systems (i.e. those based on energy steady-state simulation and on size optimization via numerical or analytical approaches [9]), it is worthwhile to

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Abbreviations: LLP, loss of load probability; NPC, net present cost; O&M, operation and maintenance; PV, photovoltaic; SOC, state of charge.

* Corresponding author.
E-mail address: stemande@gmail.com (S. Mandelli).

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Nomenclature

$(1+r)^y$	discount factor	j	specific user class
d_{ij}	functioning cycle	$LL(t)$	loss of load at time-step (t)
$E_{class,day}$	user class daily energy consumption	LT	system life-time
E_D	total user energy demand for one year	n_{ij}	amount of appliances within a class
$E_{pc,year}$	per capita yearly energy consumption	N_j	amount of users within a class
$f_{C,j}$	coincidence factor	P_{ij}	nominal power rate of an appliance
$f_{L,j}$	load factor	Rh_{ij}	maximum percentage of h_{ij} subjected to a random variation
h_{ij}	overall time each appliance is on during a day: functioning time	Rw_{ij}	maximum percentage of $w_{F,ij}$ subjected to a random variation
i	type of electrical appliances	$w_{F,ij}$	functioning windows
$Inv(y)$	investment and replacement costs		

mention that solar irradiation and electric load data are required in form of time series which are typically made of hourly values covering one year.

In rural and remote areas lack of detailed solar radiation data occurs, however information can be retrieved from weather stations usually located in the main cities, several databases are available [12–15], and a number of models have been developed [16–18]. Moreover, some methods have been elaborated in order to embrace in the sizing process the uncertainty associated with solar irradiation [19–21].

On the contrary, as Khatib et al. highlighted in their review [9], the forecast or realistic estimates of load profiles is still a main challenge for off-grid PV systems size optimization. This is even a more critical element when dealing with rural electrification actions (i.e. when considering off-grid systems to provide access to electricity to dwellers of partially- or un- electrified areas). In fact, no data are typically available in these cases. Nevertheless, we noticed that no particular attention has been devoted to methods or models dealing with daily load profiles for off-grid consumers of rural areas. Indeed most of the literature, which addresses the formulation of daily load profiles, deals with the theme of domestic electric consumptions in developed countries [22]. In practice, researchers dealing with off-grid systems sizing for rural electrification introduce daily load profiles in three manners: (i) profiles are defined without clear explanations about their origin [23–25]; (ii) profiles are adapted from similar contexts [26–31]; (iii) profiles are formulated without any defined procedure, but employing assumptions on electric appliances functioning periods [32–36]. Moreover, no methods have been developed in order to embrace in the sizing process the uncertainty associated with daily load profiles of rural consumers. Actually, few contributions in the literature address this problem: Celik in [37] brought about the issue of load profiles and off-grid PV systems sizing by comparing resulting loss of load probabilities and the costs of electricity for five different input load profiles, while Boait et al. [38] proposed a bottom-up approach for daily load profile computation which employs Monte Carlo simulation to obtain probability distribution of load values for each hour of the day on the basis of user defined electrical appliances features (number of appliances, rate power and a daily probability of use "duty cycle").

The focus of this paper is to address this issue and specifically it presents the application of an innovative stochastic method developed and validated by the authors to formulate different realistic daily load profiles for rural un-electrified areas [39], and it analyzes the effect of users' energy consumptions uncertainty on the optimum sizing of off-grid PV systems in the rural electrification frame. To this purpose a novel sizing methodology which embraces uncertainty on load profiles has been developed, implemented and employed. Such a procedure is based on: (i) the modelling of users' energy needs, (ii) the formulation of different realistic daily load profiles via the innovative stochastic method, (iii) the PV-battery techno-economic analysis via energy steady-state system simulation, and (iv) the identification of the optimum system sizing via a numerical method and based on net present cost (NPC) and loss of load probability (LLP) parameters. Moreover, since we prove that the optimum system configurations are significantly affected by the users' load profiles; an approach to identify the robust solution with regards the assumed uncertainty has been proposed.

Finally, the proposed methodology has been applied to perform the optimum sizing under load profile uncertainty of an off-grid PV system for a peri-urban area of Uganda and we discuss the results. The input data for the case study were collected during a two months in-field mission via local observations and surveys.

Methods and models for optimum sizing of off-grid PV systems under load profile uncertainty

This section introduces the methods and models that have been employed to perform the optimum sizing of off-grid PV systems considering uncertainty on the daily load profiles of rural consumers. The combination of these methods and models makes up a sizing methodology devoted to this purpose (Fig. 1).

The methodology can be described as follows:

1. in the *users' electric needs modelling* block, targeted users and their electric needs are modelled into user classes, electric appliances and usage habits;
2. the *load profiles formulation* block refers to an innovative stochastic method developed by the authors which formulates different possible realistic daily load profiles for given users' electric needs. Being capable to formulate different profiles with the same input data, this method allows embracing load profile uncertainty in the sizing process;
3. the *solar resource availability modelling* block employs a model available in the literature to formulate yearly time series of hourly solar radiation;
4. the *techno economic modelling* block considers well-known steady-state modellings of off-grid PV systems components as well as a model for life-cycle economic analysis;
5. a classical method based on energy *steady-state simulation* is employed to compute the main techno-economic performance parameters of off-grid PV system (i.e. NPC and LLP);
6. the new *size optimization method*, which has been developed to identify the robust solution with regards the assumed load uncertainty, is based on the following considerations: each possible daily load profile (formulated at step 2) has an NPC-LLP optimum in terms of sizes of PV and batteries; this optimum PV-battery combination may differ among the possible load profiles (this allow analyzing the effect of uncertainty on the

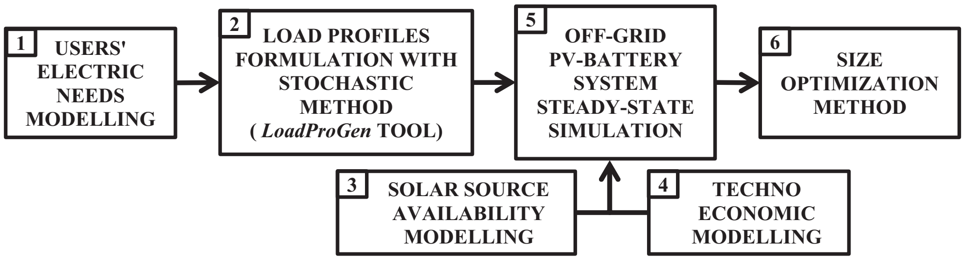

Fig. 1. Graphical representation of the proposed sizing methodology with main building-blocks.

optimum sizing); among all the *optima*, one is the most robust with regards to all the considered load profiles (this allow performing the optimum sizing considering uncertainty).

In the following the most innovative elements of the proposed sizing methodology (blocks 1, 2, 6) are described. However, hints are also provided to the methods and modellings taken from the literature.

Users' electric needs modelling

A parametric model that allows modelling the users' electric needs is proposed (Table 1):

- targeted consumers are grouped into different user classes. Such classes are defined according to the fact that consumers within a class show a broadly similar demand behavior;
- a classification of electrical appliances is required;
- the daily overall time each appliance is in use is required, i.e. the functioning time (h_{ij});
- the period(s) during the day when each appliance can be in use is required, i.e. the functioning window(s) ($w_{F,ij}$);
- each appliance is modelled with its nominal power. Furthermore its functioning is modelled as *on-off* mode considering a minimum continuous functioning cycle (d_{ij}).

Given all these parameters for the targeted users:

- the total required daily electric energy of each user class can be computed;
- a *theoretical maximum power peak* of each user class can be computed;
- a load factor for each user class relating to the theoretical maximum power peak and the total required daily electric energy can be computed.

These parameters are the input data for the daily load profile formulation method. They are the necessary-minima required to formulate a profile of a given group of consumers in rural areas and they can be assumed based on practical experience on similar context conditions or by mean of local surveys.

Table 1
Parameters for modelling users' electric needs.

i	type of electrical appliances (e.g. light, mobile charger, radio, TV)
j	specific user class (e.g. household, school, stand shop, clinics)
N_j	amount of users within each class
n_{ij}	amount of appliances within each class
h_{ij}	overall time each appliance is on during a day: *functioning time*
$w_{F,ij}$	period(s) during the day when each appliance can be on: *functioning windows*
P_{ij}	nominal power rate of each appliance
d_{ij}	*functioning cycle*, i.e. minimum continuous functioning time of the appliance once it is on

Load profile formulation with a stochastic method

We develop an innovative method to formulate daily load profiles which allows considering users' energy consumptions uncertainty. This method has been implemented in an algorithm based on MATLAB and named *LoadProGen* (i.e. Load Profile Generator). Hereafter an introduction of its main structure and features is given to the benefit of clarity for the following analyses.

The method has the following main features:

- it is based on the users' electric needs parameters;
- it builds up the coincidence behavior of the appliances and the power peak value with regards to the correlation between number of users, load factor and coincidence factor;
- it is based on a stochastic approach in order to embrace uncertainty, i.e. the method allows formulating a number of different possible realistic profiles.

In Fig. 2 a block representation of the method is presented. It is divided in three sections: input data, operational elements, and output data.

The input data are the parameters employed for modelling the users' electric needs (Table 1). Nevertheless two more parameters are introduced with the purpose of embracing uncertainty on the values of functioning times (h_{ij}) and functioning windows ($w_{F,ij}$) respectively. It has been referred to them as Rh_{ij} and Rw_{ij}, and they set the maximum percentage of h_{ij} and $w_{F,ij}$ subjected to a random variation.

As regards the operational elements and output data, the method first formulates the daily load profile for each single user class and then it computes the overall profile by aggregating the single class profiles. Hence, the applied steps to each single user class considered are the following:

- functioning times and functioning windows are randomized by means of Rh_{ij} and Rw_{ij};
- the total daily electric need of the user class, the possible theoretical maximum power peak, and the peak time are computed (*peak value computation* block). Then, the class coincidence factor is computed according with the empirical correlation existing between amount of users (N_j), load factor ($f_{L,j}$) and coincidence factor ($f_{C,j}$). The obtained value of the coincidence factor is employed to compute the reference value of the class power peak. The mentioned correlation results as follows [40]:

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

where the formulation of the coefficient a and the related parameters have been presented and empirically calculated in [41,42];

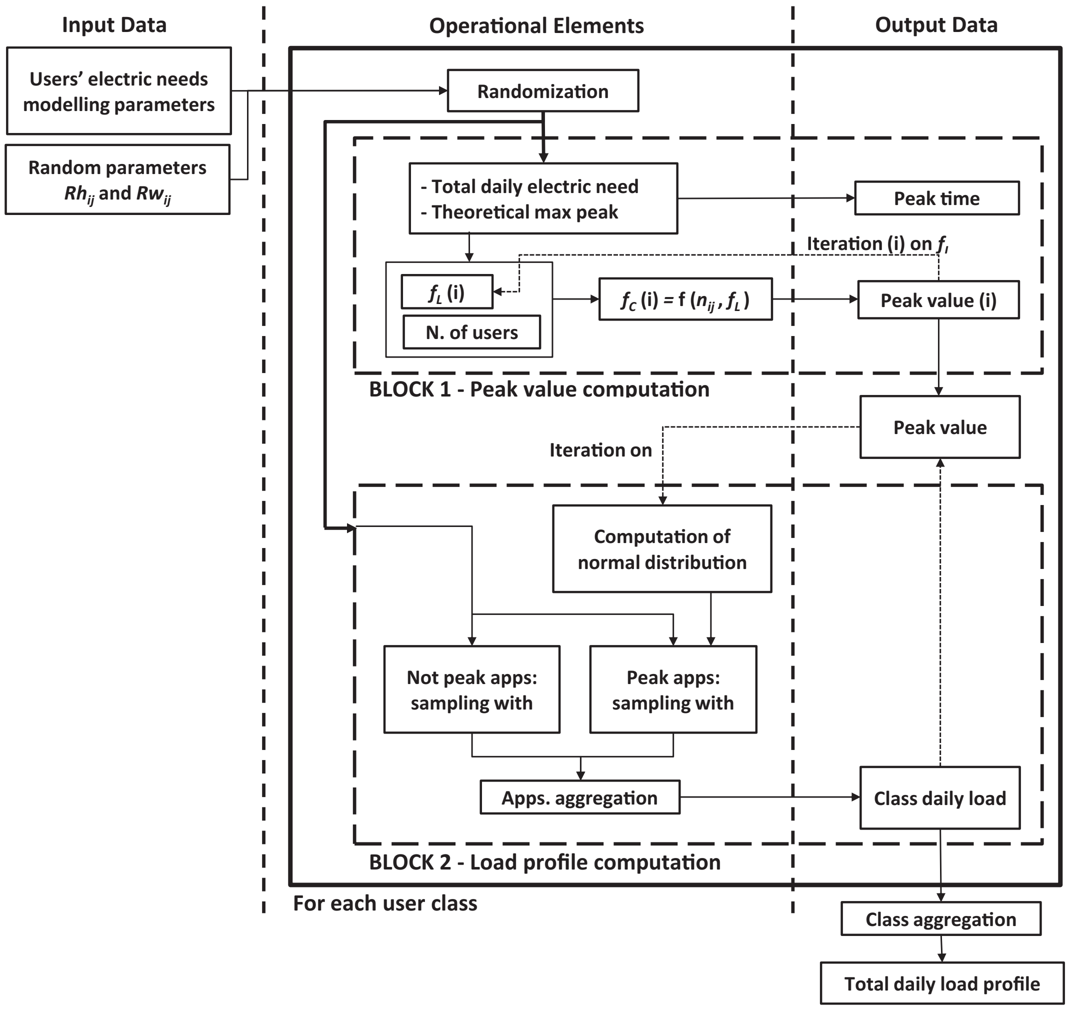

Fig. 2. Block representation of the stochastic method for load profile formulation.

- the functioning of each appliance is defined by sampling randomly the switching on times within the relative functioning windows (load curve computation block). Specifically the amount of times each appliance is switched on is defined by dividing the total amount of times the appliance ij is functioning in a day (numerator) divided by the minimum time the same appliance has been considered it operates once switched on (divisor):

$$n_{t,ij} = \frac{h_{ij} + random(h_{ij} * Rh_{ij})}{d_{ij}} \qquad (2)$$

where $random(h_{ij}{}^{*}Rh_{ij})$ refers to the computation of a random value $[-(h_{ij}{}^{*}Rh_{ij}), +(h_{ij}{}^{*}Rh_{ij})]$. Once the random sampling is carried out for all the appliances of the user class, the functionings of the single appliances are aggregated and the class daily load profile is computed. Nevertheless the resulting peak may not comply with reference power peak computed in the peak value computation block (via Eq. (1)). Therefore, an iterative process has been implemented so that the resulting power peak matches, assuming an error defined by the designer, with the reference power peak;
- repeating the previous computational steps for each user class and aggregating the different class profiles leads to compute the total daily load profile.

This stochastic method has been implemented in an algorithm based on MATLAB and named *LoadProGen*. *LoadProGen* allows formulating *realistic* load profiles since:

- by developing the load profiles of each single appliance for each user and then by aggregating them, the coincidence behavior within a class is achieved in a similar way as it occurs in real power systems [43];
- by employing the empirical correlation between amount of users, load factor and coincidence factor, it estimates realistic class power peaks according to the parameters of users' electric needs.

Moreover *LoadProGen* allows formulating *different possible* load profiles all complying with the given input data since:

- due to the stochastic approach in defining the peak time and the switching on times of each appliance, the algorithm computes a different load profile each time it is run;
- Rh_{ij} and Rw_{ij} allow considering a further degree of uncertainty as regards the functioning times and functioning windows, which are key parameters of users' electric need modelling.

Solar resource availability modelling

We retrieved from the *Surface meteorology and Solar Energy* website of NASA [12] the values of the *mean daily solar irradiations* for the targeted location which then are employed in the method presented in [17] to generate *synthetic hourly solar radiation* incident on the surface of the PV array throughout a year.

Techno-economic modelling

The considered models for the simulation stage of the off-grid PV system are those implemented in the well-known energy steady-state simulation and numerical optimization approaches [44,45]. Specifically, the off-grid PV system has been considered as composed by PV array, battery bank and inverter. Each of these components is modelled from the technical and economical point of view.

Technical modellings of the system components have the following features:

- the PV array power output depends on the solar radiation, on the effect of the PV cell's temperature [46], and on the balance of system efficiency;
- the battery bank model considers round-trip efficiency, minimum threshold in the state of charge (SOC), power-to-energy ratio, and it employs the rainflow counting method to evaluate battery life-time [47];
- the inverter model considers an energy conversion efficiency.

All the system components are economically modelled by means of investment and replacement costs based on their size. In particular, battery bank life-time depends on its operation and hence replacement cost depends on the particular load profile simulated. Yearly operation and maintenance costs are given as an overall value for the whole system according to the PV array size.

Steady-state simulation method

Steady-state simulation of the off-grid PV system is based on the solving of the energy balance between the energy produced, consumed and stored. This balance is solved for a given time-step throughout a given period of time. In the case under study, the simulation has been performed with an hourly time-step over a year (8760 h). The final purpose of the simulation is to compute, for a given power rate of the PV array and for a given capacity of the battery bank, the LLP and the NPC which are the parameters employed to identify the optimum sizing of the system components.

The simulation is performed as follows: (i) for each time-step the balance between produced and required energy is performed, (ii) the remaining energy is assigned to the battery that injects or absorbs energy accordingly, (iii) the battery SOC is computed together with the loss of load that occurs if the load remains unsatisfied because of the minimum battery SOC reached, (iv) the remaining battery life-time is evaluated. Once the simulation is performed over the whole year, the LLP is calculated as follows [44]:

$$LLP = \frac{\sum_{t=1}^{8760} LL(t)}{E_D} \qquad (3)$$

where $LL(t)$ is the loss of load at the time-step (t) and E_D is the total user energy demand for one year. Moreover, considering a system life-time (LT) in terms of years, the NPC is computed as follows [48]:

$$NPC = \sum_{y=1}^{LT} \frac{Inv(y) + O\&M(y)}{(1+r)^y} [€] \qquad (4)$$

where, for each year (y): $Inv(y)$ considers the investment and replacement costs of the system components, $O\&M(y)$ are the operation and maintenance costs, and $(1+r)^y$ is the discount factor.

Size optimization method

The optimum sizing of off-grid PV system under daily load profiles uncertainty has been performed as follows:

1. for a given load profile, ranges of PV array sizes and battery capacities are defined and the simulation stage is performed for all the possible size combinations of PV-battery. Then the PV-battery combination that results in having the minimum NPC while respecting the maximum LLP (defined by the designer) is the optimum solution.
2. Actually, this is the classical approach which is employed to perform the optimum sizing of any kind of off-grid system [23,30,32]. In this work, we employ the capability of *LoadProGen* to formulate different possible realistic load profiles in order to identify the optimum sizing under load profile uncertainty. This entails the development of two further steps;
3. for a given set of parameters of users' electric needs, n load profiles are formulated via *LoadProGen*. Then for each formulated profile the classical optimization approach is performed thus providing n optimum systems. Accordingly, this analysis allows: (a) to analyze the effect of load profile uncertainty on the optimum sizing by obtaining a region of optimum solutions instead of a single optimum solution, and (b) to identify the most robust solution since some system configuration would occur to be the optimum one more frequently;
4. for the same set of parameters of users' electric needs, but considering different combinations in the value of Rh_{ij} and Rw_{ij} (which define different *scenarios*), step 2 is repeated. This allows considering the uncertainty associated with the functioning times and functioning windows, which greatly affects the formulation of the load profiles.

Case study context: a peri-urban area of Uganda

The proposed sizing methodology has been applied to perform the optimum sizing under load profile uncertainty of an off-grid PV system to supply power to a peri-urban area of a small town in Uganda.

Uganda is a country in sub-Saharan Africa with about 39 million people and 84% living in rural areas. It has a Human Development Index of 0.484, ranking 164° over 187 countries, and standing among those nations with Low Human Development [49]. As regards the energy situation, 97% of the population relies on traditional biomass for cooking, while 55% and 7% have access to electricity in urban and rural areas respectively [50]. The electricity consumption per capita is low (about 215 kW h per year) and the supply service suffers for frequent inefficiencies with about 6 outages per month which last about 7 h [51]. Besides, the current trends shows a stable economic growth (6% in the past five years) which is reflected in a strong increase of electricity demand (10% per year) [52,53]. This results in a high pressure on the electric system of the country. However, despite the abundant domestic energy resources, the implementations of dedicated energy reforms in the past years did not provide for the expected improvements on the power sector. Furthermore, the government, in the past decade, began to consider solar photovoltaic technology as the main options for off-grid rural electrification actions [54].

In Uganda, three typologies of potential off-grid electric consumers can be identifies:

- isolated single rural households without access to electricity via the national grid which power portable devices (e.g. mobiles, radios) with small batteries;
- rural villages (i.e. agglomerate of households) often without access to electricity via the national grid, but where traditional

generators (diesel / petrol generators) are employed by few well-off households and local services (e.g. clinics, churches);

- peri-urban areas, which are typically reached by the national grid, but where only a share of households, local services and income activities are connected. In these areas, traditional generators are more common particularly for those who already have electricity and needs to find a solution to the frequent outages.

Especially for rural villages and peri-urban areas, an appropriate solution to provide access to electricity or to improve the actual power supply can be off-grid micro-grids[1] based on PV and batteries, which might also integrate the local available traditional generators. Indeed, in rural villages this can be a first-step solution to get access to electricity considering a future integration with the national grid, while in peri-urban areas PV-based micro-grids may improve the power supply service by completely replacing the national grid or by acting as back-up of the national grid, thus reducing the use of the traditional generators [55].

In both cases, the optimum sizing of the main components of a PV-based micro-grid (i.e. PV array peak power and battery capacity) is not straightforward mainly owing to the lack of data about solar resource and users' electric consumptions. In particular, with regards to users' load profiles, two typical situations occur:

1. most often data about energy consumptions or load profiles are not available because people do not have access to electricity yet;
2. more rarely it is possible to collect data in terms of energy consumptions (Wh/day) or the data gathering is limited to few daily load profiles (average load power over 1 to tens of minutes throughout a day). This is due to the fact that load metering is a challenging task in these contexts, actually simple energy meters are adopted (i.e. with limited capability in storing data) or, more frequently, the metering campaign is based on mobile apparatus (and the metering campaign itself is limited to few days/weeks) [56].

Therefore, the proposed modelling of users' electric needs as well as the stochastic method for load profiles formulation (i.e. *LoadProGen*) can support the analysis and development of the design of a PV-based micro-grid especially in the case of rural villages and peri-urban areas.

In this framework, from October to December 2013 we carried out a mission in Uganda to support the activities of Village Energy Ltd [57], a local medium enterprise which works in the designing, procurement and installation of off-grid PV systems. Main task of the mission was to develop appropriate tools for supporting the design and quotation process of small off-grid PV systems [8]. Nevertheless, the proposed sizing methodology (Fig. 1) has been also applied to perform the optimum sizing under load profile uncertainty of a PV-based micro grid that supplies power to a peri-urban area of Soroti, which is a small but expanding town in the central-east district of Uganda (1.72N/33.6E).

In Soroti the national electric grid reaches only few income activities and houses in the city center, while a number of other users employ small diesel generators to power domestic appliances and working equipment. There are large residential areas where households live without electricity and make use of kerosene lamps for lighting, and of small batteries and charging stations to power portable devices. During the mission in Uganda we did not have the possibility to carry out a metering campaign about energy consumptions and loads (in the authors' opinion this is not really a lack of the approach proposed; actually, such conditions are relevant to the most frequent scenarios for applications in developing countries), but we surveyed the typical conditions of the peripheral areas of Soroti in order to collect the required information to model the users' electric need. In particular we looked at the presence of income activities and services, at the different households' living standards, at the available electrical devices, and at the usage habits in the already electrified users. Moreover, we also collected information about the local costs of the main system components (i.e. PV panels, lead-acid batteries, off-grid inverters).

[1] We consider as an off-grid micro-grid, an energy system which comprises one or more power sources and energy storage systems which are interconnected and managed as a single virtual power plant in order to supply power to several consumers via a distribution grid.

Sizing of the PV-based micro-grid under load profiles uncertainty: calculation and results

In this section, the application of the proposed sizing methodology to the case study of Soroti is described. The case study is introduced by following the structure of the sizing process; moreover comments to the results are provided.

Modelling of local energy needs and load profiles formulation

In the case study a hypothetical PV-based micro-grid which addresses the energy needs of 100 households and 47 surrounding activities (e.g. micro and small enterprises, kiosks, market place, school, etc.) are considered. Thanks to the surveys carried out in Soroti, we assumed that the targeted households can be divided into 6 classes according to the income levels. Moreover, further 11 user classes which comprise business activities and local services have been identified. According to the collected data, we defined the parameters that model the targeted users' electric needs. These data are reported in Table 2, while Table 3 reports a summary of the user class energy consumptions.

LoadProGen has been employed to formulate the daily load profiles for the targeted users. Specifically, we consider 10 different scenarios for the formulation of the profiles. All scenarios have the same assumptions as regards the users' electric needs modelling (Table 2), but have different settings for the parameters Rh_{ij} and Rw_{ij}. In particular, all the combinations of Rh_{ij} and Rw_{ij} assuming the values 0%, 10%, 20% and 30% have been considered. For each scenario, 150 profiles have been formulated, which in the authors' opinion are adequate to represent the uncertainty associated to the daily load profiles within a scenario.

Figs. 3 and 4 report examples of the formulated profiles for the scenarios with Rh_{ij} and Rw_{ij} equal to 0% and 30% respectively. Figs. 5 and 6 show the box plots resulting from the 150 profiles generated for the same scenarios. The box plots report, for each hour, average, maximum and minimum values obtained from the 150 profiles. Moreover, key parameters of the generated load profiles for all the scenarios are reported in Table 4. These figures and the table allow highlighting the capability of *LoadProGen* to model the stochastic behavior of the load. Indeed, the "shapes" of the profiles are similar since they all refer to the same users' electric need parameters; however, the values of average power required in each hour of the day vary, thus leading to different power peak values (which can also occur at different times) and different load factors. Furthermore, increasing Rh_{ij} and Rw_{ij}, the profiles have higher variability. Specifically, when Rh_{ij} is greater than 0% the daily energy consumption varies; when Rw_{ij} is greater than 0% the switching time of each device occur in wider windows thus leading to less blocky profiles.

In order to highlight the capabilities of *LoadProGen* to formulate possible realistic load profiles, Fig. 7 shows the profile based on the

Table 2
Users' electric needs modelling for the area in Soroti.

Class Type j	N_j	App Name i	P_{ij} [W]	n_{ij}	d_{ij}[min]	h_{ij}[h]	w_{f,ij_1}		w_{f,ij_2}		w_{f,ij_3}	
							h_{start}	h_{stop}				
Household_1	50	Lights	3	4	10	6	0	2	17	24	–	–
		Phone Charger	5	2	30	3	0	9	13	15	17	24
		Security Light	5	1	30	12	0	7	17	24	–	–
Household_2	15	Lights	3	4	10	6	0	2	17	24	–	–
		Phone Charger	5	2	30	3	0	9	13	15	17	24
		Security Light	5	1	15	12	0	7	17	24	–	–
		Radio	5	1	30	4	6	9	17	24	–	–
		AC-TV (small)	100	1	30	5	11	15	17	24	–	–
Household_3	15	Lights	3	8	10	6	0	2	17	24	–	–
		Phone Charger	5	2	30	3	0	9	13	15	17	24
		Radio	5	1	15	4	6	9	17	24	–	–
		Security Light	5	2	30	12	0	7	17	24	–	–
		AC-TV (small)	100	1	30	5	11	15	17	24	–	–
		Fridge (small)	250	1	10	5	0	24	–	–	–	–
Household_4	10	Lights	3	12	10	6	0	2	17	24	–	–
		Phone Charger	5	4	30	3	0	9	13	15	17	24
		Radio	5	1	15	4	6	9	17	24	–	–
		Security Light	5	4	30	12	0	7	17	24	–	–
		AC-TV (small)	100	1	30	5	11	15	17	24	–	–
		Standing Fan	55	1	30	6	8	24	–	–	–	–
		Decoder	15	1	30	5	11	15	17	24	–	–
		Fridge (small)	250	1	10	5	0	24	–	–	–	–
		Internet Router	20	1	30	6	0	24	–	–	–	–
		Laptop (small)	55	1	30	6	0	2	11	15	17	24
Household_5	5	Lights	3	16	10	6	0	2	17	24	–	–
		Phone Charger	5	4	30	3	0	9	13	15	17	24
		Radio	5	2	15	4	6	9	17	24	–	–
		Security Light	5	6	30	12	0	7	17	24	–	–
		AC-TV (big)	200	1	30	6	11	15	17	24	–	–
		Standing Fan	55	2	30	6	8	24	–	–	–	–
		Decoder	15	1	30	6	11	15	17	24	–	–
		Fridge (big)	400	1	10	5	0	24	–	–	–	–
		Internet Router	20	1	30	8	0	24	–	–	–	–
		Laptop (big)	80	2	30	8	0	2	11	15	17	24
Household_6	5	Lights	3	16	10	6	0	2	17	24	–	–
		Phone Charger	5	4	30	3	0	9	13	15	17	24
		Radio	5	2	15	4	6	9	17	24	–	–
		Security Light	5	6	30	12	0	7	17	24	–	–
		AC-TV (big)	200	1	30	6	11	15	17	24	–	–
		Standing Fan	55	2	30	6	8	24	–	–	–	–
		Decoder	15	1	30	6	11	15	17	24	–	–
		Fridge (big)	400	1	10	5	0	24	–	–	–	–
		Internet Router	20	1	30	8	0	24	–	–	–	–
		Laptop (big)	80	2	30	8	0	2	11	15	17	24
		Hair Dryer	1000	1	5	0.5	17	24	–	–	–	–
		Printer	50	1	5	0.5	17	24	–	–	–	–
		Stereo	100	1	30	3	17	24	–	–	–	–
		Water Heater	660	1	15	2	0	2	18	24	–	–
Enterprise_1	15	Fluor. Tube (small)	36	10	60	6	7	11	16	20	–	–
		Phone Charger	5	4	30	3	7	13	15	20	–	–
		Security Light	5	4	60	12	0	7	17	24	–	–
		Internet Router	20	1	60	10	7	20	–	–	–	–
		Laptop (big)	80	1	60	8	7	13	15	20	–	–
		Laptop (small)	55	5	60	8	7	13	15	20	–	–
		Printer	50	2	5	2	7	13	15	20	–	–
		Standing Fan	55	2	30	8	7	13	15	20	–	–
Enterprise_2	5	Fluor. Tube (big)	47	20	30	6	7	11	16	20	–	–
		Phone Charger	5	15	30	3	7	13	15	20	–	–
		Security Light	5	10	30	12	0	7	17	24	–	–
		Internet Router	20	1	30	10	7	20	–	–	–	–
		Laptop (big)	80	5	30	8	7	13	15	20	–	–
		Laptop (small)	55	10	30	8	7	13	15	20	–	–
		Standing Fan	55	5	5	8	7	13	15	20	–	–
		Water dispenser	550	1	30	3	7	13	15	20	–	–
		Photocopier	750	1	15	1	7	13	15	20	–	–
		Ceiling Fan	75	5	5	8	7	13	15	20	–	–
		PC	400	1	30	10	7	20	–	–	–	–

Table 2 (*continued*)

Class Type j	N_j	App Name i	P_{ij} [W]	n_{ij}	d_{ij}[min]	h_{ij}[h]	w_{f,ij_1}		w_{f,ij_2}		w_{f,ij_3}	
							h_{start}	h_{stop}				
Mobile Money	5	Lights	3	2	10	3	8	11	16	20	–	–
		Phone Charger	5	3	30	3	8	18	–	–	–	–
		Standing Fan	55	1	30	6	10	18	–	–	–	–
Kiosk	10	Lights	3	2	10	3	8	11	16	20	–	–
		Phone Charger	5	1	30	3	8	18	–	–	–	–
		Standing Fan	55	1	30	6	10	18	–	–	–	–
		Fridge (small)	300	1	5	8	0	24	–	–	–	–
		Fridge (big)	500	1	10	8	0	24	–	–	–	–
Barber	2	Lights	3	5	10	8	8	13	15	20	–	–
		12V shaver	10	5	5	6	8	13	15	20	–	–
		Ceiling Fan	75	3	30	8	8	13	15	20	–	–
		UV sterilizer	50	1	5	2	8	13	15	20	–	–
Tailor	3	Lights	5	3	30	8	8	13	15	20	–	–
		Sewing machine	50	1	15	3	8	13	15	20	–	–
		Ceiling Fan	75	1	30	8	8	13	15	20	–	–
Market Place	1	Lights	3	25	30	3	8	11	16	20	–	–
		Security Light	5	25	30	12	0	7	17	24	–	–
		Fridge (small)	300	3	5	8	0	24	–	–	–	–
		Fridge (big)	500	3	10	8	0	24	–	–	–	–
		Standing Fan	55	10	30	8	8	13	15	20	–	–
		Radio	5	10	15	4	10	13	15	18	–	–
Club	3	Fluor. Tube (small)	36	10	30	8	0	4	17	24	–	–
		Fluor. Tube (big)	47	5	30	8	0	4	17	24	–	–
		Security Light	5	5	30	12	0	7	17	24	–	–
		Phone charger	5	10	30	8	15	24	–	–	–	–
		AC-TV (small)	130	2	30	9	0	4	15	24	–	–
		AC-TV (big)	200	1	30	9	0	4	15	24	–	–
		PC	400	1	30	9	0	4	15	24	–	–
		Laptop (big)	80	10	30	6	15	24	–	–	–	–
		Printer	50	1	5	1	15	20	–	–	–	–
		PicoProjector	18	1	30	4	0	2	20	24	–	–
		Amplifier	6	1	30	4	0	2	20	24	–	–
		Ceiling Fan	75	3	30	8	0	4	15	24	–	–
		Music System	178	1	30	8	0	4	15	24	–	–
		Internet Router	20	1	30	9	0	4	15	24	–	–
		Fridge (small)	300	2	5	8	0	24	–	–	–	–
		Fridge (big)	500	1	10	8	0	24	–	–	–	–
Street Lights	1	Lights (Street)	50	100	30	12	0	7	17	24	–	–
		Led strips	8	100	30	12	0	7	17	24	–	–
Primary School	1	Fluor.Tube (small)	36	10	30	4	8	17	–	–	–	–
		Phone Charger	5	7	30	3	8	17	–	–	–	–
		Security Light	5	4	30	12	0	7	17	24	–	–
Pharmacy	1	Lights	3	10	30	3	8	11	16	20	–	–
		Security Light	5	4	30	12	0	7	17	24	–	–
		Fridge (small)	300	3	5	8	0	24	–	–	–	–
		Fridge (big)	500	2	10	8	0	24	–	–	–	–
		Standing Fan	55	3	30	8	8	13	15	20	–	–

same users' energy modelling and resulting by the application of a classical literature-based method for load profile formulation. This method can be considered as the typical one employed in previous works about off-grid system sizing for rural electrification [39]. The resulting profile, can be compared with the examples generated by *LoadProGen* (Figs. 3 and 4). Hence: (i) being the method only based on the average power contributions of the appliances, the profile results a flat and blocky (i.e. not realistic), and (ii) the method allows computing a single profile from the given input data (i.e. it is not possible to consider load profile uncertainties).

Local availability of solar resources

Table 5 reports the data about solar resource and ambient temperature in Soroti. These data have been employed in the method presented in [17] to compute the *synthetic hourly solar radiation* incident on the PV surface and the *PV cell temperature* throughout a year. Fig. 8 shows, the resulting radiation profile for 10 days of January, and it highlights how the method employed is capable to take into accounts the variability of the solar resource.

Techno-economic data set

Technical parameters of the system components modelling are reported in Table 6, while economic parameters are shown in Table 7. Information about PV modules, batteries and off-grid inverters are the result of a survey among Ugandan local suppliers, while O&M and other investment costs have been estimated based on our experience.

Results of the optimization process under load profile uncertainty and discussion

The optimization of the PV-based micro-grid has been performed by simulating all the possible combinations of PV-battery within previously defined size ranges and for a given load profile.

Table 3
Summary of energy consumptions for the defined user classes.

	Class Type j	N_j	$E_{class,day}$ [kW h/day]	$E_{pc,year}$* [kW h/year/pc]
1	Household_1	50	8.1	7.4
2	Household_2	15	10.2	31.1
3	Household_3	15	31.0	94.2
4	Household_4	10	31.4	143.3
5	Household_5	5	30.7	280.0
6	Household_6	5	41.4	377.9
7	Enterprise_1	15	98.7	–
8	Enterprise_2	5	130.8	–
9	Mobile money	5	2.0	–
10	Kiosk	10	67.6	–
11	Barber	2	4.6	–
12	Tailor	3	2.6	–
13	Market place	1	25.5	–
14	Club	3	91.1	–
15	Street lights	1	69.0	–
16	Primary school	1	1.8	–
17	Pharmacy	1	16.9	–
	Total daily load	663.4 kW h/day		

* Considering 8 persons per households.[58]

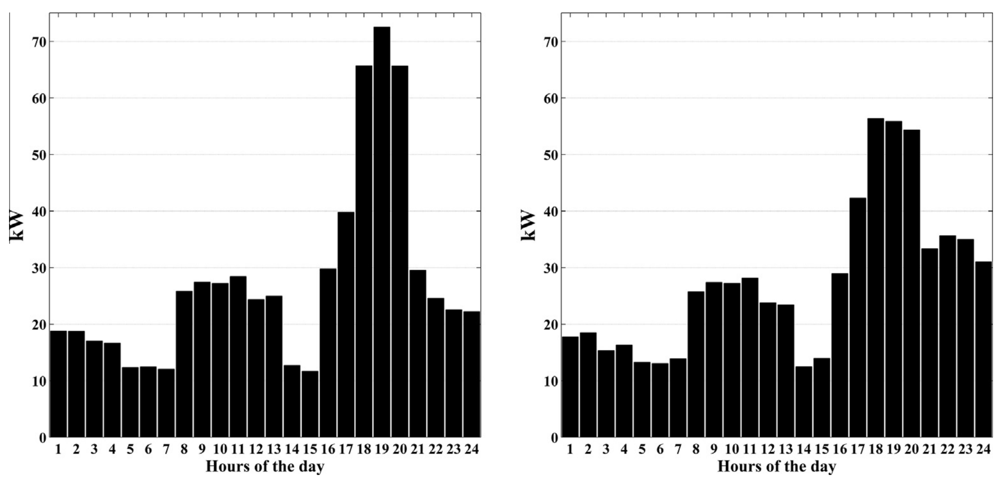

Fig. 3. Samples of load profiles generated with *LoadProGen* for the case Rh_{ij} and Rw_{ij} equal to 0%.

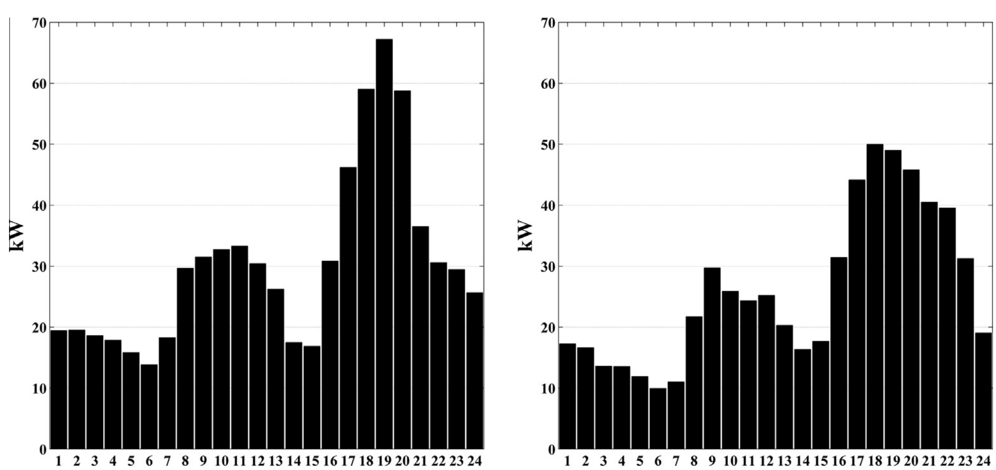

Fig. 4. Samples of load profiles generated with *LoadProGen* for the case Rh_{ij} and Rw_{ij} equal to 30%.

Specifically the simulations were performed in MATLAB by ranging PV array size from 180 to 250 kW with 3 kW step and battery bank size from 680 to 1000 kW h with 8 kW h step. Then the PV-battery combination that results in having the minimum NPC while respecting a maximum LLP of 5% is identified as the optimum solution.

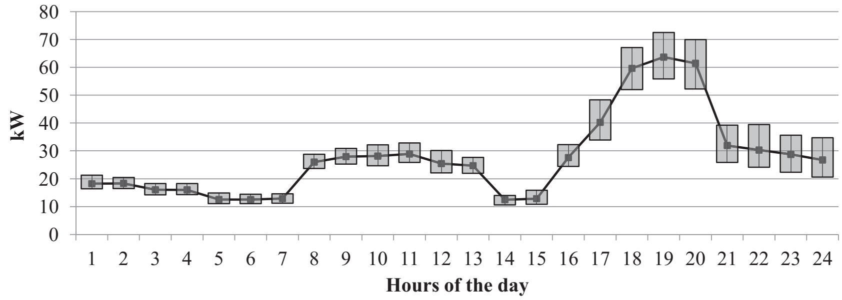

Fig. 5. Box plot for the scenario with Rh_{ij} and Rw_{ij} equal to 0%.

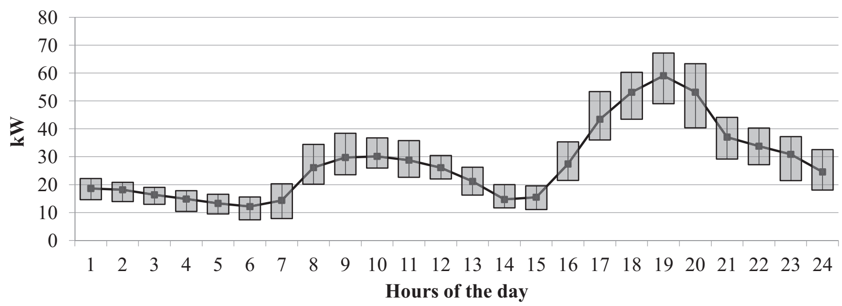

Fig. 6. Box plot for the scenario with Rh_{ij} and Rw_{ij} equal to 30%.

Table 4
Key parameters for the 150 formulated profiles within the 10 scenarios.

	Scenarios		Daily energy[kW h/day]			Load peak [kW]			Load factor		
	Rh_{ij}	Rw_{ij}	min	av.	max	min	av.	max	min	av.	max
1	0%	0%	“	663.4	“	56.4	64.1	72.5	0.38	0.43	0.49
2	0%	10%	“	663.4	“	56.0	62.9	72.6	0.38	0.44	0.49
3	10%	0%	646.7	663.9	687.2	55.5	63.7	73.9	0.38	0.44	0.50
4	0%	20%	“	663.4	“	54.2	62.3	70.6	0.39	0.44	0.51
5	20%	0%	630.6	663.9	698.9	54.2	63.4	73.5	0.38	0.44	0.49
6	0%	30%	“	663.4	“	52.9	60.3	69.8	0.40	0.46	0.52
7	30%	0%	608.6	665.4	717.9	52.3	63.0	72.1	0.38	0.44	0.51
8	10%	10%	647.9	663.7	679.3	53.2	63.3	72.4	0.39	0.44	0.52
9	20%	20%	628.9	665.2	697.7	52.9	61.6	70.3	0.39	0.45	0.52
10	30%	30%	601.4	662.3	726.1	50.0	59.1	67.2	0.40	0.47	0.55

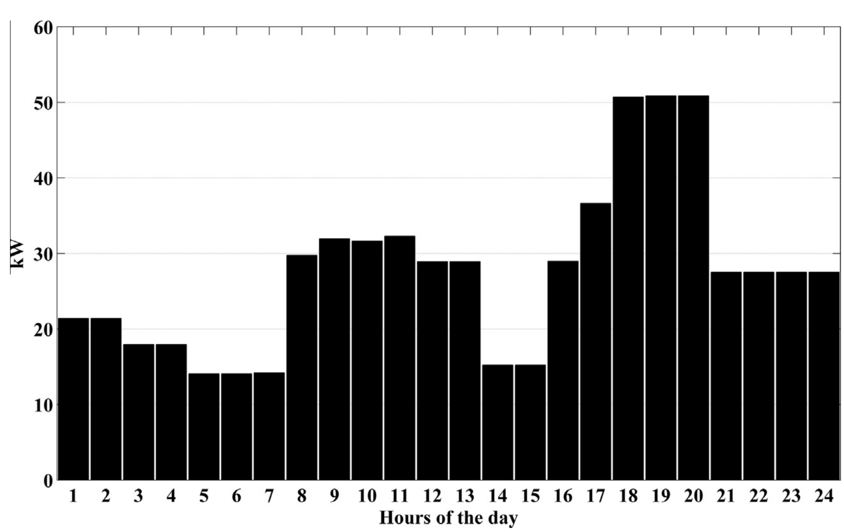

Fig. 7. Load profile computed via classical literature-based method.

Table 5
Solar resource and temperature data for Soroti [7].

Month	Mean daily irradiation [kW h/m^2/day]	Ambient Temperature [°C]
January	6.22	21.9
February	6.56	22.5
March	6.36	21.9
April	5.99	21.1
May	5.72	20.7
June	5.39	20.7
July	5.29	20.8
August	5.67	21.1
September	6.22	20.8
October	6.01	20.5
November	5.83	20.6
December	6.07	21.2

Table 6
Technical modelling assumptions.

Balance of system efficiency	85	%
Minimum battery SOC	40	%
Battery power-to-energy ratio	50	%
Battery round-trip efficiency	75	%
Inverter efficiency	90	%

Table 7
Economic modelling assumptions.

	Note	Cost	
PV modules	Monocrystalline	1000	€/kW
Battery	Lead-acid (sealed)	140	€/kW h
Off-grid inverter		500	€/kW
Other investment costs	% on main component costs	20	%
O&M		50	€/kW/year
Plant lifetime	*LT*	20	Years
Discount rate	*r*	6	%

The effect of load profiles uncertainty on the optimum sizing has been introduced by employing *LoadProGen* to formulate different possible realistic load profiles for a single reference context (i.e. for a set of users' electric needs, Table 1). In practice, we looked for the optimum PV-battery combinations resulting from the optimization process applied to each load profile within each scenario (i.e. 150 profiles formulated for each scenario, 10 scenarios considered. cf. Section 4.1). Fig. 9 shows the results of this analysis. In particular, each *rainbow colormap*:

- refers to a particular scenario, defined by a combination of the parameters *Rh* and *Rw*;
- covers the search space of the optimum solutions defined by the PV and battery sizes ranges;
- identifies with different colors (according to the *colorbar*) the frequency at which a specific combination of PV-battery sizes has resulted to be the optimum one. In the figure, the frequency has been normalized to 100 and according to the most frequent combination in the considered scenario.

With reference to Fig. 9 some considerations can be reported:

- the fact that the optimum combinations cover an areas of the search space (i.e. they generate a spot of optimum solutions) proves that load profiles affect the optimum design of the PV-based micro-grid. The effect is significant since optimum sizes of PV and batteries range between about 205–225 kW and about 800–900 kW h respectively even in the scenarios with *Rh* and *Rw* equal to zero;
- the effect of *Rw* is more relevant on the battery capacity rather than on the PV power size when moving from scenario with *Rh* = 0% and *Rw* = 0% to scenario with *Rh* = 0% and *Rw* = 10–20–30%. This is due to the fact that random changes on $w_{F,ij}$ may lead to move the power peak of the load profiles (and the related period with relative high energy requirement) from day to night (or vice versa), thus leading to need more (less) storage capacity;
- the effect of *Rh* is relevant both on the battery capacity and the PV power size and it increases (i.e. the spot expands steadily) when moving from scenario with *Rh* = 0% and *Rw* = 0% to scenario with *Rh* = 10–20–30% and *Rw* = 0%. Indeed, random changes on h_{ij} lead to higher (lower) daily energy requirements, thus requiring larger (smaller) size of PV and battery capacity to cover and store more (less) energy.

Beside the analysis of the effect of the load profiles uncertainty on the optimum sizing, it is worthwhile to investigate the identification of the robust solution among those that define the spot of optimum solutions. Two options have been compared: (i) the robust solution is the most frequent combination of PV and battery that has occurred, (ii) the robust solution is the barycenter of the spot of optimum solutions. Table 8 reports a summary of this analysis. It presents the scenarios according to the values of *Rh* and *Rw*, data about the most frequent solutions and the barycenters. With regards to the most frequent solutions, their frequencies among the 150 load profiles considered in each scenario have been

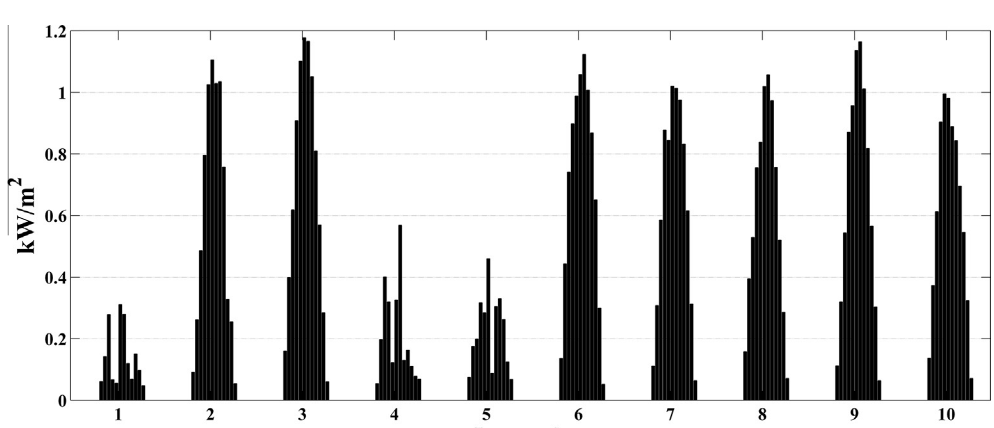

Fig. 8. Solar radiation hourly profile for 10 days of January in Soroti.

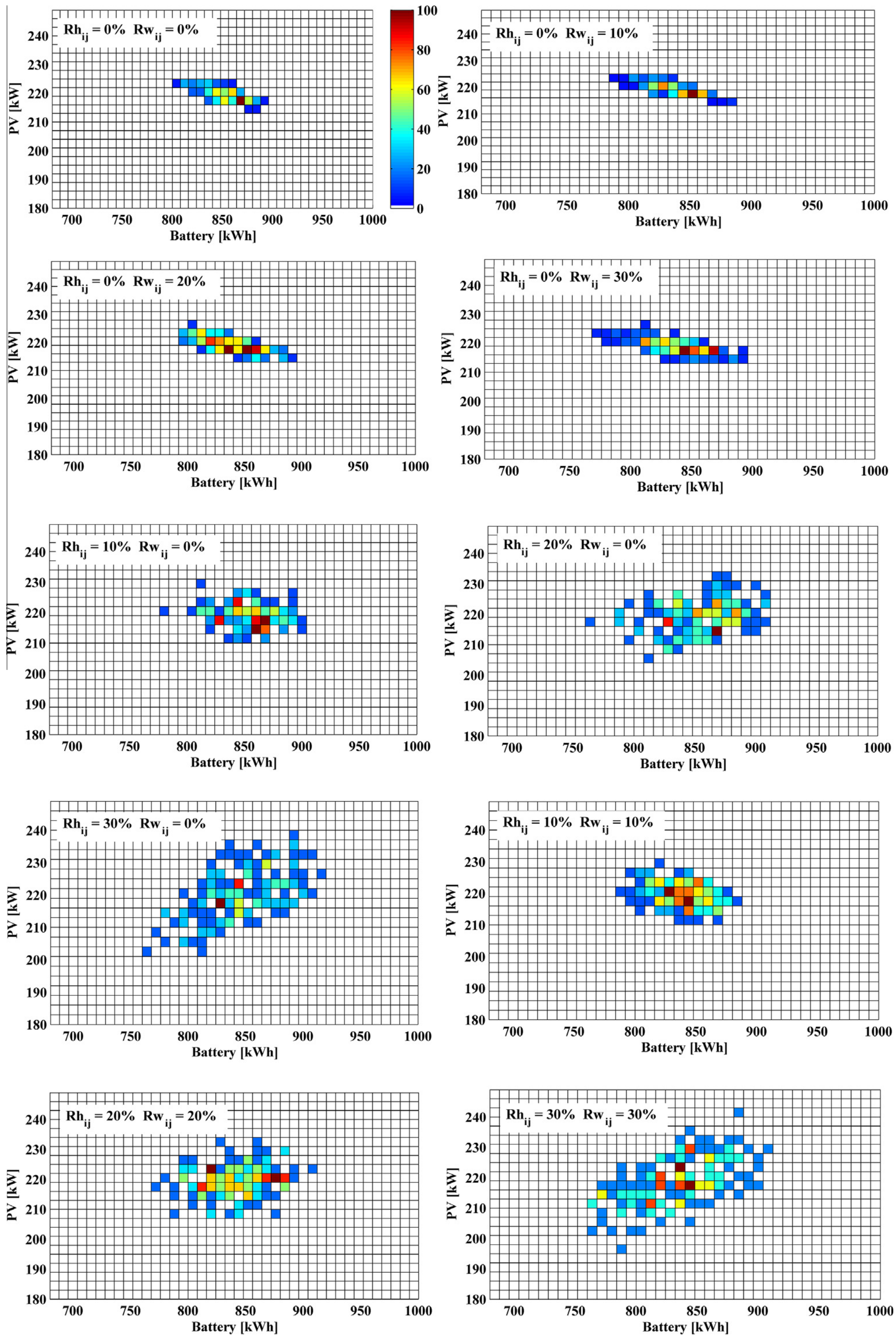

Fig. 9. Rainbow colormaps of the PV-battery optimum sizing combinations for different *LoadProGen* parameters hypotheses.

reported. Accordingly, as expected the frequency generally decreases when considering scenarios with *Rh* and *Rw* greater than 0: from 22 occurrences whit *Rh* and *Rw* equal to 0% and 10% respectively, to 5 occurrences with *Rh* and *Rw* equal to 0% and 30% respectively. Nevertheless, the optimum solutions are weakly affected by the change in the *Rh* and *Rw* parameters.

This analysis has been completed by considering also the spot of optimum solutions resulting from overlapping all the scenarios. This could be a way to embrace uncertainty on the *LoadProGen* parameters which most likely are not known by the system designer. Therefore, the overlapping of all the scenarios allows identifying the most robust solution with regards the overall degree of uncertainty considered in the problem.

Accordingly, Fig. 10 shows the rainbow colormap for this latter case. The most frequent system configuration has occurred 72 times over a total of 1500 (each one refer to a formulated load profile) and is composed by a PV array of 219 kW peak and a battery bank of 856 kW h. The barycenter identifies the most robust solu-

Table 8
Robust solutions identified by the most frequent and barycenter for each scenario.

	Scenarios		The most frequent			Barycenter	
	Rh_{ij}	Rw_{ij}	Frequency among 150	PV [kW]	Battery [kW h]	PV [kW]	Battery [kW h]
1	0%	0%	20	219	872	222	856
2	0%	10%	22	219	856	222	840
3	10%	0%	9	216	864	222	840
				219	872		
4	0%	20%	11	219	840	219	840
				219	856		
5	20%	0%	7	216	872	219	856
6	0%	30%	14	219	848	222	856
7	30%	0%	7	219	832	222	848
8	10%	10%	8	219	848	222	840
				222	832		
9	20%	20%	6	222	880	222	848
				225	824		
10	30%	30%	5	219	848	219	840
				225	840		

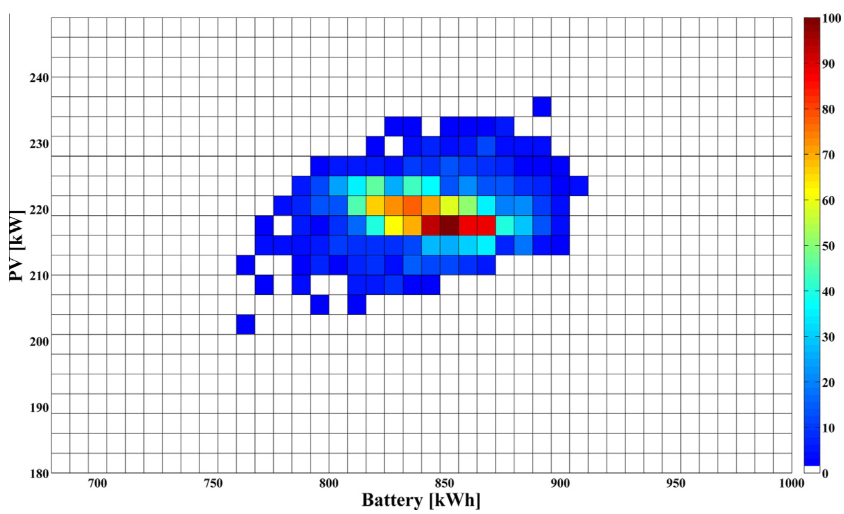

Fig. 10. Rainbow colormap of the PV-battery optimum sizing combinations for all the *LoadProGen* scenarios.

tion as composed by a PV array of 222 kW peak and a battery bank of 848 kW h. Finally, the dispersion of the optimum solutions is characterized by PV array powers that range from 198 kW to 243 kW, while battery capacities that range from 768 kW h to 920 kW h.

Conclusions

In this paper we highlighted the effect of load profiles uncertainty on the sizing of PV-battery systems with particular reference to off-grid applications for rural electrification. This has been carried out by employing a new stochastic method which formulates possible realistic daily load profiles for given set of users' electric needs, on the basis of classical approaches for steady-state simulation, and by means of a new approach to identify the robust solution with regards the assumed uncertainty. Accordingly, a numerical case study has been proposed based on data collected during a field mission in Uganda.

Specifically, for the given set of parameters of users' electric needs, several possible realistic load profiles have been formulated via *LoadProGen* (an algorithm which implements the new stochastic method). Then for each formulated profile the classical sizing approach has been performed thus providing several optimum systems. Moreover, the analysis has been completed by focusing on further uncertainties introduced on the given set of users' electric needs.

The results confirmed the hypothesis concerning the effect of load profiles uncertainty on the optimum sizing of off-grid PV systems. The case study also highlight that it is possible to recognize a *robust* solution among all the optimum ones. Some systems configurations turned out to be the optimum one more often being capable to optimally adapt to different load profiles. It resulted that the introduction of further stochastic effect on the input parameters does not significantly affect the robust solution, while it affects the dispersion of the optimum systems configurations.

In conclusion, this work highlighted that attention is required when defining load profiles for off-grid PV-battery system sizing since, given the typical inputs for users' electric needs, several system configurations may be the optimum one. Besides, a further development of this analysis should consider not only the uncertainty on load profiles for given *static* users' electric needs, but also possible evolution in time (year by year for instance) according to change in the consumers' welfare and habits.

References

[1] Lopes JAP, Hatziargyriou N, Mutale J, Djapic P, Jenkins N. Integrating distributed generation into electric power systems: a review of drivers,

challenges and opportunities. Electr Power Syst Res 2007;77:1189–203. http://dx.doi.org/10.1016/j.epsr.2006.08.016.
[2] Moshövel J, Kairies K-P, Magnor D, Leuthold M, Bost M, Gährs S, et al. Analysis of the maximal possible grid relief from PV-peak-power impacts by using storage systems for increased self-consumption. Appl Energy 2015;137:567–75. http://dx.doi.org/10.1016/j.apenergy.2014.07.021.
[3] Bhattacharyya SC. Energy access programmes and sustainable development: a critical review and analysis. Energy Sustainable Dev 2012;16:260–71. http://dx.doi.org/10.1016/j.esd.2012.05.002.
[4] Mandelli S, Molinas M, Park E, Leonardi M, Colombo E, Merlo M. The role of storage in emerging country scenarios. Energy Procedia 2015;73:112–23. http://dx.doi.org/10.1016/j.egypro.2015.07.657.
[5] Sharif I, Mithila M. Rural electrification using PV: the success story of Bangladesh. Energy Procedia 2013;33:343–54. http://dx.doi.org/10.1016/j.egypro.2013.05.075.
[6] Chaurey A, Kandpal TC. Assessment and evaluation of PV based decentralized rural electrification: an overview. Renewable Sustainable Energy Rev 2010;14:2266–78. http://dx.doi.org/10.1016/j.rser.2010.04.005.
[7] Palit D, Chaurey A. Off-grid rural electrification experiences from South Asia: status and best practices. Energy Sustainable Dev 2011;15:266–76. http://dx.doi.org/10.1016/j.esd.2011.07.004.
[8] 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;8:778–88.
[9] Khatib T, Mohamed A, Sopian K. A review of photovoltaic systems size optimization techniques. Renewable Sustainable Energy Rev 2013;22:454–65. http://dx.doi.org/10.1016/j.rser.2013.02.023.
[10] Bhattacharyya SC. Review of alternative methodologies for analysing off-grid electricity supply. Renewable Sustainable Energy Rev 2012;16:677–94. http://dx.doi.org/10.1016/j.rser.2011.08.033.
[11] Rojas-Zerpa JC, Yusta JM. Methodologies, technologies and applications for electric supply planning in rural remote areas. Energy Sustainable Dev 2014;20:66–76. http://dx.doi.org/10.1016/j.esd.2014.03.003.
[12] NASA. Surface meteorology and Solar Energy 2010.
[13] GeoModel Solar. Solargis n.d.
[14] IRENA. Global Atlas for Renewable Energy – Wind 2015.
[15] SANEDI. Wind Atlas for South Africa n.d.
[16] Huld T, Müller R, Gambardella A. A new solar radiation database for estimating PV performance in Europe and Africa. Sol Energy 2012;86:1803–15. http://dx.doi.org/10.1016/j.solener.2012.03.006.
[17] Graham VA, Hollands KGT. A method to generate synthetic hourly solar radiation globally. Sol Energy 1990;44:333–41. http://dx.doi.org/10.1016/0038-092X(90)90137-2.
[18] Oliva RB. Simulation and measurement procedures for effective isolated wind and hybrid system development in south Patagonia. Energy Sustainable Dev 2008;12:17–26. http://dx.doi.org/10.1016/S0973-0826(08)60425-1.
[19] Arun P, Banerjee R, Bandyopadhyay S. Optimum sizing of photovoltaic battery systems incorporating uncertainty through design space approach. Sol Energy 2009;83:1013–25. http://dx.doi.org/10.1016/j.solener.2009.01.003.
[20] Egido M, Lorenzo E. The sizing of stand alone PV-system: a review and a proposed new method. Sol Energy Mater Sol Cells 1992;26:51–69. http://dx.doi.org/10.1016/0927-0248(92)90125-9.
[21] Bagul AD, Salameh ZM, Borowy B. Sizing of a stand-alone hybrid wind-photovoltaic system using a three-event probability density approximation. Sol Energy 1996;56:323–35. http://dx.doi.org/10.1016/0038-092X(95)00116-9.
[22] Grandjean A, Adnot J, Binet G. A review and an analysis of the residential electric load curve models. Renewable Sustainable Energy Rev 2012;16:6539–65. http://dx.doi.org/10.1016/j.rser.2012.08.013.
[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. Renewable Energy 2011;36:2809–21. http://dx.doi.org/10.1016/j.renene.2011.04.022.
[24] 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 Sustainable Dev 2009;13:137–42. http://dx.doi.org/10.1016/j.esd.2009.07.002.
[25] Nandi SK, Ghosh HR. Prospect of wind-PV-battery hybrid power system as an alternative to grid extension in Bangladesh. Energy 2010;35:3040–7. http://dx.doi.org/10.1016/j.energy.2010.03.044.
[26] 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. http://dx.doi.org/10.1016/j.egypro.2013.07.041.
[27] 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;14:1. http://dx.doi.org/10.1016/j.egypro.2011.12.887.
[28] Nfah EM, Ngundam JM. Evaluation of optimal power options for base transceiver stations of Mobile Telephone Networks Cameroon. Sol Energy 2012;86:2935–49. http://dx.doi.org/10.1016/j.solener.2012.06.029.
[29] Nfah EM, Ngundam JM. Feasibility of pico-hydro and photovoltaic hybrid power systems for remote villages in Cameroon. Renewable Energy 2009;34:1445–50. http://dx.doi.org/10.1016/j.renene.2008.10.019.
[30] Sen R, Bhattacharyya SC. Off-grid electricity generation with renewable energy technologies in India: an application of HOMER. Renewable Energy 2014;62:388–98. http://dx.doi.org/10.1016/j.renene.2013.07.028.
[31] Kulworawanichpong T, Mwambeleko JJ. Design and costing of a stand-alone solar photovoltaic system for a Tanzanian rural household. Sustainable Energy Technol Assess 2015;12:53–9. http://dx.doi.org/10.1016/j.seta.2015.10.001.
[32] Bekele G, Tadesse G. Feasibility study of small Hydro/PV/Wind hybrid system for off-grid rural electrification in Ethiopia. Appl Energy 2012;97:5–15. http://dx.doi.org/10.1016/j.apenergy.2011.11.059.
[33] 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 2010;84:710–4. http://dx.doi.org/10.1016/j.solener.2010.01.024.
[34] Gupta A, Saini RP, Sharma MP. Steady-state modelling of hybrid energy system for off grid electrification of cluster of villages. Renewable Energy 2010;35:520–35. http://dx.doi.org/10.1016/j.renene.2009.06.014.
[35] Olatomiwa L, Mekhilef S, Ohunakin OS. Hybrid renewable power supply for rural health clinics (RHC) in six geo-political zones of Nigeria. Sustainable Energy Technol Assess 2016;13:1–12. http://dx.doi.org/10.1016/j.seta.2015.11.001.
[36] Kolhe ML, Ranaweera KMIU, Gunawardana A. GBS. Techno-economic sizing of off-grid hybrid renewable energy system for rural electrification in Sri Lanka. Sustainable Energy Technol Assess 2015;11:53–64. http://dx.doi.org/10.1016/j.seta.2015.03.008.
[37] Celik AN. Effect of different load profiles on the loss-of-load probability of stand-alone photovoltaic systems. Renewable Energy 2007;32:2096–115. http://dx.doi.org/10.1016/j.renene.2006.11.002.
[38] Boait P, Advani V, Gammon R. Estimation of demand diversity and daily demand profile for off-grid electrification in developing countries. Energy Sustainable Dev 2015;29:135–41. http://dx.doi.org/10.1016/j.esd.2015.10.009.
[39] Mandelli S, Merlo M, Colombo E. Novel procedure to formulate load profiles for off-grid rural areas. Energy Sustainable Dev 2016;31:130–42. http://dx.doi.org/10.1016/j.esd.2016.01.005.
[40] Hamilton RF. The summation of load curves. Electr Eng 1944;63:729–35. http://dx.doi.org/10.1109/EE.1944.6440529.
[41] Bary C. Coincidence-factor relationships of electric-service-load characteristics. Am Inst Electr Eng Trans 1945;64:623–9. http://dx.doi.org/10.1109/T-AIEE.1945.5059190.
[42] Willis HL, Northcote-Green JED. Spatial electric load forecasting: a tutorial review. Proc IEEE 1983;71:232–53.
[43] Willis HL. Spatial Electric Load Forecasting. 2002.
[44] Shen WX. Optimally sizing of solar array and battery in a standalone photovoltaic system in Malaysia. Renewable Energy 2009;34:348–52. http://dx.doi.org/10.1016/j.renene.2008.03.015.
[45] Kaldellis J. Optimum technoeconomic energy autonomous photovoltaic solution for remote consumers throughout Greece. Energy Convers Manage 2004;45:2745–60. http://dx.doi.org/10.1016/j.enconman.2003.12.007.
[46] Duffie JA, Beckman WA. Design of Photovoltaic Systems. In: John Wiley & Sons, editor. Sol. Eng. Therm. Process. Fourth, New York: 2013, p. 936.
[47] Dufo-López R, Lujano-Rojas JM, Bernal-Agustín JL. Comparison of different lead–acid battery lifetime prediction models for use in simulation of stand-alone photovoltaic systems. Appl Energy 2014;115:242–53. http://dx.doi.org/10.1016/j.apenergy.2013.11.021.
[48] Gilman P, Lilienthal P. Micropower system modeling with Homer. In: Farret F, Simoes M, editors. Integr. Altern. Sources Energy. John Wiley & Sons, Inc.; 2006. p. 379–418.
[49] UNDP. Human Development Report 2014. Sustaining Human Progress: Reducing Vulnerabilities and Building Resilience. Communicat. New York: 2014.
[50] IEA. World Energy Outlook 2014. OECD Publishing; 2014.
[51] The World Bank. Enterprise Surveys, What Businesses Experience. 2012.
[52] The World Bank. World Development Indicators 2012. World Bank Publications; 2012.
[53] Ministry of Energy and Mineral Development. Strategic Investment Plan 2014/15 – 2018/19 2013:106.
[54] Mandelli S, Barbieri J, Mattarolo L, Colombo E. Sustainable energy in Africa: a comprehensive data and policies review. Renewable Sustainable Energy Rev 2014;37:656–86. http://dx.doi.org/10.1016/j.rser.2014.05.069.
[55] Welsch M, Bazilian M, Howells M, Divan D, Elzinga D, Strbac G, et al. Smart and just grids for sub-Saharan Africa: exploring options. Renewable Sustainable Energy Rev 2013;20:336–52. http://dx.doi.org/10.1016/j.rser.2012.11.004.
[56] Carmeli MS, Mauri M, Brivio C, Guidetti P, Mandelli S, Merlo M, et al. Hybrid micro-grid experimental application in Tanzania, Proc. – 2015 Int. Conf. Clean Electr. Power. IEEE; 2015. p. 534–41.
[57] Village Energy. Village Energy LtD 2014.
[58] UBOS. Uganda Bureau of Statistics 2010.