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Probabilistic Optimal Sizing of Stand-Alone PV Systems with Modeling of Variable Solar Radiation and Load Demand

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***Abstract*—This paper presents a comprehensive sizing methodology which could contain all key elements necessary to obtain a practical sizing result for a stand-alone photovoltaic (PV) system. First, a stochastic solar radiation model based on limited/incomplete local weather data is formulated to synthesis various chronological solar radiation patterns. This enables us to evaluate a long-term system performance and characterize any extreme weather conditions. Second, a stochastic load simulator is developed to simulate realistic load patterns. Third, two reliability indices, Expected-Energy-Not-Supplied (EENS) and Expected-Excessive-Energy-Supplied (EEES), are incorporated with an Annualized Cost of System (ACS) to form a new objective function called an Annualized Reliability and Cost of System (ARCS) for optimization. We then apply a particle swarm optimization (PSO) algorithm to obtain the optimum system configuration for a given acceptable risk level. An actual case study is conducted to demonstrate the feasibility and applicability of the proposed methodology.**

***Index Terms*—Stand-alone PV system, sizing optimization, Expected-Energy-Not-Supplied (EENS), load signatures, particle swarm optimization (PSO).**

I. Introduction

With increasing emphasis on climate change and sustainable development, renewable resources are more widely used in power generation to reduce carbon emissions. Among all renewable resources, solar energy is one of the most abundant ones and photovoltaic (PV) technologies have seen significant improvement in cost and performance in recent years. Although PV technology is still costly, it has become feasible and cost competitive in small-scale stand-alone system. Since solar energy is intermittent with diurnal characteristics, energy storage such as a battery bank is essential to act as a backup to ensure a reliable supply [1].

For sizing evaluation, there are two main types of simulation scenario [2], namely chronological and analytical. The former requires a time series data while the latter uses a probability density function (pdf) to simulate the stochastic characteristic of the renewable resources. The chronological simulation is used in this paper because it emulates system conditions in a continuous time-line to enable detailed evaluation of the batteries [3].

Accurate solar radiation data is one of the most important parameters for the feasibility study of a PV project because it is the main cause of failure/inadequacy in a stand-alone system if all energies (generated and stored) are depleted [4]. Industrial PV sizing practice requires historical and measured solar data on site. However, typical durations of measured data are from a few months to a year which can only offer a limited view to project its long-term performance. To enhance the accuracy, modeling solar radiation using artificial neural network (ANN) [5]-[7] and regressive model [8]-[10] has been proposed but share different degree of limitations. In this paper, we propose to use two commonly accessible weather data, namely solar radiation and total rainfall, to synthesis variable chronological solar radiation patterns.

On the demand side of the power balance equation, load is also varying with time and common practices just use a constant value (e.g. maximum). However, assuming a constant load pattern may oversimplify the stochastic load nature. We therefore propose a load simulator based on load signatures as described in [11], [12] to generate a more realistic and chronologically-based consumption pattern for our studies.

The optimum design of the system is mainly evaluated by two objectives: reliability and cost. For reliability, a commonly used index is Loss-of-Load-Probability (LOLP) [2], [3], [13]. However, this index is not able to measure the severity of the shortage period and neglect the excessive energy that could not be captured by battery due to its capacity. In order to incorporate these, the Expected-Energy-Not-Supplied (EENS) [14] and the Expected-Excessive-Energy-Supplied (EEES) are bundled with an Annualized Cost of System (ACS) [3] to form a new objective function called Annualized Reliability and Cost of System (ARCS) for the optimization process.

Among various optimization techniques proposed to solve similar sizing problem (e.g. probabilistic approach [14], graphical construction method [13] and artificial intelligence method [3], [7]), we propose to use a particle swarm optimization (PSO) algorithm to obtain the optimum configuration of PV modules and batteries because it is generally recognized to be robust in finding global optimal solutions, especially in multi-model and non-linear

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optimization problems [15]. This paper is organized as follows. Section II provides a mathematical formulation of various system components. The modeling of meteorological conditions is presented in Section III. Section IV presents a probabilistic load simulator. Reliability and cost assessment tools are given in Section V. A stochastic optimal sizing optimization formulation and the use of PSO algorithm to solve the problem are described in Section VI. Simulation and results based on a case study is presented in Section VII and finally the conclusion.

II. Models of System Components

A stand-alone PV system mainly includes three components: 1) PV array, 2) battery bank and 3) inverter. This paper focuses on the system sizing in which the PV arrays and the batteries are configured in parallel. When solar energy is available, surplus PV energy will go into the battery until it is fully charged. Conversely, the battery will be discharged to meet the load if solar energy is inadequate or inexistent. This section describes the mathematical formulations of the system components.

A. PV Array Power Model

PV array is consisted of modules which are the basic power conversion units. The number of PV modules is one of the decision variables in our sizing problem because it determines the total PV power output as shown in (1):

$$P_{PV}(t) = P_{mod}(t)N_{PV};\, t = 1,2,\dots,T \tag{1}$$

where $P_{PV}(t)$ is the total PV power output at time t in W; $P_{mod}(t)$ is the power output of PV module at time t in W; and N_{PV} is the number of PV modules.

To determine the total PV power output, an accurate model of PV module in terms of received solar radiation is necessary. In this paper, a regression model is used [16] and formulated as follows:

$$\begin{aligned} P_{mod}(t) = b_1 S(t) + b_2 S(t)^2 + b_3 S(t) T_{amb}(t) \\ + b_4 S(t) V(t);\, t = 1,2,\dots,T \end{aligned} \tag{2}$$

where $S(t)$ is the solar radiation at time t in W/m^2; $V(t)$ is the wind speed at time t in m/s; $T_{amb}(t)$ is the ambient temperature at time t in ^{o}C; and b_1, b_2, b_3 and b_4 are regression coefficients which can be estimated from measured data.

B. Battery Bank & Inverter Model

A proper sized battery bank requires a detailed formulation of charging and discharging processes and this can be characterized by the State-Of-Charge (SOC) of the battery. SOC at any time, says t, is related to the previous state of SOC and to the battery power $P_{bat}(t)$ as follows:

$$\begin{aligned} SOC(t) = SOC(t-1)\cdot(1-\sigma) \\ + \frac{P_{bat}(t)\eta_{bat}\Delta t}{N_{bat}E_{bat}};\, t = 1,2,\dots,T \end{aligned} \tag{3}$$

where $SOC(t)$ and $SOC(t-1)$ are the SOC at time t and t–1, respectively; σ is a self-discharge rate of the battery bank; η_{bat} is a round-trip efficiency; Δt is the time step; E_{bat} is the energy capacity of a single battery in kWh; N_{bat} is the number of batteries; and T is the simulation period. An initial condition of the SOC, i.e. $SOC(0)$, is set to be 0.8 in this paper.

In order to prevent the battery bank from overcharging and overdischarging, SOC is commonly used as a decision variable of the bi-directional inverter with the following SOC constraints:

$$\underline{SOC} \le SOC(t) \le \overline{SOC};\, t = 1,2,\dots,T \tag{4}$$

where $\underline{SOC}$ and $\overline{SOC}$ are the minimum and maximum SOC values of the battery bank, respectively.

The sign of battery power $P_{bat}(t)$ can be positive or negative depending on whether the battery bank is in charging or in discharging modes as shown by following power balance equation of the system:

$$P_{bat}(t) = P_{PV}(t) - \frac{P_L(t)}{\eta_{inv}};\, t = 1,2,\dots,T \tag{5}$$

where $P_L(t)$ is the load demand at time t in W; η_{inv} is the inverter efficiency. Since there is a power conversion loss in the bi-directional inverter, this efficiency loss is considered as part of the load demand.

III. Models of Meteorological Conditions

In this section, we provide a statistical method to synthesis the meteorological conditions in a chronological manner. The meteorological data include solar radiation, ambient temperature and wind speed, which are required to determine the power output of PV arrays.

A. Modeling of Solar Radiation

To generate the chronological solar radiation, we have to consider two key elements: 1) weather for two consecutive days and 2) profile of solar radiation for each day.

1) Weather for two consecutive days

The Markov chain model is widely used to simulate different meteorological conditions such as solar radiation [17] and wind speed [18]. We apply a first-order Markov chain model with daily total rainfall as a variable to simulate the daily weather sequences. The first-order Markov chain model indicates that the next step only depends on the present state and not on any earlier states.

In our study, the Hong Kong weather data from 2009 to 2010 are used to model the variations of daily weather conditions. For simplicity, the daily total rainfall is categorized into three states:

1) Sunny day (i.e. total rainfall = 0)
2) Light raining day (i.e. 0 < total rainfall ≤ 10 mm)
3) Heavy raining day (i.e. total rainfall > 10 mm)

With above categorization, the 3×3 daily transition probability matrix $P_{d,d+1}$ derived from the weather data is shown as follows:

$$P_{d,d+1} = \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{33} & p_{31} \end{bmatrix} = \begin{bmatrix} 0.80 & 0.19 & 0.01 \\ 0.36 & 0.58 & 0.06 \\ 0.16 & 0.67 & 0.17 \end{bmatrix} \quad (6)$$

Matrix in (6) contains the transition probabilities p_{ij} from a state *i* at day *d* to a state *j* at day *d*+1. Any loss of load is likely to occur in a system if several heavy raining days happen in a continuous manner.

In order to generate the daily weather sequences, the following procedures are proposed based on [18]:

1) A cumulative probability transition matrix P_c is obtained by summing cumulatively along each row of $P_{d,d+1}$;
2) An initial state, says *i*, is randomly set;
3) A uniform random value between 0 and 1 is generated and compared with the elements in row *i* of P_c to determine the next state. If this number is larger than the cumulative probability of the previous state but smaller than or equal to the cumulative probability of the following state, the following state is determined to be the next state;
4) Step 3 is repeated until a desired number of days are generated in the simulation (e.g. 10,000 days).

2) Profile of solar radiation for each day

With the daily weather state generated as above, the next step is to simulate the daily profile of solar radiation. Table I summaries the mean μ and standard deviation σ of solar energy for the three proposed weather states based on the actual data. In general, we can assume that the distribution of solar energy for each weather state follows a normal distribution. With the parameters of Table I and using a normally distributed random number generator, the stochastic daily solar energy can be obtained for each state. Then, based on this value, an iterative procedure is used to simulate the daily profile of solar radiation.

TABLE I
MEAN AND STANDARD DEVIATION OF WEATHER STATES

Weather state	Mean (kWh/m2)	Standard deviation (kWh/m2)
1) Sunny day	4.40	1.11
2) Light raining day	2.56	1.71
3) Heavy raining day	0.93	0.45

We know that for perfect sunny day, the daily profile of solar radiation looks like a Gaussian distribution and the energy (which is the area under the shape) is around 6.63kWh/m^2 as shown in Fig. 2. If the present state is a sunny day, and the daily energy is randomly assigned to be 5.53kWh/m^2. By adding some random fluctuations, we can iteratively curtail an area of 1.10kWh/m^2 in Fig. 2 to obtain solar irradiances at different times. Fig. 3 shows a series of simulated solar radiation profile.

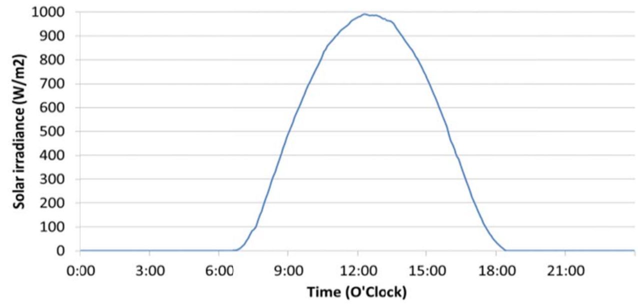

Fig. 2 Solar radiation profile for perfect sunny day

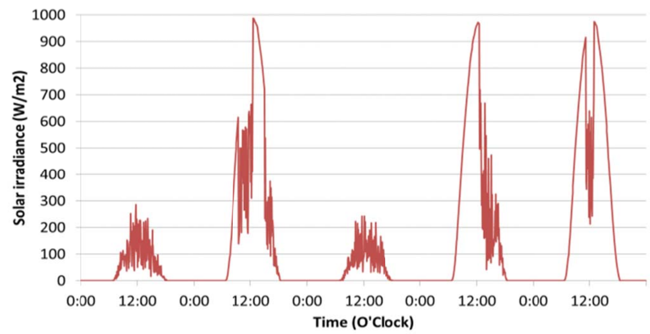

Fig. 3 Simulated chronological solar radiation

B. Modeling of Ambient Temperature

In this paper, we use a linear regression model to approximate the ambient temperature given the simulated solar irradiance as shown in (7):

$$T_{amb}(t) = a_1 S(t) + a_2; t = 1,2,\ldots,T \quad (7)$$

where a_1 and a_2 are regression coefficients which can be estimated from measured/historical data.

C. Modeling of Wind Speed

The wind speed near ground level is also used as input parameters for the PV power output because it can affect the module temperature. The first-order Markov chain model as mentioned in modeling the solar radiation can also be applied to model the wind speed [18].

IV. MODELS OF STOCHASTIC LOADS

By simulating different household appliances individually, the load profile can be emulated. Such a detailed model is viable, flexible and representative [12]. A good estimation of consumption patterns is necessary in order to size the system economically and reliably. The pre-requisite of the accurate estimation of load patterns is to have an appliance database which contains expected household equipment of the consumers. Then, the load simulator begins with the simulation of on-off operations of each appliance in the database. The load profile can be simulated by summing up individual appliance's operations.

In general, household appliances can be classified into four types based on their natures and operating characteristics [12] and this classification is shown in Table II.

TABLE II
TYPE OF APPLIANCE

Type of appliance	Operating period	Number of occurrence per case	Examples
A	Fixed	Fixed	Rice cooker
B	Variable	Fixed	Induction cooker
C	Fixed	Variable	Toaster
D	Variable	Variable	Air conditioner

With such classification, the following load simulation procedures are presented:

1) In each case, i.e. 24 hrs, time segments are defined (e.g. four segments in this paper);
2) For each appliance, we assign a probability for it to operate in each time segment, e.g. 0.1 for segment 1 (00:00 – 06:00), 0.7 for segment 2 (06:00 – 12:00), 0.1 for segment 3 (12:00 – 18:00) and 0.1 for segment 4 (18:00 – 24:00). These probabilities are derived from actual usage;
3) A random number between 0 and 1 is drawn in each time step to determine whether the appliance is switched on. If this number is smaller than the assigned probability in the segment, the appliance will be on at this time interval. This process only determines the randomness of an appliance's on time and the off time is based on the expected operating period as shown in Table II;
4) The number of occurrence of the appliance is counted during the simulation. The step 3) will be terminated if the predefined switching frequency is reached;
5) Steps 2) – 4) are repeated for other appliances.

Fig. 4 shows a simulation result by using appliances mentioned in Table II.

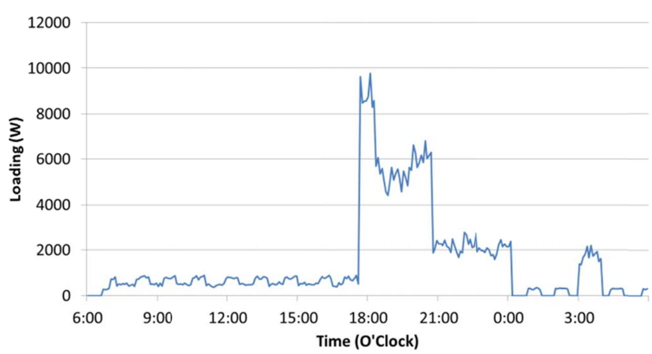

Fig. 4 Simulated result of load simulator

V. SYSTEM PERFORMANCE ASSESSMENT TOOLS

A. Reliability Model

The optimum design of the system is evaluated by two objectives concurrently: reliability and cost. These two objectives are usually evaluated separately and we propose a unifying objective function as follows. The LOLP is a well-known index to analyze system reliability. Mathematically, it can be represented in terms of SOC as follows:

$$LOLP = \sum_{t=1}^{T} Prob\{SOC(t) \le \underline{SOC}\} \tag{8}$$

Through simulation, we can easily obtain the LOLP by estimating the probability of the SOC falls below the minimum value. Since this index is associated with the risk level, we have defined it as one of the constraints in the optimization problem. In addition to LOLP, we also proposed to use two other reliability indices. The first one is EENS which is given as follows:

$$EENS = \sum_{t=1}^{T} E\{P_L(t) - P_{PV}(t) | SOC(t) \le \underline{SOC}\} \tag{9}$$

We can obtain the EENS by summing up the deficient energy in the simulation and it can be considered together with the system cost in our objective function

To avoid oversizing the system, another index which is called EEES, is also considered with the objective function and it can be defined as:

$$EEES = \sum_{t=1}^{T} E\{P_{PV}(t) - P_L(t) | SOC(t) \ge \overline{SOC}\} \tag{10}$$

This index aims to evaluate the excessive energy generated by PV arrays given the SOC has reached the upper bound.

B. Economic Model

The stand-alone PV system consists of various components with uneven life expectancy. The lifetime of PV modules usually is the longest (e.g. 25 years). For others, their lifetimes are much shorter (e.g. 5 years for batteries). Since PV project is a long-term investment, a net present value (NPV) method with the concept of Annualized Cost of System (ACS) is used to properly benchmark the system costs. In essence, the ACS consists of three main components: 1) annualized capital cost (C_{acap}); 2) annualized replacement cost (C_{arep}) and 3) annualized maintenance cost (C_{amain}). In our study, we only consider the costs of two main parts, namely PV array and battery bank, and the cost of inverter is included in the first one for simplicity.

1) Annualized capital cost

The annualized capital costs of the PV array and the battery bank are given as follows:

$$C_{acap} = C_{cap} CRF(r, L_{com}) = C_{cap} \frac{r(1+r)^{L_{com}}}{(1+r)^{L_{com}} - 1} \tag{11}$$

where C_{cap} is the initial capital cost of a component in \$; *CRF* is the capital recovery factor which represents the present value of a series of equal annual cash flows; L_{com} is the component lifetime in year; and r is the annual real interest rate.

2) Annualized replacement cost

The replacement cost is required for a component if it gets a lifetime which is shorter than the project lifetime. In this paper, only the battery bank requires to be replaced during the project lifetime (of course, one can also include the inverters if desired). The annualized replacement cost of the battery bank is given as follows:

$$C_{arep} = C_{rep}SFF(r, L_{bat}) = C_{rep}\frac{r}{(1+r)^{L_{bat}}-1} \quad (12)$$

where C_{rep} is the replacement cost of the battery bank in \$; L_{bat} is the battery bank lifetime in year; *SFF* is the sinking fund factor obtained from the future value of a series of equal annual cash flows.

3) Annualized maintenance cost

The annualized maintenance cost is constant for each year and for simplicity, it is not considered with annuity.

VI. System Optimization Model with Particle Swarm Optimization

A. Optimization Formulation

In this paper, EENS and EEES are bundled with the ACS to form a new objective function called Annualized Reliability and Cost of System (ARCS) which can simultaneously optimize both reliability and system cost. The mathematical formulation of the sizing problem can be written as follows:

$$\begin{aligned}\min_{N_{PV},N_{bat}} ARCS = \{&VoLL \cdot EENS_a + VOEE \cdot EEES_a \\ &+ (C_{acap}^{PV} + C_{amain}^{PV})P_{PV}^{peak}N_{PV} \\ &+ (C_{acap}^{bat} + C_{arep}^{bat} \\ &+ C_{amain}^{bat})N_{bat}E_{bat}\}\end{aligned} \quad (13)$$

Subject to

$$LOLP \le \overline{LOLP} \quad (14)$$

$$N_{PV} = 0,1,2 \ldots \quad (15)$$

$$N_{bat} = 0,1,2 \ldots \quad (16)$$

where $VoLL$ is the value of lost load in \$/kWh; $EENS_a$ is the annualized EENS in kWh/year; $VoEE$ is the value of excessive energy in \$/kWh; $EEES_a$ is the annualized EEES in kWh/year; $\overline{LOLP}$ is the upper bound of the $LOLP$.

The first two terms in (13) are the reliability cost which quantifies the severity of loss of load power with $VoLL$ and the wastage of excessive solar energy with $VoEE$. The third and fourth terms are the ACS for the PV array and the battery bank, respectively.

Constraint (14) is to ensure the reliability of the proposed sizing should be lower than an acceptable risk level, such as 1% in the simulation. Constraints (15) and (16) impose the discrete natures of the decision variables.

B. Sizing Framework

Based on the proposed models and evaluation indices, a flowchart to obtain the optimum design parameters (i.e. N_{PV} and N_{bat}) of the PV system by using a PSO algorithm is shown in Fig. 5.

The PSO algorithm is based on the evolution of a population of particles and there are two fitness values to guide the particles toward the best solutions, namely *pbest* (local) and *gbest* (global) [15]. The procedures of Fig. 5 are summarized as follows:

1. An initial guess of the decision parameters is made and an initial set of particles for the PSO algorithm is generated randomly.
2. A local weather data at the potential PV site is used to generate a time series of meteorological conditions with the period equal to the project lifetime. Those conditions are then used to determine the PV array power output. Based on the simulated load profile and PV power output, the SOC can be calculated in each time step.
3. The PSO algorithm is then used to optimize the system configuration. It iteratively searches for the optimal configuration (i.e. N_{PV}^* and N_{bat}^*) to minimize the ARCS as shown in (13). The sizing constraints which are associated with reliability indices as shown in (14) will be examined for each system configuration.
4. The optimal configuration is obtained either by reaching a maximum number of iterations of the PSO algorithm, or by satisfying the imposed constraints. Otherwise, the least cost configurations will be used to update the particles for the next Monte Carlo simulation. It should be noted that since there are only two decision variables in the problem, the PSO algorithm can search a near optimal solution during the very early iterations (e.g. less than 10 iterations).

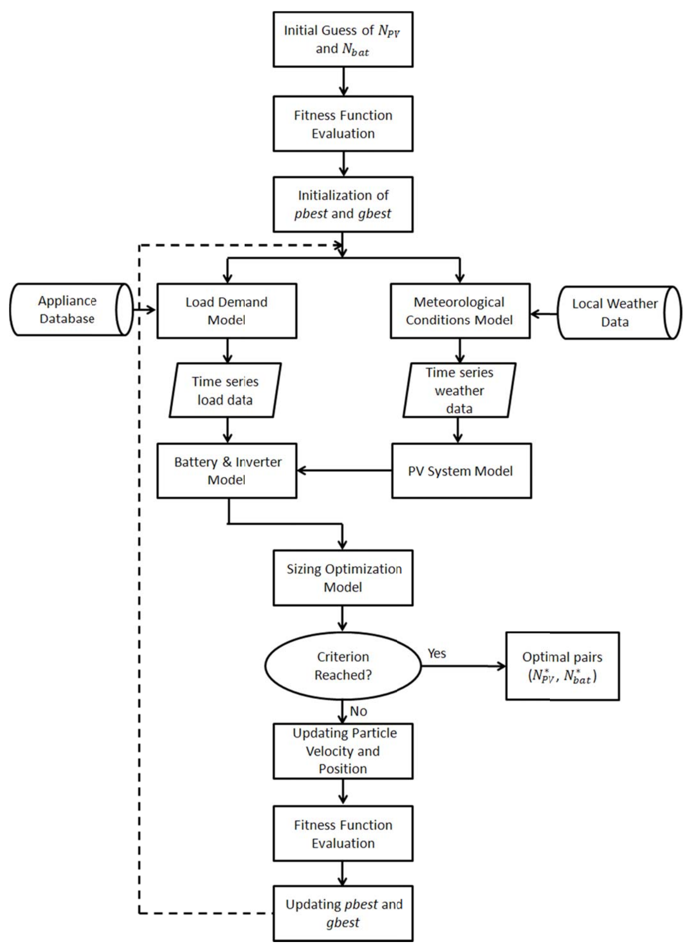

Fig. 5 Framework of optimal sizing by PSO

VII. Simulation and Results

To demonstrate the proposed sizing method, a case study was conducted using actual meteorological data obtained from a real stand-alone system installed in a remote island near Hong Kong. The meteorological conditions from 05/2010 to 04/2011 are used to derive the weather models. The technical parameters of the PV module and the battery bank are given in Tables III and IV, respectively. The expected household appliances are given in Table V. Based on the proposed load simulator, a sample of chronological load simulation is shown in Fig. 6. It can be seen that the peak load usually occur at night with peak power around 14kW. The average daily load consumption is about 61kWh.

TABLE III
SPECIFICATIONS OF PV MODULE

b_1	b_2	b_3	b_4	P_{PV}^{peak}(W)
4.73	-0.01	0.24	0.11	200

TABLE IV
SPECIFICATIONS OF BATTERY BANK

σ	η_{bat}	η_{inv}	E_{bat}(kWh)	$\underline{SOC}$	$\overline{SOC}$
0.20/day	0.90	0.97	10	0.20	0.95

TABLE V
ESTIMATED APPLIANCE DATABASE

ID	Appliance	Power (kW)	Quantity
1	Air conditioner	1.50	2
2	Water pump	4.00	1
3	Induction cooker	1.80	2
4	Lighting	0.50	4
5	Microwave oven	1.00	2
6	Refrigerator	0.20	1
7	Rice Cooker	0.50	1
8	Water Boiler	0.70	2
9	TV	0.07	2
10	PC	0.06	2

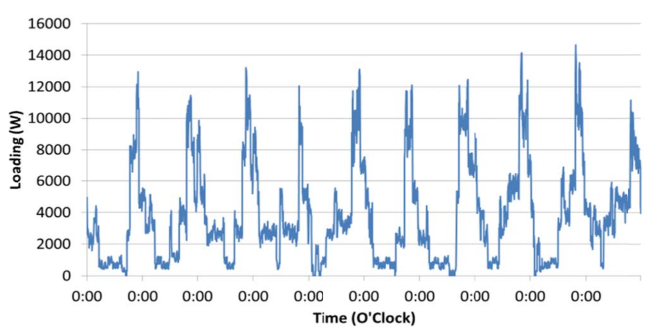

Fig. 6 Simulated load profile for case study

Table VI shows a typical initial capital cost, replacement cost, maintenance cost and lifetime of each component in the system based on generic cost reference [3]. The value of $VoLL$ and $VoEE$ are assumed to be \$32/kWh and \$12/kWh, respectively. There are several parameters involved in the PSO algorithm such as the number of particles m, weighting factors c_1 and c_2, the inertia factor ω and the maximum number of iterations g and their values are given in Table VII.

TABLE VI
COSTS AND LIFETIME OF SYSTEM COMPONENTS

	Initial capital cost	Replacement cost	Maintenance cost (/year)	Lifetime (year)
PV array	3000 US\$/kW	N/A	5 US\$/kW	20
Battery	100 US\$/kWh	500 US\$/kWh	50 US\$/kW	5

TABLE VII
PARAMETERS OF PSO ALGORITHM

m	c_1	c_2	ω	g
60	0.7	0.7	1.2	100

Based on the proposed sizing method, the optimal sizing results for $\overline{LOLP}$ achieving 1%, 2% and 5% are given in Table VIII, giving a minimum ACS of US\$65,441, US\$60,324 and US\$51,883, respectively.

A sensitively analysis is also conducted to provide an in-depth study on the sizing results by varying the number of PV modules given the fixed number of batteries (i.e. N_{bat} = 23) and the corresponding result is given in Table IX. The optimal system configuration based on 2% $\overline{LOLP}$ is given by bold letter in the table. From Table IX, it is observed that increasing the number of PV modules causes a conflicting result between the EENS and the EEES. On one hand, it is reasonable to observe that the EENS drop significantly with increasing number of PV modules. On the other hand, the EEES is also increasing with the number of PV modules.

TABLE VIII
OPTIMAL SIZING RESULTS OF DIFFERENT RISK LEVELS USING PSO ALGORITHM

Acceptable LOLP	N_{PV}^*	N_{bat}^*	ACS(US\$)
1%	125	26	65,441
2%	120	23	60,324
5%	112	18	51,883

TABLE IX
SENSITIVITY ANALYSIS OF VARYING NUMBER OF PV MODULES

	Number of PV modules				
	100	110	**120**	130	140
EENS/year (kWh)	2,557	1,142	**493**	235	122
EEES/year (kWh)	62	635	**1,992**	3,753	5667
ACS (US\$)	55,157	57,741	**60,324**	62,908	65,491
ARCS(US\$)	137,725	101,905	**100,004**	115,464	137,399

VIII. Conclusion

In this paper, we presented a sizing methodology which includes stochastic models of solar radiation and load patterns for a stand-alone PV system using a chronological Monte Carlo simulation method. A Markov chain method to synthesis a time series weather data was proposed which is essential to describe the intermittent solar power outputs. We also presented a stochastic load model to produce a more realistic consumption pattern for sizing studies. The optimal sizing objective was also developed such that reliability and system cost can be considered simultaneously. The proposed sizing framework was solved by a PSO algorithm. We finally applied the proposed framework to a case study to demonstrate the feasibility of the method.

IX. Acknowledgement

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