Electrical Power and Energy Systems 83 (2016) 514–524

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Optimal sizing of a grid independent hybrid renewable energy system incorporating resource uncertainty, and load uncertainty

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ARTICLE INFO

Article history:
Received 7 May 2015
Received in revised form 17 March 2016
Accepted 4 April 2016

Keywords:
Hybrid system
Optimal sizing
Uncertainty
Particle Swarm Optimization Algorithm-based Monte Carlo Simulation

ABSTRACT

Wind speed (WS) and solar radiation (SR) are innately uncertain and bring about more uncertainties in the power system. Therefore, due to the nonlinear nature of photovoltaic cells and wind turbines, the mean values of solar radiation and wind speed cannot be assuredly measured and a small change in these values alters the results of the study. Furthermore the mean values of WS and SR occur with a low degree of probability, that is, if the mean values one utilized in system design, it will mean that not all possible states have been considered. Therefore, in hybrid system analysis, it has been suggested that the degree of uncertainty be taken into calculation in order for all possibilities to be covered. For this purpose, the Monte Carlo Simulation Method and Particle Swarm Optimization Algorithm have been used in this article. The proposed methodology is applied to a real case study and the results are discussed. In this regard, an off-grid hybrid multisource system (photovoltaic–wind–battery) is considered, modeled, optimally sized, and compared of different seasons in terms of the total annual cost and uncertainty in WS, SR, and electricity demand.

Introduction

Being engaged with environmentally-friendly concerns obliges that the pollutants emitted to our surrounding world must be extremely lowered. The energy intensive sectors are of the highest amount of polluters. Accordingly, based on the European 2050 energy roadmap, the European Union and the G8 aim to reduce greenhouse gas emissions by at least 80% below 1990 levels by 2050 [1,2]. On this pathway, one solution is to utilize non-emission energy conversion technologies or at least low-emission ones, such as renewable energies, more frequently. It is aimed to produce 20% of the final energy consumption of the European Union from renewables by 2020 as an objective of 2020 projects [1]. In recent years, the investigation of off-grid hybrid systems based on renewable sources has attracted significant attention [3–16]. One of the most important factors in the hybrid systems, which leads to having a cost-effective system, is optimal sizing. In the literature, Shrestha and Goel [3] have presented a methodology for optimal sizing based on energy generation simulation. Diaf et al. [4] have optimized a hybrid system size based on the loss of power supply probability and the levelized cost of energy. Roy et al. [5] have proposed a methodology to incorporate wind speed (WS) uncertainty in sizing wind–battery system for isolated applications. The uncertainty associated with the WS is incorporated using chance constraint programming approach. Lujano-Rojas et al. [6] have presented a mathematical model for stochastic simulation and optimization of small wind energy systems. This model is able to consider the operation of the charge controller, the coulombic efficiency during charge and discharge processes, the influence of temperature on the battery bank capacity, the wind speed variability, and load uncertainty. Maheri [7] has optimized a standalone wind–PV–diesel hybrid system in a multi-objective optimization problem with conflicting objectives of cost and reliability. Uncertainties in renewable resources, demand load, and power modeling make deterministic methods of multi-objective optimization fall short in optimal design of stand-alone hybrid renewable energy systems. Ma et al. [8] have presented a detailed feasibility study and techno-economic evaluation of a stand-alone hybrid solar–wind system with battery energy storage for a remote island. Sharafi and ELMekkawy [10] have presented a novel approach for the optimal design of hybrid renewable energy

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http://dx.doi.org/10.1016/j.ijepes.2016.04.008
0142-0615/

Abbreviations

ACC	annual capital cost	PV	Photovoltaic
AMC	annual maintenance cost	SOC	State of Charge
CRF	capital recovery factor	SR	Solar radiation
DOD	maximum depth of discharge	SD	standard deviation
MCS	Monte-Carlo Simulation	TAC	total annual cost
PSO	Particle Swarm Optimization	WS	wind speed
PSOMCS	Particle Swarm Optimization Algorithm-based Monte Carlo Simulation	WT	wind turbine

systems including various generators and storage devices. Although various aspects of photovoltaic (PV)/wind/battery-based hybrid systems have been considered in the literature, an informative model and efficient optimization tool for optimal sizing is rarely found. Also, detailed inspection of the modeling, sizing and cost analysis of a PV/wind/battery hybrid system considering resource uncertainty and load uncertainty for electrification to a remote area is rarely found. However, high variability and uncertainty associated with renewable energy sources pose major challenges in designing isolated power systems. In order to overcome the diurnal and seasonal fluctuations of power supplied by renewable energy technologies, integration of an energy storage device becomes necessary. Many applications such as a remote telecommunication towers, hospitals, and commercial energy systems are required to abide by rigorous norms of power supply reliability, thus, making it obligatory to design the system by accounting for uncertainty associated with various design variables. A reliability-based technique will lead to higher customer satisfaction and eventually bring societal acceptability of renewable based technologies. A methodology for the designing of a stand-alone PV–wind–battery power system by considering the uncertainty in wind speed, solar radiation (SR), and electricity demand has been proposed in this paper. Therefore, it is suggested in the analysis of hybrid systems that the uncertainty is considered in order to check all possibilities. The Monte Carlo Simulation (MCS) method is used in this article. MCS is a simulation-based approach that uses random numbers and probability in order to solve the problems having uncertainties in their parameters. It is a method to iteratively solving a given problem using sets of random numbers as inputs. This method is often used when the model is complicated, nonlinear, or involves more than just a couple of uncertain parameters. Hence, Particle Swarm Optimization Algorithm-based Monte Carlo Simulation (PSOMCS) is the promise of algorithms that have a higher chance than the others of finding the optimal decision variables. The effectiveness of MCS has led to its application to optimization problems in different areas [17–24]. Different approaches have been developed for simulating the intelligent MCS [25–27]. In this paper, at first an informative mathematical model is introduced for each system component and then, Particle Swarm Optimization Algorithm-based Monte Carlo Simulation (PSOMCS) is proposed to optimally find the number of each component.

Unit sizing

The schematic drawing of a typical stand-alone (photovoltaic–wind–battery) hybrid system is shown in Fig. 1. Battery chargers connected to a DC/DC bus are used to charge the battery bank from the respective wind turbines and photovoltaic panels input power sources, wind turbines connected to an AC/DC and DC/DC bus, and photovoltaic panels connected to a DC/DC bus. With regard to design, the optimal sizing of a hybrid system is very important and leads to a good ratio between performance and cost. The difference between the power generated ($P_{\mathrm{Gen}}(t)$) and the demand of renewable energies ($P_{\mathrm{Dmd}}(t)$) according to Eq. (1) must be minimum.

$$\Delta P = P_{\mathrm{Gen}}(t) - P_{\mathrm{Dmd}} \tag{1}$$

Resource and load data

The hourly wind speed data and solar insolation data during a one-year period, which were collected in a remote area in Iran's southern (Rafsanjan) regions, are shown in Figs. 2 and 3, respectively [28], which has the following geographical coordinates: latitude = 30.29° (30°24′24″N) and longitude = 56.05° (55°59′38″E). The mean elevation of the city is about 1469 m above sea level. Average wind speed of 4.60 m/s, and a maximum wind speed of about 22.39 m/s at 10 m high. Total annual solar irradiance of 2239.56 kW h/m^2, and average ambient temperature of about 18.60 °C. The hourly load demand profile of ten typical residential buildings with the total annual electrical energy consumption of 34556.5 kW h located in Iran is shown in Fig. 4. For better observation, the seasonal profile is shown in Fig. 5.

Wind turbine (WT)

For a wind turbine (WT), if the wind speed exceeds the cut-in value, the wind turbine generator starts generating. If the wind speed exceeds the rated speed of the WT, it generates constant output power, and if the wind speed exceeds the cut-out value, the wind turbine generator stops running to protect the generator. The power of the WT is described in terms of the wind speed by Eq. (2) [29,30]. The specifications of a typical wind turbine used in the present work are shown in Table 1

$$P_{\mathrm{WT\text{-}Each}}(t) = \begin{cases} 0 & \text{if } \upsilon \leqslant V_i \\ a(\upsilon) - b(P_r) & \text{if } V_i < \upsilon < V_r \\ P_r & \text{if } V_r \leqslant \upsilon < V_o \\ 0 & \text{if } \upsilon \geqslant V_o \end{cases} \tag{2}$$

That the parameters a, and b calculated by Eq. (3).

$$\begin{cases} a = P_r/(V_r - V_i) \\ b = V_i/(V_r - V_i) \end{cases} \tag{3}$$

where $P_{\mathrm{WT\text{-}Each}}(t)$ is the power generated by each WT; υ is the wind speed; V_i, V_o, V_r, are cut-in, cut-out, rated, or nominal speed of the WT, respectively; and P_r is the wind turbine rated power.

Photovoltaic cells (PV)

The output power of each photovoltaic panel, with respect to the solar radiation power, can be calculated by Eq. (4) [30,31]. The characteristics of PV panels used in the present study are presented in Table 2

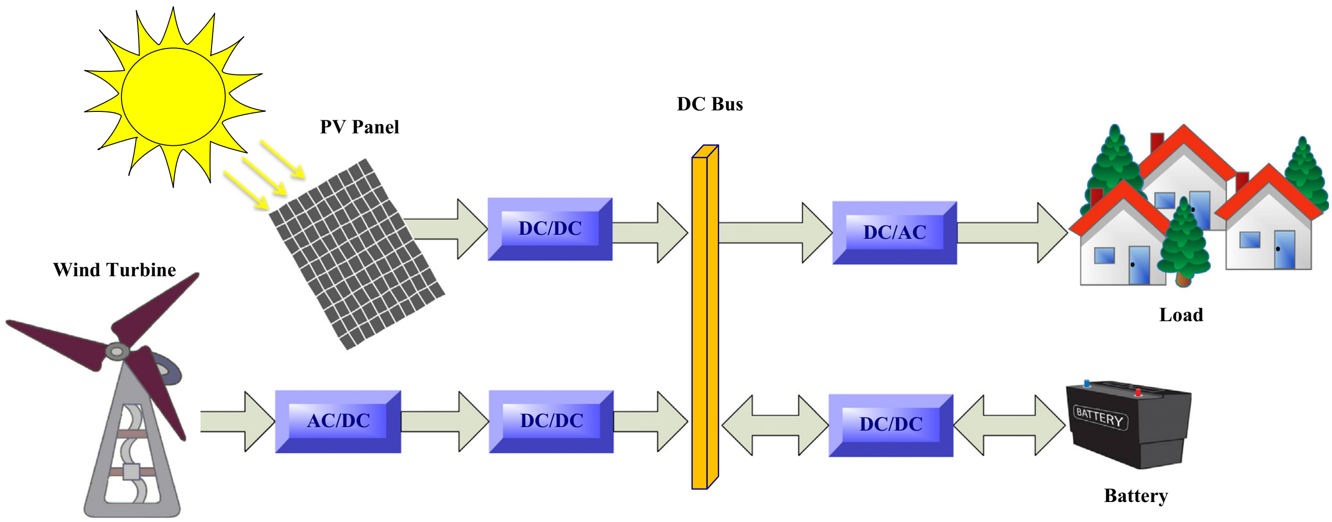

Fig. 1. Schematic of the PV/WT/battery-based hybrid system.

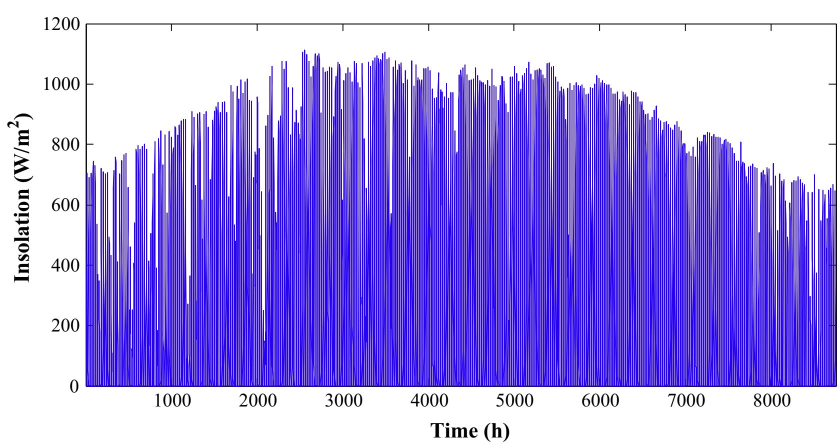

Fig. 2. Hourly profile of insolation during a year.

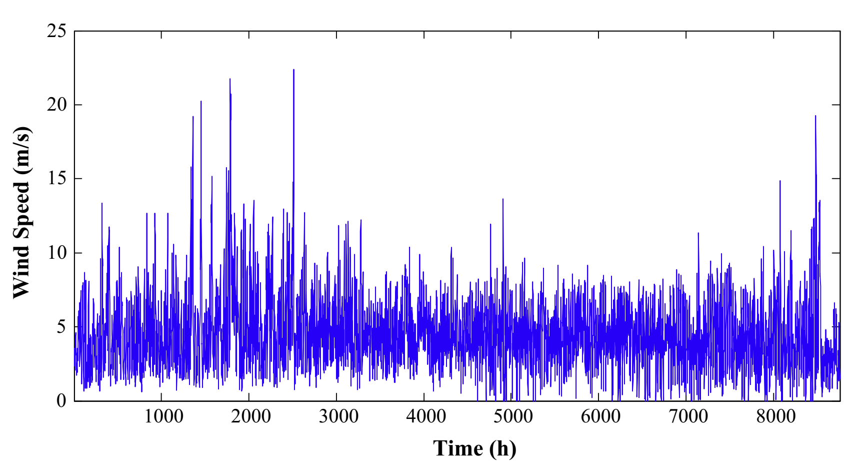

Fig. 3. Hourly wind speed during a year (at height of 10 m).

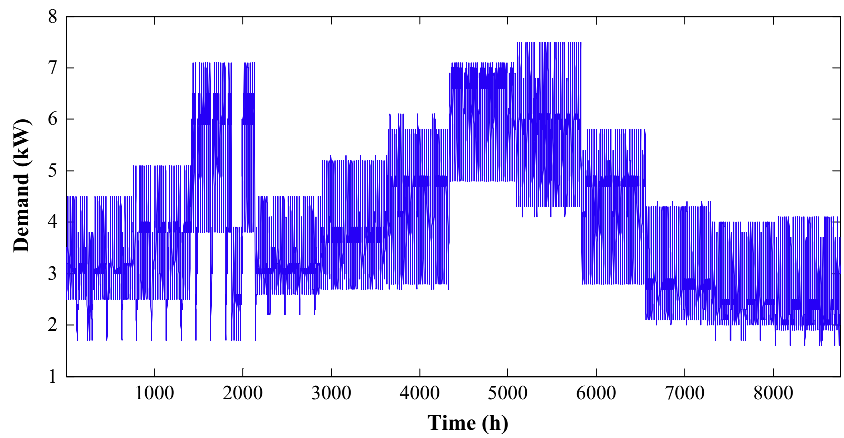

Fig. 4. Hourly load demand during a year.

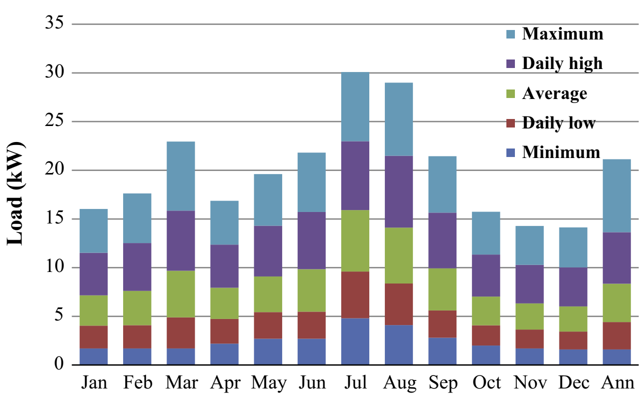

Fig. 5. The seasonal profile of the considered load.

Table 1
Wind turbine parameters.

P_r	V_i	V_o	V_r	T_p	T_{if}	$C_{\text{Main-WT}}$	Life span
1 kW	3 m/s	20 m/s	9 m/s	\$1443	$0.25 \times T_p$	100 \$/year	20 years

Table 2
PV panel parameters.

P_{rs}	P_p	P_{if}	$C_{\text{Main-PV}}$	Life span
260 W	\$312	$0.5 \times P_p$	20 \$/year	20 years

$$P_{\text{PV-Each}}(t) = \begin{cases} c \cdot P_{rs} & \text{if } 0 \leqslant r < R_{\text{CR}} \\ d \cdot P_{rs} & \text{if } R_{\text{CR}} \leqslant r < R_{\text{SRS}} \\ P_{rs} & \text{if } R_{\text{SRS}} \leqslant r \end{cases} \tag{4}$$

That the parameters c, and d calculated by Eq. (5).

$$\begin{cases} c = r^2/R_{\text{SRS}} \cdot R_{\text{CR}} \\ d = r/R_{\text{SRS}} \end{cases} \tag{5}$$

where $P_{\text{PV-Each}}(t)$ is the power generated by each PV panel, P_{rs} is the PV rated power, r is the solar radiation factor, R_{CR} is a certain radiation point set usually as 150 (W/m^2), and R_{SRS} is the solar radiation in the standard environment set usually as 1000 (W/m^2).

Battery

Battery discharging or charging of the input power can be negative or positive. State of Charge (SOC) battery, according to the calculations of productivity and time consumption, is obtained thus:

If $P_{\text{PV}}(t) + P_{\text{WT}}(t) = P_{\text{Dmd}}(t)$, then the battery capacity will not change. When the total output power of the photovoltaic panels and wind turbines is more than the load power, $P_{\text{PV}}(t) + P_{\text{WT}}(t) > P_{\text{Dmd}}(t)$ than the load power, the battery bank is in charging state, and the charged amount of the battery at time (t) is expressed by Eq. (6) [30,32].

$$\text{SOC}(t) = \text{SOC}(t-1) \times (1-\sigma) + \left[(P_{\text{WT}}(t) + P_{\text{PV}}(t)) - \frac{P_L(t)}{\eta_{Inv}} \right] \times \eta_{BC} \tag{6}$$

In this equation, SOC(t) and SOC$(t-1)$ are the charge quantities of battery bank at time t, and $t-1$, σ is the hourly self-discharge rate, $P_{\text{PV}}(t)$ is the power generated by the photovoltaic panels, $P_{\text{WT}}(t)$ is the power generated by the wind turbines, η_{Inv} is the efficiency of the inverter, $P_L(t)$ is the energy demand for the particular hour, and η_{BC} is the charge efficiency of battery bank.

When $P_{\text{PV}}(t) + P_{\text{WT}}(t) < P_{\text{Dmd}}(t)$, the total output powers of the photovoltaic panels and wind turbines are less than the load power, the battery is in the state of discharge, and the charged quantity of the battery at time (t) is expressed by Eq. (7) [30,32]. The battery bank with the nominal capacity is only allowed to be discharged to a limited extent.

$$\begin{aligned} \text{SOC}(t) &= \text{SOC}(t-1) \times (1-\sigma) \\ &\quad + \left[\frac{P_L(t)}{\eta_{Inv}} - (P_{\text{WT}}(t) + P_{\text{PV}}(t)) \right] \Big/ \eta_{BF} \times \eta_{Inv} \end{aligned} \tag{7}$$

where η_{BF} is the discharging efficiency of battery bank. The profile battery banks used are shown in Table 3.

Table 3
Component parameters.

S_{Batt}	η_{BC}	η_{BF}	P_{Batt}	Life span	DOD	σ	Voltage
Battery							
2.1 kWh	85%	100 %	\$170	5 years	0.8	0.0002	12 V
Rated power		η_{Inv}		Voltage	P_{Inv}		Life span
Inverter							
2000 W		95%		24 V	\$751.24		10 years

Formulation of the optimum design problem

Objective function

In this section, the objective function of the optimum design problem is the minimization of the total annual cost (TAC). The TAC consists of the annual capital cost (ACC) and the annual maintenance cost (AMC). To optimally design the hybrid generation system, the optimization problem defined by Eq. (8), should be solved using an optimization method,

$$\text{Minimize} \quad \text{TAC} = \text{ACC} + \text{AMC} \tag{8}$$

Capital cost occurs at the beginning of a project while maintenance cost occurs during the project life.

In order to convert the initial capital cost (P) to the annual capital cost (A), capital recovery factor (CRF), defined by Eq. (9), is used [30].

$$\text{CRF} = \frac{A}{P} = \frac{j(1+j)^n}{(1+j)^n - 1} \tag{9}$$

In this equation, j is the interest rate and n denotes the life span of the system; in this paper $n = 20$ years and j is set at 6%.

Some components of PV/WT/battery system need to be replaced several times over the project's lifetime. In this paper, the lifetime of battery is assumed to be 5 years. By using the single payment present worth factor, we have

$$C_{\text{Batt}} = P_{\text{Batt}} \times \sum_{k=0,5,10,15} \frac{1}{(1+j)^k} \tag{10}$$

where C_{Batt} is the present worth of battery, and P_{Batt} is the battery price.

In the same way, the lifetime of converter/inverter is assumed to be 10 years. By using the single payment present worth factor, we have

$$C_{\text{Conv/Inv}} = P_{\text{Conv/Inv}} \times \sum_{k=0,10} \frac{1}{(1+j)^k} \tag{11}$$

where $C_{\text{Conv/Inv}}$ is the present worth of converter/inverter components, and $P_{\text{Conv/Inv}}$ is the converter/inverter price.

By breaking up the capital cost into the annual costs of the wind turbine, photovoltaic panels, converter/inverter, battery, and backup generator, Eq. (12) is obtained.

$$\begin{aligned} \text{ACC} = \text{CRF} \\ \times \left[N_{\text{WT}} \times C_{\text{WT}} + N_{\text{PV}} \times C_{\text{PV}} + N_{\text{Batt}} \times C_{\text{Batt}} + N_{\text{Conv/Inv}} \times C_{\text{Conv/Inv}}\right] \end{aligned} \tag{12}$$

In this equation, N_{WT} is the number of wind turbines; C_{WT} is the unit cost of wind turbine, which is defined as the sum of turbine price (T_p) and turbine installation fee (T_{if}); NPV is the number of photovoltaic panels; C_{PV} is the unit cost of photovoltaic panels, which is defined as the sum of panel price (P_p) and panel installation fee (P_{if}); N_{Batt} is the number of batteries; and $N_{\text{Conv/Inv}}$ is the number of converter/inverter systems.

For the annual maintenance cost, Eq. (13) is obtained.

$$\text{AMC} = C_{\text{Main-WT}} \times N_{\text{WT}} + C_{\text{Main-PV}} \times N_{\text{PV}} \tag{13}$$

In this equation, $C_{\text{Main-WT}}$ is the wind turbine maintenance cost and $C_{\text{Main-PV}}$ is the PV panel maintenance cost. The maintenance costs of inverter and battery bank are ignored.

Constraints

The ultimate of the optimization of the hybrid PV/WT/battery system is the minimization of the system total cost (TAC) subject to some restriction. Therefore, the restriction is defined by:

$$0 \leqslant N_{\text{PV}} \leqslant N_{\text{PV-max}} \tag{14}$$

$$0 \leqslant N_{\text{WT}} \leqslant N_{\text{WT-max}} \tag{15}$$

$$0 \leqslant N_{\text{Batt}} \leqslant N_{\text{Batt-max}} \tag{16}$$

In this problem, three decision variables of N_{PV}, N_{WT}, and N_{Batt} should be optimally adjusted where N_{PV}, N_{WT}, and N_{Batt} are integer decision variables, $N_{\text{PV-max}}$, $N_{\text{WT-max}}$, and $N_{\text{Batt-max}}$ are the maximum available number of PV panels, wind turbines, and batteries, respectively.

At any time, the charge quantity of battery bank should satisfy the constraint of $\text{SOC}(t_{\min}) \leqslant \text{SOC}(t) \leqslant \text{SOC}(t_{\max})$

$$\text{SOC}(t_{\min}) = (1 - \text{DOD}) \times S_{\text{Batt}} \tag{17}$$

where $\text{SOC}(t_{\min})$ is the minimum charge quantity of the battery bank, $\text{SOC}(t_{\max})$ is the maximum charge quantity of battery bank, DOD is the obtained by maximum depth of discharge battery bank, and S_{Batt} is the value of nominal capacity of battery bank.

Methodology

Monte Carlo Simulation (MCS) method

Monte-Carlo Simulation (MCS) or Monte-Carlo method provides approximate solutions to quantitative problems by performing statistical sampling experiments [33]. Equations become harder to define when interactions between elements grow more intricate. In this case, a number of random configurations can be utilized to generate data and sample to represent the system as a whole. MCS, by specifying inputs as probability distribution, succeeds at explicitly depicting uncertainties [22,34]. More details about this method can be found in [33,34]. The MCS presented in the study mainly consists of ways to generate stochastic profiles. MCS can be summarized as follows:

1. Create a parametric model.
2. Generate a set of random input using their probability density function.
3. Evaluate the model using the generated input data.
4. Repeat steps 2 and 3.
5. Analyze the result.

Particle Swarm Optimization Algorithm (PSO)

Particle Swarm Optimization (PSO) originally invented by Kennedy and Eberhart in 1995 [35], is a population-based metaheuristic algorithm attempting to discover the global solution to an optimization problem by simulating the animals' social behavior such as fish schooling and bird flocking. In PSO algorithm, each feasible solution of the problem is called a particle which is specified by a vector containing the problem variables. Particles have memory, and thus retain part of their previous state. There is no restriction for particles to share the same point in belief space but their individuality is protected. Each particle's movement is the composition of two randomly weighted influences and an initial random velocity: sociality, the tendency to move towards the neighborhood's best previous position and individuality, the tendency to return to the particle's best previous location.

The standard PSO algorithm utilizes a real-valued multidimensional space as belief space, and evolves. The particles fly through the n dimensional domain space of the function to be optimized (in this paper, minimization is assumed). The state of each particle is represented by its position $X_i = (X_{i1}, X_{i2}, \ldots, X_{in})$ and velocity $V_i = (V_{i1}, V_{i2}, \ldots, V_{in})$. The states of the particles are updated. The three key parameters to particle swarm optimization algorithm are in the velocity update equation. First is the momentum component, which is the cognitive component. Here the acceleration constant c_1 controls how much the particle heads toward its personal best position. The second component is the inertial constant w, which controls how much the particle remembers its previous velocity [36]. The third component, referred to as the social component, draws the particle toward swarm's best ever position; the acceleration constant c_2 controls this tendency. At the beginning of the algorithm, a group of particles is randomly initialized in the search space. Each particle makes use of its memory and flies through the search space for obtaining a better position than its current one. In its memory a particle memorizes the best experience found by itself (p_{best}) as well as the group's best experience (g_{best}) [35,36]. The position of each particle in that space is achieved using the following equations:

$$v_{id}^{k+1} = w^k . v_{id}^k + c_1 . r_1^k . \left(p_{best_{id}}^k - x_i^k\right) + c_2 \cdot r_2^k \cdot \left(g_{best_d}^k - x_{id}^k\right) \quad (18)$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \quad (19)$$

where v_{id}^k is the component in dimension d of the ith particle velocity in iteration k, x_{id}^k is the component in dimension d of the ith particle position in iteration k, c_1 and c_2 are constant weight factors, $p_{best_{id}}^k$ is the best position achieved so far by particle i at its "k" times and the d-dimension quantity of its position, $g_{best_d}^k$ is the d-dimension quantity of the swarm at its most optimal position, r_1 and r_2 are random factors in the interval between 0 and 1, and w is known as inertia weight, which is starts from a positive initial value (w_0) and decreases during the iterations by $w^{k+1} = \beta \times w^k$.

Particle Swarm Optimization Algorithm-based Monte Carlo Simulation (PSOMCS)

The procedure of PSOMCS is described in steps 1–4:

1. Compute mean value and standard deviation (SD) value for WS, SR, and load data.
2. Generate randomly many arrays based on mean value and SD value.
3. Run the optimization algorithm (PSO) for any arrays that were already generated
   3.1. A population is randomly generated in the search space.
   3.2. The initial velocity of each particle is randomly generated.
   3.3. Objective function value for each particle is calculated.
   3.4. The initial position of each particle is selected as its p_{best}, and the best particle among the population is chosen as g_{best}.
   3.5. Particles move to new positions based on Eqs. (18) and (19).
   3.6. If a particle exceeds the allowed range, it is replaced by its previous position.
   3.7. Objective function value for each particle is calculated.
   3.8. p_{best} and g_{best} are updated.
   3.9. The stopping criterion is checked. If it is satisfied, the algorithm is terminated and g_{best} is selected as the optimal solution. Otherwise, Steps 3.5–3.8 are repeated.
4. Compute mean value and SD of optimization algorithm's results.

The flowchart of PSOMCS algorithm is shown in Fig. 6.

Results and cost analysis

The experimental data used here for wind speed and solar insolation are obtained from Rafsanjan located in the south of Iran. In Tables 1–3, economic and technical data used in the system is shown in dollar. Profile load of a 8760-h prototype, the model of which is shown in Fig. 4. MATLAB environment is used to implement and code the proposed methodology. To calculate the accuracy of results, thousand independent runs are performed and the results are reported. The parameter setting of PSOMCS is as follows:

$$N_p = 50; \quad c_1 = 2; \quad c_2 = 2, \quad \beta = 0.99; \quad w_0 = 1; \quad iter_{\max} = 200.$$

where N_p is the size of population (number of particles), c_1 is the personal learning coefficient, c_2 is the global learning coefficient, β is inertia weight damping ratio, w_0 is inertia weight, and itermax is maximum number of iterations.

The algorithms attempt to find the optimum number of PV panels, wind turbines, and batteries (NBatt) in PV/WT/battery system. The minimum and maximum numbers of each component are set to 0 and 4000, respectively. At initial moment, it is assumed that the charge of each battery is 30% of its nominal capacity.

The optimum results of PSOMCS in the south of Iran have been achieved individually. For this region, the results of the hybrid systems, photovoltaic systems, and wind turbines are individually investigated and shown in Tables 4–8. In these tables, the mean (Mean), standard deviation (SD), minimum (Min) and maximum (Max) indexes of each hybrid system for each case are given.

Table 4 summarizes the results of optimum sizing for the PV/WT/battery system for the first month (January). In this table, the optimum sizes of PV/battery and WT/battery systems have also been indicated. This table shows the mean numbers of the batteries as 59, 1148, and 60 for hybrid, PV/battery, and WT/battery systems respectively. It is seen that from economical point of view, the WT/battery system is a better choice since its mean total annual cost is $17183.11 which is lower than that of the other hybrid systems (PV/WT/battery and PV/battery). Fig. 7 shows the number of WT and battery of the WT/battery-based hybrid system for the first month (January); it can be concluded that the number of WT and battery is very different in various situations and one of the most effective components of hybrid systems.

Tables 5–7 show the optimal number of each component and the system costs in detail for the hybrid systems for the fourth, seventh and tenth month (April, July and October). The optimal sizes of the systems are as follows:

April: PV/wind/battery $N_{PV} = 0$, $N_{Wind} = 34$, $N_{Batt} = 103$; PV/battery: $N_{PV} = 239$, $N_{Batt} = 1166$; wind/battery $N_{Wind} = 33$, $N_{Batt} = 100$; July: PV/wind/battery $N_{PV} = 46$, $N_{Wind} = 108$, $N_{Batt} = 239$; PV/battery: $N_{PV} = 219$, $N_{Batt} = 1871$; wind/battery $N_{Wind} = 104$, $N_{Batt} = 224$; and October: PV/wind/battery $N_{PV} = 0$, $N_{Wind} = 60$, $N_{Batt} = 166$; PV/battery: $N_{PV} = 263$, $N_{Batt} = 1115$; wind/battery $N_{Wind} = 45$, $N_{Batt} = 44$. It is seen that economically speaking, the WT/battery systems for the fourth, seventh and tenth month are a better choice since their mean total annual cost is $13137.71, $36407.42, and $13964.8, respectively, which are lower than those of the other hybrid systems (PV/WT/battery and PV/battery). The systems introduced to the listed area can ensure the required load with high reliability and proper cost. Weather conditions and system component prices are also important factors to be considered in the selected hybrid systems.

Figs. 8–10 show the number of WT and battery of the WT/battery-based hybrid system for the different months (April, July and October); it also shows the maximum and minimum number of WT and battery of the hybrid system for three months

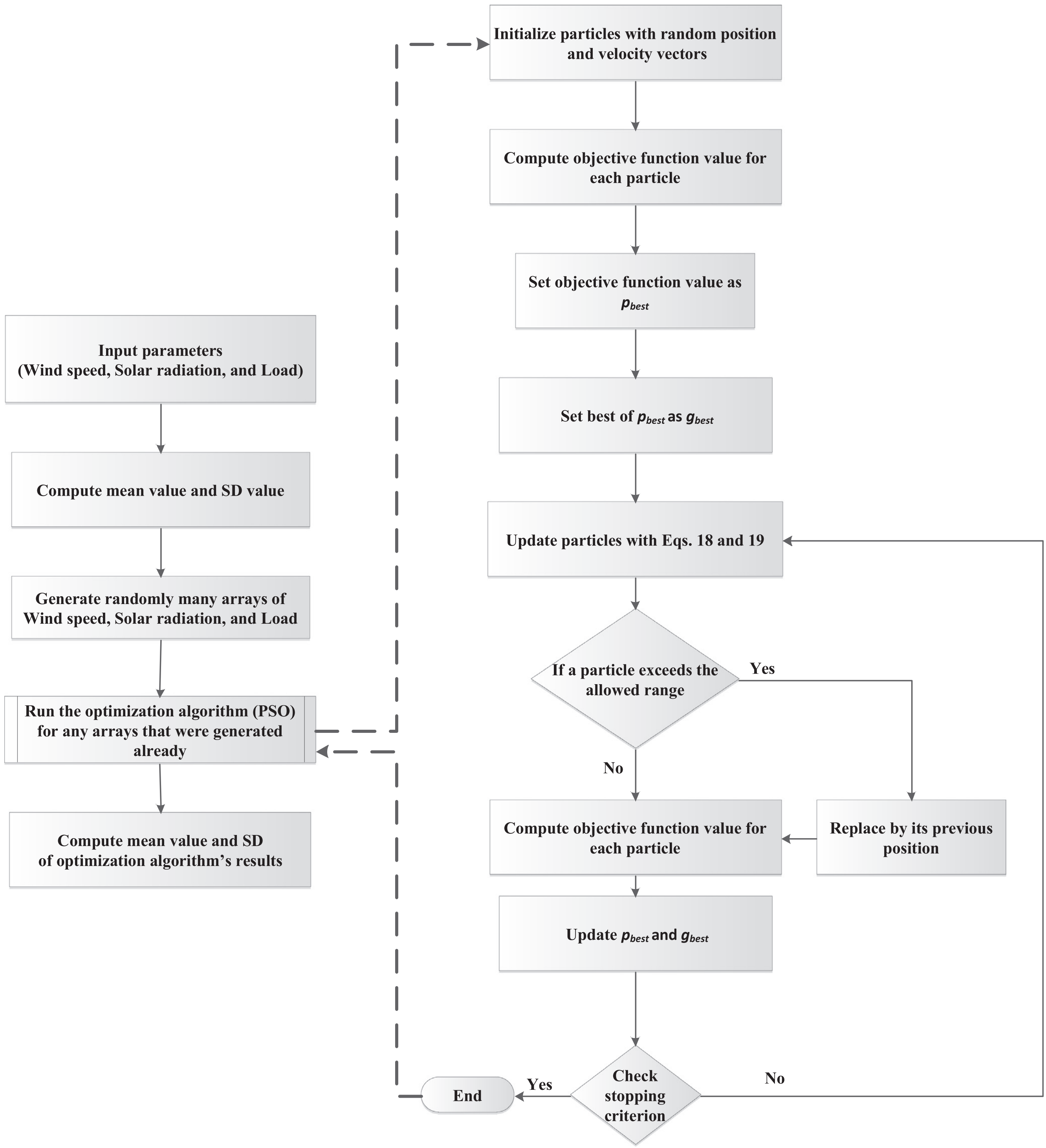

Fig. 6. Flowchart of PSOMCS algorithm.

as well as the mean line number of WT and battery of the hybrid system (red[1] line).

Table 8 reveals that for the site under study and the time period considered (12 months), the hybrid WT/battery system is the best configuration to use, needing minimum storage capacity. On the other hand, regarding the unpredictable nature of wind energy resources, the hybrid system would certainly reduce the probability of having no wind generation and would make the system more reliable. Hence, this type of configuration is recommended for the present case study in Rafsanjan. When a hybrid system is used to supply the load demand, the mean optimum sizing is $N_{Wind} = 54$, and $N_{Batt} = 85$. As Table 8 shows, the minimum, maximum, and mean total annual cost is \$9001.15, \$79472.67, and \$17934.79, respectively for Rafsanjan. This higher storage need is due to the low efficiency of the PV/battery system compared to the hybrid and WT/battery system. In this case, the mean numbers

[1] **For interpretation of color in Figs. 8–10, the reader is referred to the web version of this article.**

Table 4
Summary of the results for the hybrid systems obtained by PSOMCS algorithm for the first month (January).

Hybrid systems	Index	N_{PV}	N_{WT}	N_{Batt}	PV cost ($)	WT cost ($)	Battery cost ($)	Total cost ($)
PV/WT/battery	Mean	0	55	59	0	14149.25	2381.09	17244.82
	Min	0	32	21	0	8232.29	847.51	9794.28
	Max	0	105	199	0	27012.21	8031.12	35757.82
	SD	0	11.65	50.45	N/A	N/A	N/A	N/A
PV/battery	Mean	248	N/A	1148	15078.99	N/A	46330.28	61919.62
	Min	16	N/A	729	972.84	N/A	29420.53	30903.72
	Max	1066	N/A	1512	64815.33	N/A	61020.37	126346.05
	SD	213.52	N/A	325.93	N/A	N/A	N/A	N/A
WT/battery	Mean	N/A	55	60	N/A	14149.25	2421.44	17183.11
	Min	N/A	32	13	N/A	8232.29	524.65	9369.36
	Max	N/A	123	198	N/A	31642.87	7990.76	40246.05
	SD	N/A	11.33	52.61	N/A	N/A	N/A	N/A

Table 5
Summary of the results for the hybrid systems obtained by PSOMCS algorithm for the fourth month (April).

Hybrid systems	Index	N_{PV}	N_{WT}	N_{Batt}	PV cost ($)	WT cost ($)	Battery cost ($)	Total cost ($)
PV/WT/battery	Mean	0	34	103	0	8746.81	4156.81	13618.11
	Min	0	27	14	0	6946	565	8225.49
	Max	398	176	2051	24199.34	45277.61	82773	152964.44
	SD	12.59	9.81	96.4	N/A	N/A	N/A	N/A
PV/battery	Mean	239	N/A	1166	14531.77	N/A	47056.71	62098.83
	Min	16	N/A	788	972.84	N/A	31801.62	33284.81
	Max	528	N/A	2071	32103.65	N/A	83580.15	116194.15
	SD	213.52	N/A	325.93	N/A	N/A	N/A	N/A
WT/battery	Mean	N/A	33	100	N/A	8489.55	4035.74	13137.71
	Min	N/A	25	13	N/A	6431.48	524.65	7568.54
	Max	N/A	77	200	N/A	19808.95	8071.48	28492.85
	SD	N/A	6.07	61.24	N/A	N/A	N/A	N/A

Table 6
Summary of the results for the hybrid systems obtained by PSOMCS algorithm for the seventh month (July).

Hybrid systems	Index	N_{PV}	N_{WT}	N_{Batt}	PV cost ($)	WT cost ($)	Battery cost ($)	Total cost ($)
PV/WT/battery	Mean	46	108	239	2796.91	27783.99	9645.42	40940.8
	Min	0	54	38	0	13891.99	1533.58	16140.06
	Max	1624	11	2972	98743.05	2829.85	119942.16	222229.55
	SD	186.62	44.06	42.86	N/A	N/A	N/A	N/A
PV/battery	Mean	219	N/A	1871	13315.72	N/A	75508.67	89334.74
	Min	27	N/A	1540	1641.66	N/A	62150.38	64302.39
	Max	649	N/A	2602	39460.74	N/A	105009.92	144981.01
	SD	180.08	N/A	281.94	N/A	N/A	N/A	N/A
WT/battery	Mean	N/A	104	224	N/A	26754.95	9040.05	36407.42
	Min	N/A	60	17	N/A	15435.55	686.08	16734.04
	Max	N/A	32	2633	N/A	8232.29	106261	115105.71
	SD	N/A	34.73	303.61	N/A	N/A	N/A	N/A

Table 7
Summary of the results for the hybrid systems obtained by PSOMCS algorithm for the tenth month (October).

Hybrid systems	Index	N_{PV}	N_{WT}	N_{Batt}	PV cost ($)	WT cost ($)	Battery cost ($)	Total cost ($)
PV/WT/battery	Mean	0	60	166	0	15435.55	6699.33	22849.36
	Min	0	23	19	0	5916.96	766.79	7398.24
	Max	29	258	1109	1763.27	66372.86	44756.34	113606.96
	SD	0.91	12.29	49.95	N/A	N/A	N/A	N/A
PV/battery	Mean	263	N/A	1115	15991.02	N/A	44998.49	61499.86
	Min	21	N/A	741	1276.85	N/A	29904.82	31692.02
	Max	415	N/A	2196	25232.98	N/A	88624.82	114368.16
	SD	221.83	N/A	324.75	N/A	N/A	N/A	N/A
WT/battery	Mean	N/A	45	44	N/A	11576.66	1775.73	13964.8
	Min	N/A	25	16	N/A	6431.48	645.72	7689.61
	Max	N/A	195	348	N/A	50165.53	14044.37	64822.32
	SD	N/A	12.6	36.31	N/A	N/A	N/A	N/A

Table 8
Summary of the results for the hybrid systems obtained by PSOMCS algorithm for the whole year.

Hybrid systems	Index	N_{PV}	N_{WT}	N_{Batt}	PV cost ($)	WT cost ($)	Battery cost ($)	Total cost ($)
PV/WT/battery	Mean	0	55	81	0	14149.25	3268.95	18132.69
	Min	0	31	21	0	7975.03	847.51	9537.02
	Max	0	139	200	0	35759.02	8071.48	44544.98
	SD	0	11.99	62.16	N/A	N/A	N/A	N/A
PV/battery	Mean	263	N/A	1338	15991.02	N/A	53998.19	70499.56
	Min	20	N/A	859	1216.05	N/A	34666	36393.39
	Max	1472	N/A	1115	89501.09	N/A	44998.49	135009.93
	SD	220.31	N/A	315.64	N/A	N/A	N/A	N/A
WT/battery	Mean	N/A	54	85	N/A	13891.99	3430.38	17934.79
	Min	N/A	29	23	N/A	7460.52	928.22	9001.15
	Max	N/A	163	915	N/A	41933.24	36927.01	79472.67
	SD	N/A	13.07	76.56	N/A	N/A	N/A	N/A

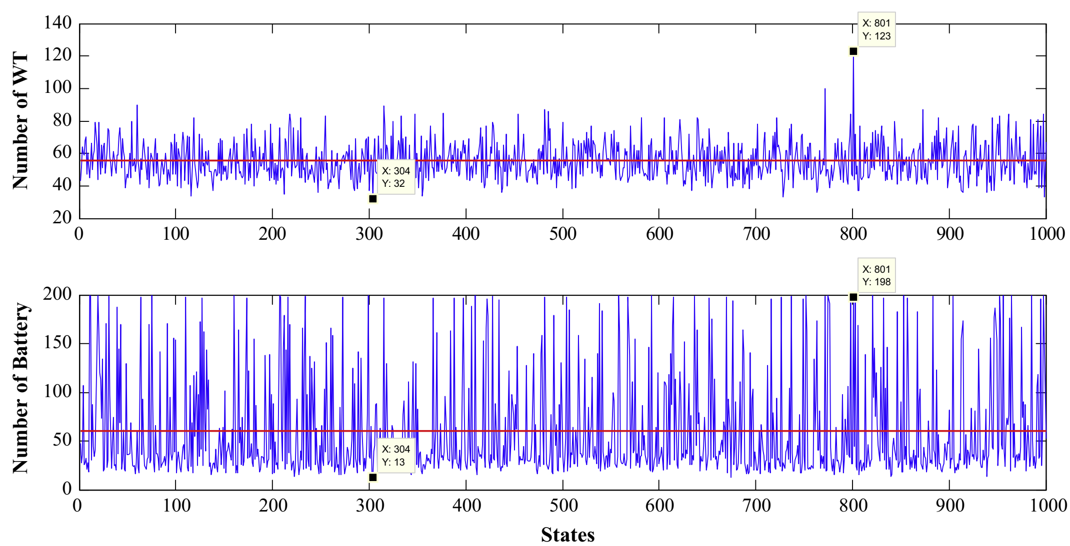

Fig. 7. The number of WT and battery of the WT/battery-based hybrid system for the first month (January).

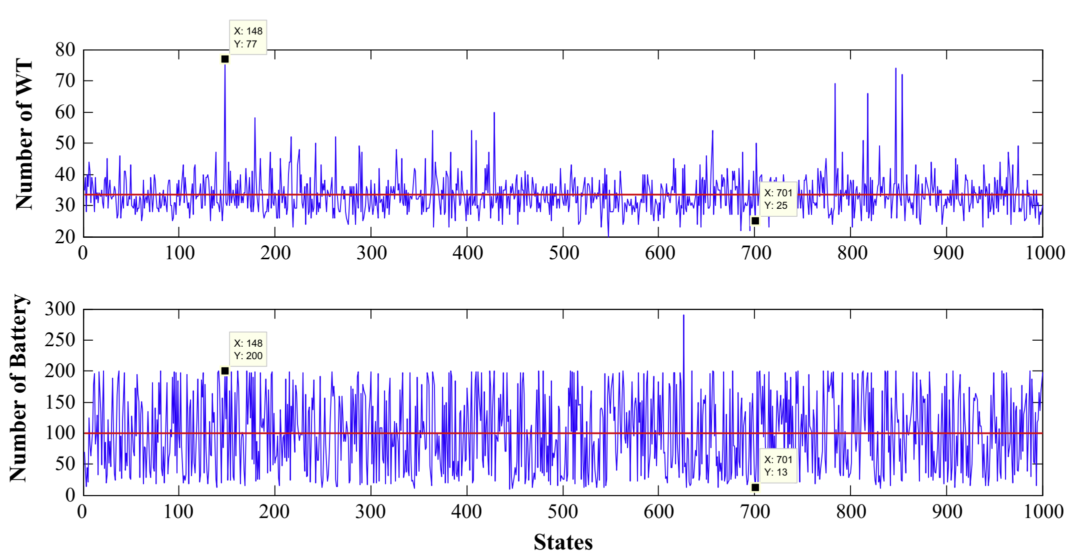

Fig. 8. The number of WT and battery of the WT/battery-based hybrid system for the fourth month (April).

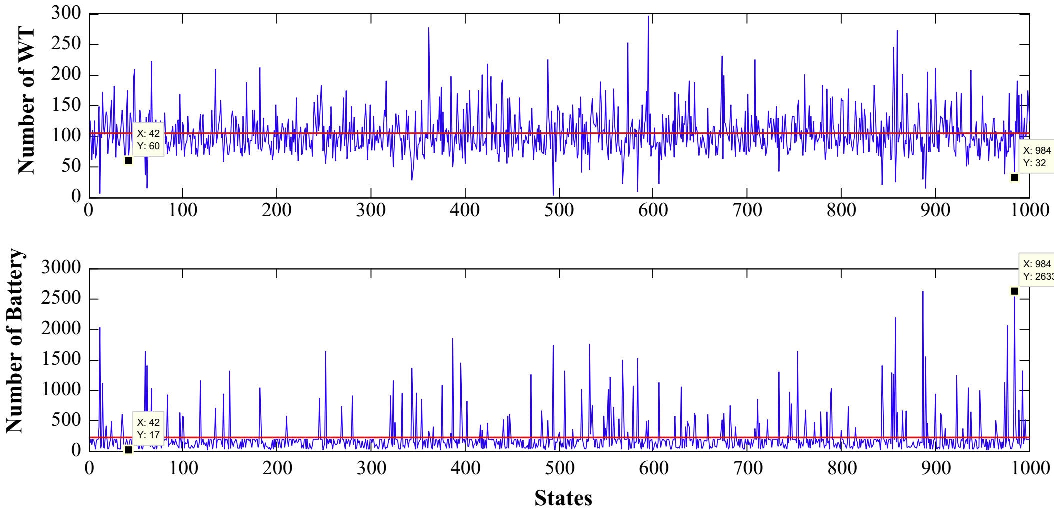

Fig. 9. The number of WT and battery of the WT/battery-based hybrid system for the seventh month (July).

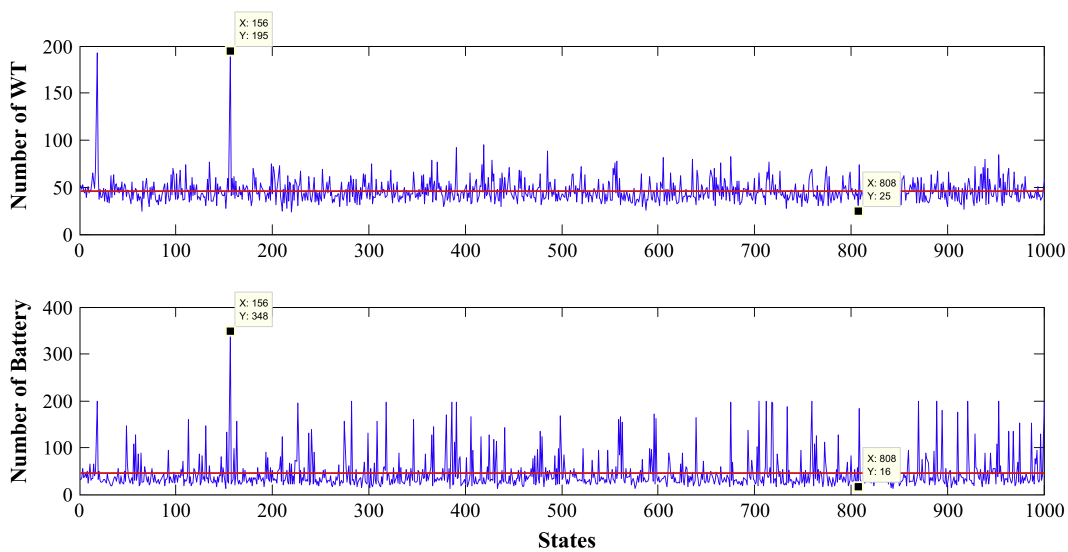

Fig. 10. The number of WT and battery of the WT/battery-based hybrid system for the tenth month (October).

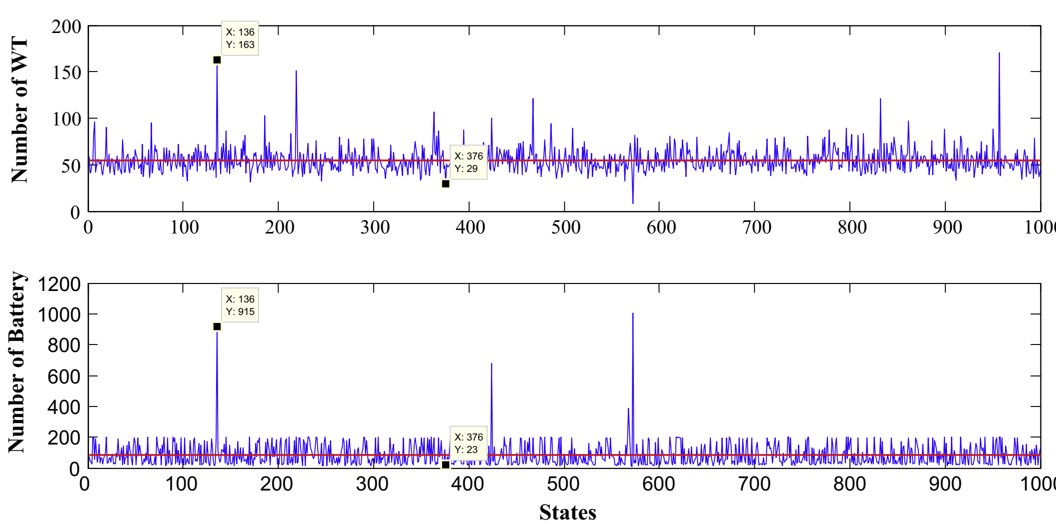

Fig. 11. The number of WT and battery of the WT/battery-based hybrid system during a year.

of the batteries are 81, 1338, and 85 for hybrid, PV/battery, and WT/battery systems, respectively Fig. 11 shows the number of WT and battery of the WT/battery-based hybrid system during a year.

Conclusion

This paper presents the modeling and optimization of a PV/WT/battery-based hybrid system for electrification to an off-grid remote area located in Rafsanjan, Iran by Particle Swarm Optimization Algorithm-based Monte Carlo Method. Monte Carlo Simulation generates stochastic demand and supply profiles, including normal load profiles at households, solar PVs' generation profiles, and micro wind-turbine generation profiles. The results of the present study prove that the Monte Carlo Simulation Method can provide a novel approach to the tools already present in the field of optimization. For the case study, it is found that using WT/battery is the most cost-effective system for different months (January, April, July, and October) and the whole year.

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