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Research article

Using firefly algorithm to optimally size a hybrid renewable energy system constrained by battery degradation and considering uncertainties of power sources and loads

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ABSTRACT

In this paper, the planning of a hybrid system of wind turbine units, photovoltaic panels, and battery storage is presented by taking into account the limitation of the storage degradation. The scheme minimizes the construction and maintenance cost of power sources and storage equipment. The constraints of the problem include the operating model of the mentioned elements, the limitation of the number of the mentioned elements, the limitation of the storage degradation, and the power balance in the hybrid system. This scheme is subject to uncertainties of the demand and output power generation of wind turbines and photovoltaics, which are modeled using a scenario-based stochastic optimization. The problem has a mixed-integer non-linear structure, and the paper adopts the firefly algorithm to solve the problem. The contributions of the paper include considering the degradation model of the battery, presenting a stochastic modelling for planning the islanded system, and taking into account the uncertainties of load and renewable power. Finally, based on the numerical results, a low planning cost is obtained for the hybrid system in the case of using renewable resources. Batteries are capable of providing flexibility for the hybrid system so that they can cover oscillations of renewable power with respect to the load. The firefly algorithm can find a reliable optimal solution. Stochastic modeling raises the planning cost of the islanded system in comparison to the deterministic model, but it yields a more reliable solution. The battery degradation model incurs no additional costs in system planning, although it offers a far more precise representation of the battery's behavior.

1. Introduction

1.1. Motivation

According to the European Energy Roadmap for 2050, the European Union (EU) in cooperation with the Group of Eight (G8) should contribute significantly to the reduction of pollutant emissions by 2050 [1,2]. One approach to realize this amount of reduction is adopting energy transformations that lead to negligible emissions or zero emission, including renewable energy sources (RESs) like

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Table 1
A review of the literature stated in this paper.

Ref.	Modelling of battery degradation	Uncertainty parameter			Stochastic modeling
		PV	WT	Load	
[6]	No	No	No	No	No
[7]	No	No	No	No	No
[8]	No	No	No	No	No
[9]	No	No	No	No	No
[10]	No	No	No	No	No
[11]	No	No	No	No	No
[12]	No	No	No	No	No
[13]	No	No	No	No	No
[14]	No	No	No	No	No
[15]	No	No	No	No	No
[16]	No	No	No	No	No
[17]	No	No	No	No	No
[18]	No	No	No	No	No
[19]	No	No	No	No	No
[20]	No	No	No	No	No
[21]	No	No	No	No	No
[22]	No	No	No	No	No
[23]	No	No	No	No	No
Current paper	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

wind turbines (WT) and photovoltaics (PVs). The EU also had a plan to supply 20% of the demand until 2020 by using RESs [1]. Recently, RES-based hybrid systems have widely been analyzed and incorporated all over the world by scholars and engineers [3]. Off-grid systems generally incorporate RESs along with energy storage to feed the electrical load. Resources are prioritized in supplying the load because these resources are environmentally friendly [4]. In the following, storage devices are used to cover the gap between load and renewable power profiles. Thus, if the consumed energy is less than the produced energy, the surplus energy will be stored in the storage device. If the opposite holds, the storage device is in discharge mode and delivers energy to the load [5]. In the remaining, it should be noted that finding optimal size and place of a hybrid system elements can greatly decrease the cost and provide economic benefits.

1.2. Research background

In the field of planning or optimization of the size of elements in a hybrid system, various pieces of research have been proposed as stated below. Ref. [6] discusses the technical and economic aspects of a hybrid RESs in both grid-connected and islanded modes by investigating a case study in China. Various loads in terms of period (like real-time demand, monthly demand, and daily demand) are analyzed in Ref. [7] to find a relationship between the load type and cost of electrical power supplied by grid-disconnected PV/battery systems. To do this, optimal size of elements of the system is found using energy management methods and optimization techniques. Hybrid RESs have also been applied to electrify some districts in India [8]. The RES is controlled, sized, and its elements are selected optimally so that inexpensive energy is supplied to customers. The paper also attempts to reduce energy cost and amount of emissions. A PV system disconnected from the network to supply residential demand has been discussed in Ref. [9]. The system is designed and investigated by adopting mathematical methods. The optimal site and size of a PV-diesel system to feed customers of a rural region using a novel approach is discussed in Ref. [10], in which several indices including technical, economic, reliability and environment aspects are taken into account to find the most appropriate location of the system. In the next step, the proper size of the system is achieved using an optimization method. Such a model with several objective functions was introduced in Ref. [11], in which the loss of load probability (LLP), the cost of energy (COE), and the cost of battery degradation are considered. The method also takes the operating cost and maintenance and repair costs into account to provide a more accurate model of a hybrid system. Ref. [12] compares network expansion and incorporation of a hybrid system so that it could choose between them. Different elements of a hybrid system including WT, PV, and battery are optimally selected and sized in Ref. [13]. The changes in temperature and size degradation of battery are also modeled. A robust and resilient system is designed in Ref. [14] while taking into account technical and economic aspects and several microgrid scenarios are investigated so that a rural microgrid is suitably redesigned and its financial budget is reassigned. The authors in Ref. [15] evaluate the feasibility of implementing a hybrid RES considering technical and economic perspectives. In addition, the study presents simulation findings, optimization techniques, and a sensitivity analysis. A renewable system's grid-disconnected operating mode was covered in Ref. [16]. Battery storage, PVs, and generating units were all under optimum control. The reward function in the article was designed using a Gaussian distribution. An integrated grid-disconnected energy system was created by Ref. [17] to deliver hydrogen storage and adapt to different home demands. Together with a number of additional parts, the system consists of wind turbines, photovoltaics, battery cells, electrolyzers, thermal storage, and hydrogen storage. To address the system's costs and dynamic performance, a multipurpose energy system was developed based on novel configurations and control schemes [18]. The findings of a hybrid PV/wind optimization sizing technique are presented in Ref. [19], which takes into consideration the strong combination of the storage capacity, a particular demand profile, and the intermittent energy supply (solar and

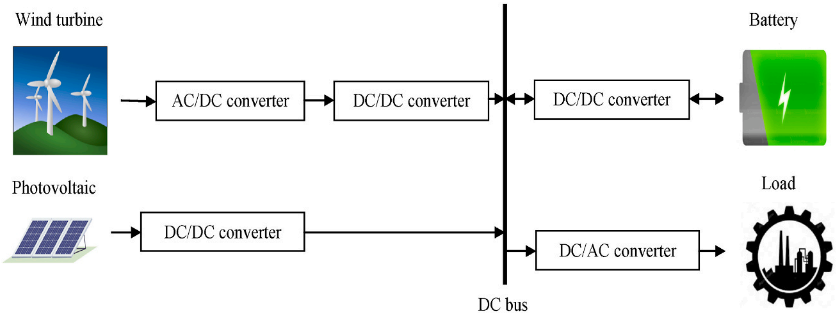

Fig. 1. Configuration of the proposed system.

wind). The foundation of this optimization strategy is the use of metaheuristic methods. Ref. [20] aims to create the best possible hybrid energy system model with battery storage, using the solar and wind energy resources that are currently accessible to meet the electrical demands of three isolated, unelectrified villages in the Senapati district of Manipur, India. The best configuration for the hybrid system is found using a technique based on the Firefly algorithm. Anenergy management method for a photovoltaic system with fuel cells and battery storage is presented in Ref. [21]. In order to evaluate the practicality of the suggested approach, the system was crafted to meet a household's daily energy needs of 2808 kWh. The selected location is Bejaia, a seaside city in eastern Algeria with solar potential of 1.2 kWh/m^2/day. Ref. [22] tackles the issue of power outages in remote locations by using the available renewable energy resources in the surrounding area. This was accomplished by proposing to link the utility to a hybrid system comprised of photovoltaic (PV), wind turbine (WT), and fuel cell (FC) plants, with the hybrid system serving as a backup system when the grid is unavailable. Ref. [23] proposes a novel strategy for optimizing the size of an off-grid renewable energy infrastructure. To make an exact examination of the distribution of exchanged energy with all storage components, the discrete Fourier transform tool was employed. Table 1 is a collection of several research publications on the topic area under investigation.

1.3. Research gaps

Based on the research background, the main research gaps in the field of hybrid system planning are as follows:

- Researchers generally have presented the planning of the hybrid system according to the specific situation of the load and renewable power. However, these parameters have uncertainty and they are possible to have different values in each scenario.
- Moreover, the successive charging/discharging of batteries reduces the useful lifespan of the battery. Yet, in a few studies, the battery degradation limitation has been observed in the charging and discharging performance of the storage device.

1.4. Contributions

The questions that arise in the proposed research are as follows:

- Can stochastic optimization provide a reliable solution to the uncertainties in the islanded hybrid system?
- Does the firefly algorithm have the ability to achieve the optimal solution for planning the hybrid islanded system?
- Can the combined wind, solar, and battery systems supply energy to consumers in the hybrid islanded system?
- To what extent is the effect of battery degradation?

Therefore, in this paper, to fill the proposed research gaps, the stochastic planning of the hybrid system is presented considering battery degradation. The established optimization problem minimizes construction and maintenance cost of RESs [24–28] and batteries. Also, the constraints of the problem include the limitation of the number of constructed elements, the balance of supply and demand, and the specifications of the elements in the proposed scheme. In this model, the limitation of battery degradation on the performance of the storage device [29–33] is also considered. The mentioned problem is mixed-integer nonlinear programming (MINLP), which is difficult and time-consuming to solve based on mathematical rules. The paper uses the firefly algorithm to reach solutions to the problem. Also, in this scheme, the combination of the roulette wheel mechanism (RWM) and the simultaneous backward method (SBM) helps model the uncertainties related to the demand and renewable [34–38] power based on scenario-based stochastic programming (SBSP). The following are novelties of the present article:

- Planning of the hybrid PV/WT/batteries system based on stochastic optimization
- Considering the limitation of battery degradation on battery operation during consecutive charge/discharge operation
- Modeling the uncertainties of the demand and output power of PVs and WTs.

1.5. Paper organization

Section 2 describes the modeling of the hybrid system planning problem and uncertainty modeling. The solution method is presented in Section 3. Section 4 provides the numerical results. In the end, the conclusions are stated in Section 5.

2. Optimal sizing of the proposed system

Fig. 1 depicts the configuration of the hybrid PV/WT/battery system, which includes PV units and WTs as RESs [39–43], where surplus energy is stored in the batteries and thus reliability enhances. An inverter has also been adopted, because a majority of the electrical devices or consumers need AC power. In the proposed system, the priority of load supply (*Pl*) is by RESs [44–48] (PV and WT) (*Pr*). Now, if the RESs were able to supply the load and also their output generation is greater than the demand, the excess power is stored in the storage device [49–53] (battery). Conversely, if RESs are not able to sufficiently meet the load, and in other words, their generation is smaller than the demand, the surplus power consumption is met by the storage device [54–63]. Finally, the step-by-step process of this strategy is described as follows [64]:

- **Step 1.** If $Pr\ (t) > Pl\ (t)$, go to Step 2, otherwise go to Step 3.
- **Step 2.** The excess generation of RESs should be stored in the battery. Set $t = t + 1$ and go to Step 1.
- **Step 3.** The excess consumption is met by the battery. The state of charge (SOC) must be greater than the minimum allowed amount of the battery. Set $t = t + 1$ and go to Step 1.

The details of this problem are written as follows:

A) PV system model

The power generation by the PV [65] system (p_{pv}) at time t is calculated based on solar irradiance as Eq. (1) [9]:

$$p_{pv}(t) = I(t) \times A \times \eta_{pv} \tag{1}$$

Parameter I represents irradiance, A is the area of the PV panel and η_{pv} is the efficiency of the PV panel along with its DC/DC converter. In this model, the PV panels operate in their maximum power point tracking (MPPT) mode. It should also be noted that if the mentioned system has N_{pv} panels, then $P_{pv}(t) = N_{pv}p_{pv}(t)$. In addition, the changes are assumed to not significantly impact the PV output power, and it is also neglected.

B) Wind turbine model

For a wind turbine, if the wind speed (v) is smaller than the cut-in speed (v_{cut_in}), the output power of the wind turbine (p_{wt}) is zero, and also if the wind speed is higher than the cut-in speed and lower than the rated speed (v_r), the output power will change linearly with the wind speed. Also, if the wind speed is higher than the rated speed and lower than the cut-out speed (v_{cut_out}), the power of the wind turbine will not change and equal to its rated power (p_r). Finally, in the case the wind speed is higher than the cut-off speed, then the wind turbine is switched off. Hence, we have Eq. (2) to calculate the wind turbine generation power [13]:

$$p_{wt}(t) = \begin{cases} 0 \quad v(t) \le v_{cut\_in} \quad or \quad v(t) \ge v_{cut\_out} \\ p_r \dfrac{v(t) - v_{cut\_in}}{v_r - v_{cut\_out}} \quad v_{cut\_in} \le v(t) \le v_r \\ p_r \quad v_r \le v(t) \le v_{cut\_out} \end{cases} \tag{2}$$

It should also be noted that if the mentioned system has N_{wt} wind system, the output power of the set of wind systems (P_{wt}) will be $P_{wt}(t) = N_{wt}p_{wt}(t)$.

C) Battery model

Due to the intermittent behavior of PV and WT output power, the capacity of the battery needs to be changed for the mentioned hybrid system constantly. In the proposed system, the SOC or battery energy is as follows [64]:

- When the total output power of the PV and WT systems is more than the consumption, the battery is charged and the quantity of charging energy of the battery at time t is calculated by Eq. (3):

$$E_b(t) = E_b(t-1) \times (1-\sigma) + \left[(E_{PV}(t) + E_{wt}(t)) - \frac{E_l(t)}{\eta_{inv}} \right] \times \eta_b \tag{3}$$

where E_b is the charge level of the battery and σ is the hourly self-charging rate. η_b and η_{inv} are equal to the efficiency of the battery and AC load inverter. E_l, E_{PV} and E_{wt} are equal to the consumed energy, PV energy and wind system energy.

- When the power set of PV and WT systems cannot meet the demand, the battery operates in discharging mode. The present study assumes that the discharge efficiency is 1. Therefore, the amount of battery charging energy at the moment t will be as Eq. (4):

$$E_b(t) = E_b(t-1) \times (1-\sigma) - \left[\frac{E_l(t)}{\eta_{inv}} - (E_{PV}(t) + E_{wt}(t))\right] \tag{4}$$

D) Objective function

The objective function aims at minimizing the overall annual cost (CT). CT is calculated by adding up the annual costs of construction (C_{cpt}) and maintenance (C_{mtn}). The solution to the problem formulated in Eq. (5) can be found by optimization techniques so that the hybrid system under discussion is optimally designed.

$$\min \quad C_T = C_{cpt} + C_{mtn} \tag{5}$$

The maintenance and construction cost are imposed respectively during and at the start of the design. It should also be noted that the cost of construction is converted into the annual cost of construction. In this paper, the capital recovery factor (CRF) is used, which is given as Eq. (6) [64]:

$$CFR = \frac{i(1+i)^n}{(1+i)^n - 1} \tag{6}$$

here i represents the annual rate, while n denotes the lifetime. In this hybrid system, useful lifespan of the battery is considered to be five years, so for 20 years of planning, the single payment present worth factor (SPPWF) only for the battery will be as Eq. (7):

$$C_b = \rho_b \times \left(1 + \frac{1}{(1+i)^5} + \frac{1}{(1+i)^{10}} + \frac{1}{(1+i)^{15}}\right) \tag{7}$$

In which, C_b and ρ_b are the current price of the battery and the price of the battery, respectively. Also, in the same method, the useful lifespan of the inverter is considered 10 years. So, the SPPWF for the inverter only is as Eq. (8):

$$C_{inv} = \rho_{inv} \times \left(1 + \frac{1}{(1+i)^{10}}\right) \tag{8}$$

where C_{inv} and ρ_{inv} are equal to the current price of the inverter and the price of the inverter, respectively. The annual maintenance and investment costs of the system are expressed by Eq. (9) and Eq. (10):

$$C_{cpt} = \frac{i(1+i)^n}{(1+i)^n - 1}\left[N_{wt}C_{wt} + N_{pv}C_{pv} + N_bC_b + N_{inv}C_{inv}\right] \tag{9}$$

$$C_{mtn} = N_{wt}C_{mtn}^{wt} + N_{pv}C_{mtn}^{pv} \tag{10}$$

where C_{wt} and C_{pv} are the price of a PV and WT unit, respectively. It should be noted that the useful lifespan of these units is considered to be 20 years. N_b and N_{inv} show the number of batteries and inverters. Also, C_{mtn}^{pv} and C_{mtn}^{wt} are equal to the maintenance cost of PV and WT, respectively.

E) Constraints

The constraints of (11)–(14) should be satisfied for the proposed system:

$$N_{wt} = \text{integer} \quad 0 \le N_{wt} \le N_{wt}^{\max} \tag{11}$$

$$N_{pv} = \text{integer} \quad 0 \le N_{pv} \le N_{pv}^{\max} \tag{12}$$

$$N_b = \text{integer} \quad 0 \le N_b \le N_b^{\max} \tag{13}$$

$$N_{inv} = \text{integer} \quad 0 \le N_{inv} \le N_{inv}^{\max} \tag{14}$$

$N_{wt}^{\max}$, $N_{pv}^{\max}$, $N_b^{\max}$ and $N_{inv}^{\max}$ are respectively the maximum number of WT units, PV systems, batteries and inverters. It should also be noted that the battery energy has the minimum and maximum allowed values (E^{min} and E^{max}) as Eq. (15), whose minimum value as Eq. (16) relies on the depth of discharge (DOD) and size of the battery (S_b).

$$E_b^{\min} \le E_b(t) \le E_b^{\max} \tag{15}$$

$$E_b^{\min} = (1 - DOD) \times S_b \tag{16}$$

The term *DOD* corresponds to the constraint on battery degradation or reduction of battery life during the consecutive charging/discharging operation of the storage device. In this condition, value of DOD is 0.8. Considering the parameter mentioned in (16) is proportional to considering the limitation of battery degradation.

The approach under discussion includes a mathematical model [66–70]. The mathematical model presented in this study is based on the optimization formulation [71–75]. The optimization model includes an objective function [76–80]. The objective function contains a min (max) term to compute the function's minimal (maximum) value [81–84, 85]. It may be expressed as a single or multiple objective function [86–91]. The optimization issue incorporates several restrictions [92–96]. Constraints are defined as equality and inequality formulation [97−102]. Constraints are classified as non-linear, linear, mixed integer non-linear, or mixed integer linear models [103−108]. To execute the optimization model on a network or hybrid system, intelligent devices are required [109–113]. Smart systems are built on telecommunications equipment [114–120]. These systems coordinate the various power components [121−123]. In this scenario, network administration is simple, and system processing is fast [124–126].

F) Uncertainties modeling

The problem presented in the previous sections has uncertainties of consumption load and the power of RES, namely Pl, P_{pv} and P_{wt}. Therefore, the proposed problem model must be repeated for each scenario, and from this model, the proposed problem will be stochastic [127–134]. In this paper, scenario generation is realized using the RWM. In each scenario, this method determines the values of uncertainty parameters according to their average and standard deviation values. Next, the probabilities of the selected values for the load, PV power and wind system are found based on the normal, beta and Weibull probability distribution functions (PDFs), respectively. To obtain the probability of individual scenarios, it does suffice to multiply the probability of uncertainty parameters of the specific scenario. Scenario reduction is based on SBM [135]. This method selects a small number of the produced scenarios, which are then used for the problem. In this method, scenarios that are in a small distance with respect to each other are chosen.

At first, a substantial quantity of scenarios are generated in a random manner. Nevertheless, the scenario set should be lowered in order to lessen the computational demands. Several distinct strategies for reducing scenarios are presented in the literature [135]. This research utilizes the simultaneous backward approach for its computing efficiency and high level of accuracy. This method computes the distance between various situations in order to identify the most distinct and likely scenarios. The subsequent procedures are utilized to diminish the occurrences:

Step 1. Regard ξ as the initial collection of possibilities. Furthermore, let DS represent the collection of scenarios that remain after undergoing the scenario reduction procedure, which is initially devoid of any elements. Calculate the distance between any two scenarios using the Eq. (17):

$$DT_{w,w'} = DT(R_w, R_{w'}) = \sqrt{\sum_{g=1}^{e} \left(r_{w,g} - r_{w',g} \right)} \quad \forall w, w' = 1, 2, ..., N_S \tag{17}$$

Step 2. Calculate the minimum distance between each scenario and other scenarios, R_e by Eq. (18):

$$DT_{w,l} = \min \quad DT_{w,w'} \quad \forall w, w' = 1, 2, ..., N_S, w \neq w' \tag{18}$$

The variable "l" represents the count of scenarios that have the minimum distance from scenario "s".

Step 3. The probability of each scenario, pr_w, as Eq. (19) is multiplied by the distance it has from the other scenarios.

$$PD_{w',l} = pr_l DT_{w',l} \quad \forall w' = 1, 2, ..., N_S \tag{19}$$

Step 4. Exclude the dth scenario with the minimum value for the given criterion from the initial list of scenarios, ξ_s as Eqs. (20) and (21):

$$PD_d = \min \quad PD_w \quad \forall w = 1, 2, ..., N_S \tag{20}$$

$$\xi = \xi - \{d\}, DS = DS + \{d\}, pr_l = pr_l + pr_d \tag{21}$$

Step 5. Continue doing Steps 2 to 4 again until the appropriate number of scenarios is achieved.

The aforementioned process for scenario reduction will exclude comparable scenarios as well as possibilities with low likelihood. The remaining set of scenarios is sufficiently diversified to represent the whole range of uncertainty for the situation.

Every scenario will establish a foundation for the stochastic problem that is similar in terms of determinism. The ultimate optimal solution is constructed by aggregating the optimal answers from several scenarios. The value of γ_w is as Eq. (22):

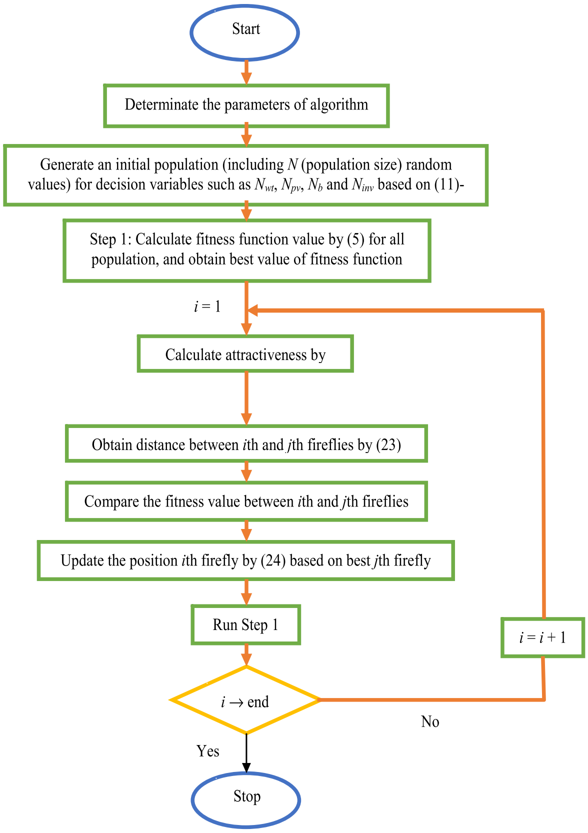

Fig. 2. Flowchart of the firefly algorithm for the proposed scheme.

$$\gamma_w = \frac{\gamma_w^0}{\sum_{k=1}^{N_S} \gamma_k^0} \tag{22}$$

As opposed to a collection of solutions, the equation above ascertains a solitary optimal solution for the stochastic problem. By employing this aggregation procedure, not only is it feasible to deduce each individual scenario, but the primary stochastic problem's framework is also maintained.

3. Problem solution based on firefly algorithm

The problem presented in the previous section is a MINLP. Adopting mathematical rules to solve the proposed problem is overwhelming and the execution time of solving the problem is expected to be very high. Therefore, the present article adopts the firefly algorithm and finds a solution to the problem this is thanks to the suitable features of the proposed algorithm that will provide important capabilities in solving problem [136]. Fireflies are found in groups and a firefly with poor brightness always moves towards the brighter one. In this algorithm, we consider three main assumptions: 1) fireflies of the discussion are of the same species, 2) the brightness of a firefly directly determines its attractiveness, and 3) the brightness has a direct relationship with the value of the objective function.

To find the maximum value of the objective function, the illuminance (I) in a certain region x is stated as $I(x)$ or $f(x)$. But, attractiveness (β) is not an absolute value and depends on how other fireflies are bright. Therefore, fireflies i and j will change with the distance r_{ij}. Also, the brightness decrease depends on the distance from its source. Also, media absorbs the light and it should be considered that the attractiveness changes with the amount of absorption.

$$I = \frac{I_s}{r^2} \tag{23}$$

In Eq. (23), I_s shows the intensity of the source light. If the light absorption coefficient γ of a medium is constant, the intensity of light changes with r (distance) as Eq. (24):

$$I = I_s e^{-\gamma r} \tag{24}$$

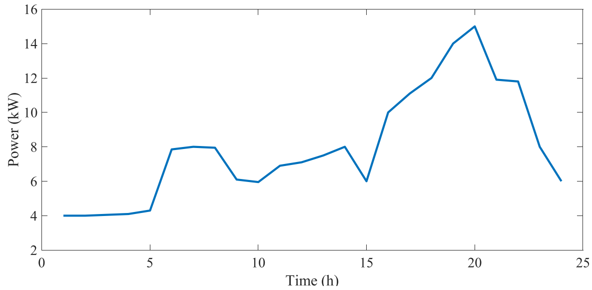

Fig. 3. Annual average daily load curve [64].

To tackle with the singularity $r = 0$ in the term $\frac{I_s}{r^2}$, by combining the effect of both inverse square law and absorption, the formula's Gaussian expression can be written by Eq. (25):

$$I(r) = I_s e^{-\gamma r^2} \tag{25}$$

Since a firefly's attractiveness has a direct relationship with the intensity of light seen by its neighboring fireflies, attractiveness is calculated as Eq. (26):

$$\beta(r) = \beta_0 e^{-\gamma r^2} \tag{26}$$

where β_0 is the attraction at $r = 0$. It is worth noting that in practical realizations, the attractiveness function β *(r)* will be shown by any uniformly descending function like Eq. (27):

$$\beta(r) = \beta_0 e^{-\gamma r^m} \quad m \geq 1 \tag{27}$$

The distance between fireflies i and j located at positions x_i and x_j can be calculated by Eq. (28):

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d} (x_{ik} - x_{jk})^2} \tag{28}$$

where $x_{i,k}$ is equal to the kth component of x_i of the i-th firefly. Therefore, in the two-dimensional system, we will have Eq. (29):

$$r_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{29}$$

The movement of firefly i toward a brighter firefly j is defined as Eq. (30):

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2} (x_i - x_j) + \alpha \varepsilon_i \tag{30}$$

where the second term concerns attractiveness, α is a randomizing parameter, and ε_i is a random vector containing numbers obtained from a Gaussian distribution or a uniform distribution. Finally, the algorithm are can be summarized using the following steps and flowchart in Fig. 2:

1. Establish the initial population of fireflies randomly
2. Find the objective function value for individual fireflies and select the best answer
3. Calculate the attractiveness and distance between any two fireflies
4. Compare the objective function value of each firefly with that of other fireflies
5. The movement of firefly i toward the best firefly j
6. Calculate the new position of fireflies
7. If the loop is not terminated, go back to Step 2

4. Numerical results and discussion

4.1. Problem data

The problem model applied to the system is presented in Fig. 1, which has wind and PV systems along with a battery storage system. AC/DC or DC/DC converters are adopted to connect wind and PV systems to the DC bus. Also, the load of the network is in the form of AC, so it will be connected to the DC bus by the DC/AC converter. In the proposed problem model, the consumption load should be supplied by WT and PV systems as much as possible, and also the excess energy produced by these systems is used to charge the storage device. Now, if the amount of load is greater than the production power of WT and PV systems, the excess load power must be provided by batteries or storage devices. Therefore, it can be said that the mentioned system can operate similarly to an islanded microgrid

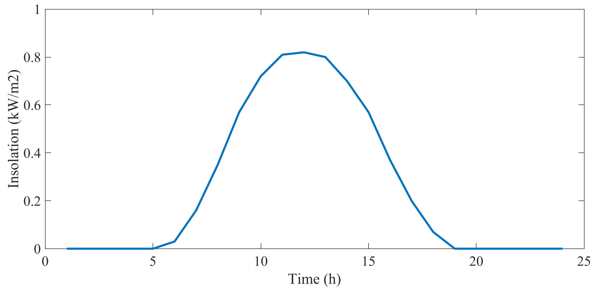

Fig. 4. Annual average daily curve of solar radiation on a PV [64].

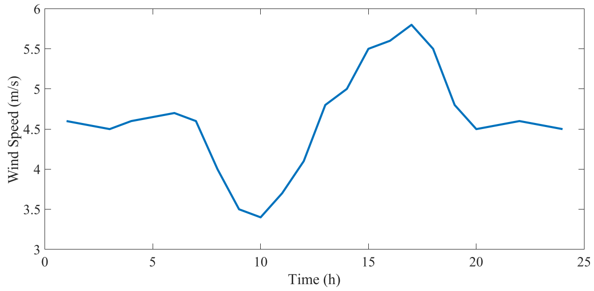

Fig. 5. Annual average daily wind speed curve for a wind unit [64].

Table 2
Hybrid system component parameters [64].

Interest rate (r') in %	10
WT data:	
Rate power (kW)	1
Cut-in wind speed (m/s)	2.5
Rate wind speed (m/s)	10
Cut-out wind speed (m/s)	13
Construction cost ($)	3200
Maintenance cost ($/year)	5
Maximum number	30
Life span (year)	20
Data of PV including rate power of 120 W:	
Area (m^2)	1.07
Efficiency (%)	12
Construction cost ($)	614
Maintenance cost ($/year)	0
Maximum number	100
Life span (year)	20
Battery data:	
Maximum stored energy (kWh)	1.35
σ	0.0002
Efficiency (%)	90
Construction cost ($)	130
Maintenance cost ($/year)	0
Maximum number	60
Life span (year)	5
Converter data:	
Efficiency (%)	95
Maintenance cost ($/year)	667
Maximum number	0
Capacity (kW)	60
Life span (year)	10

because in this plan, it is assumed that the load will be fed by RESs and batteries, and there is no need for network support. Hence, this will increase the reliability of the proposed system. The system under study is in Rafsanjan, Kerman province, Iran. Average hourly data for a day (24 h) is shown in Figs. 3–5. These figures illustrate the daily average consumption load, solar radiation for PV and wind

Table 3
Economic results of the proposed scheme for different case studies.

Case study		Unit	Case I	Case II	Case III
Number of PV panels		–	–	212	58
Number of wind units		–	35	–	27
Number of batteries		–	18	92	26
Number of power electronic converters		–	23	26	23
Cost of PV system		$	–	12445.0171	2857.599
Cost of wind system		$	9268.0188	–	7149.6145
Cost of storage system		$	540.481	2762.4586	780.6948
Total cost of converters		$	5957.2104	6734.2379	5957.2104
Total cost of the proposed system		$	20605.47	21941.71	18116.28
Best value of parameters of Firefly algorithm	Randomness factor (α)	–	0.51	0.50	0.51
	Initial attractiveness of a firefly (β_0)	–	0.18	0.19	0.19
	Light absorption coefficient of medium (γ)	–	0.98	0.98	0.98

Table 4
Evaluation of the different algorithm response for cost in different case studies.

Case study	Index	Unit	Firefly algorithm	Grey Wolf Optimizer	Differential evolution	Genetic algorithm
Case I	Average	$	20605.47	20994.32	21522.37	21945.67
	Standard deviation	%	0.01	0.07	0.21	0.43
	Best	$	20602.41	20979.45	21478.16	21896.2
	Worst	$	20651.12	21011.31	21592.75	22011.38
	Convergence iteration	–	322	589	1013	2098
	Convergence time	Sec	108	189	308	511
Case II	Average	$	21941.71	22355.74	22942.11	23441.53
	Standard deviation	%	0.01	0.08	0.23	0.45
	Best	$	21937.37	22338.46	22919.45	23419.28
	Worst	$	21998.71	22393.78	22999.36	23511.72
	Convergence iteration	–	298	580	1005	2003
	Convergence time	Sec	106	188	305	478
Case III	Average	$	18116.28	18456.27	18948.22	19308.82
	Standard deviation	%	0.01	0.09	0.24	0.47
	Best	$	18115.437	18450.39	18939.29	19294.78
	Worst	$	18236.023	18497.11	18992.49	19367.88
	Convergence iteration	–	408	702	1189	2367
	Convergence time	Sec	121	236	401	673

speed for a wind unit, respectively. Also, all the parameters of the proposed design are mentioned in Table 2 [64]. Other specifications such as data of power sources, battery and power converters are presented in Table 2 [64].

It is noteworthy that, at first, 1000 scenarios are generated by the RWM and then the number of scenarios is reduced to 40 by using the SBM. The proposed problem is solved by the firefly algorithm. The number of populations in this algorithm is equal to 60 and also the maximum number of iterations of solving the problem is considered 3000. The setting parameters of this algorithm are also selected based on [19–20, 136].

4.2. Results

A) Evaluation of economic results

This part of the article provides the economic results obtained from the proposed problem model. Three case studies are examined, which are as follows:

- **Case I**: Analysis of economic results of the suggested scheme by taking into account wind and battery systems
- **Case II**: Analysis of economic results of the suggested scheme by taking into account PV and battery systems
- **Case III**: Analysis of economic results of the suggested scheme by taking into account WT, PV and battery systems

The results of this section are presented in Tables 3 and 4. The economic results of different study cases obtained from the firefly algorithm are reported in Table 3. As the table reports, the highest cost is extracted for the proposed scheme in Case II and the lowest cost was obtained in Case III. The reason for the high cost in Case II is that the load must be fed by PV and battery systems. Since the PV system does not produce power in most hours, the number of PV systems and batteries to feed the load increases. It is found, therefore, that the total expected cost in Case II will be high. In Case III, because there are different power generation systems, these systems are selected such that the overall cost of the proposed scheme is less than that in other study cases.

It should be noted that, the parameters of the firefly algorithm include Randomness factor (α), Initial attractiveness of a firefly (β_0),

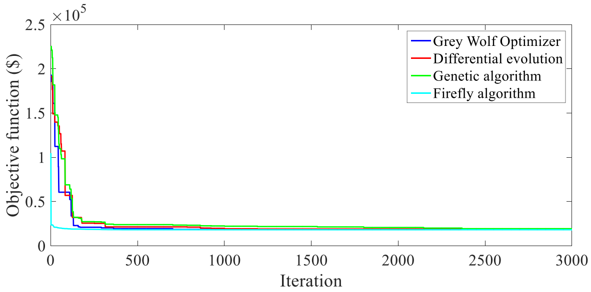

Fig. 6. The convergence curve of different algorithms in Case III.

Table 5
Economic results of the scheme for stochastic and deterministic models based on firefly algorithm.

Case study	Planning cost ($)		Cost ($) due to uncertainty modeling
	Stochastic model	Deterministic model	
I	20605.47	19776.55	828.92
II	21941.71	21122.58	819.13
III	18116.28	17247.417	868.863

and Light absorption coefficient of medium (γ). The favorable values of these parameters, as given in [136], are about 0.5, 0.2, and 1. However, we may need to change these values depending on the changes applied to the model and problem data. So, to achieve the desirable values of these parameters, the proposed problem was solved using the firefly algorithm for different values of α, β_0, and γ. Then, by comparing the obtained solution, the case that gives the optimal value of the objective function (5) was selected. In this method, α, β_0, and γ were changed between 0.4 and 0.6, 0.1–0.3, and 0.9–1.1 with steps of 0.01. Eventually, the best values of these parameters were reported for cases I to III in Table 2. For the reported values, the optimal value of the objective function was obtained. According to Table 3, the setting parameters of the firefly algorithm did not change significantly in different case studies.

Fig. 6 illustrates the convergence curve of solution of the proposed problem obtained from Firefly algorithm (FA) [136], Grey Wolf Optimizer (GWO) [137], Differential evolution (DE) [138] and Genetic algorithm (GA) [139] for Case III. It is noteworthy that the mentioned algorithms have different setting parameters. The values of these parameters are selected based on [136–139]. According to this figure, it is observed that the Firefly algorithm succeeded to reach the optimal point more quickly, and the value of objective function for this algorithm is the lowest (optimal) compared to that of other solvers. More details on the convergence trend of different algorithms for various case studies are listed in Table 4.

Table 4 reports the average, standard deviation, best and worst costs of different study cases based on results of Firefly algorithm, Grey Wolf Optimizer, Differential evolution and Genetic algorithm. The population size for all algorithms is 60 and their maximum iterations is 3000. The setting parameters of the algorithms are given in [136–139]. To evaluate the results of this section, the proposed problem has been repeated 20 times and then the different values given in Table 3 have been calculated. Based on Tables 4 and it can be seen that the optimal (minimum) value of the objective function or planning cost in Firefly algorithm has been calculated for all the study cases so that in Case III, the lowest amount of cost obtained with Firefly algorithm is equal to $18,116.28, but this cost in other algorithms is more than $18,450 and it has increased to $19308.82 in the Genetic algorithm. In addition, based on Table 4, the standard deviation of Firefly algorithm has the lowest value. This means that the dispersion of the final response in this algorithm is low, so the worst, best, and average values of the objective function in this algorithm are close to each other. However, this is not true in other algorithms and also the standard deviation changes with the change in the data of the problem. Yet, it was constant for Firefly algorithm. So, Firefly algorithm has a low standard deviation for different data. As another point, in Firefly algorithm, the convergence iteration is low compared to other algorithms. In Case III, the convergence iteration for Firefly algorithm is 408, but it is more than 700 for other algorithms. Also, in Firefly algorithm, the computation time is the lowest. Therefore, Firefly algorithm has the most optimal solution for solving the proposed problem compared to Grey Wolf Optimizer, Differential Evolution, and Genetic algorithm, which provides higher convergence speed and lower standard deviation in the final response.

In Table 5, the value of the objective function or the planning cost of the hybrid islanded system in terms of modeling and not modeling the uncertainties is stated. The deterministic model takes into account the conditions that the modeling of uncertainties is not considered. But, in stochastic optimization, uncertainty modeling is considered, which is based on the combination of RWM and SBM as given in Section 3. Based on Table 5, the planning cost in all cases of studies in stochastic modeling is higher than that in deterministic modeling. This case is caused by considering the modeling of uncertainties in stochastic optimization. In other words, it is possible that in a scenario, the amount of load is higher than the predicted amount, and the power generation by renewable resources is lower than its predicted value. Therefore, the number of sources and storage devices increases compared to the deterministic model. This has the result of increasing the planning cost in stochastic modeling. In the last column of Table 5, the amount of cost due to uncertainty modeling is reported, which is equal to the difference of planning cost in two deterministic and stochastic models. Based on this table, the cost of uncertainty modeling is the lowest in Case II, but it is the highest in Case III. In Case II, only PVs are used, which

Table 6
Effect of battery degradation model.

Case study	Scheme		Cost ($) due to battery degradation model
	With battery degradation model	Without battery degradation model	
I	20605.47	20099.67	505.8
II	21941.71	21157.04	884.67
III	18116.28	17598.617	517.663

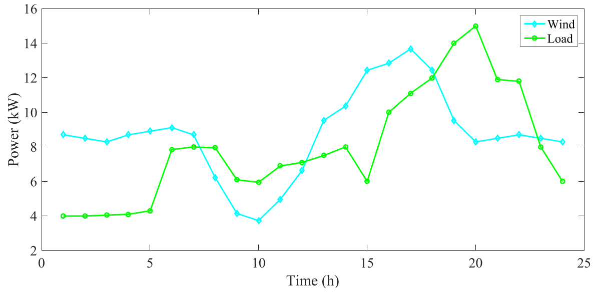

Fig. 7. The average daily curve of the WT generation power for Case I.

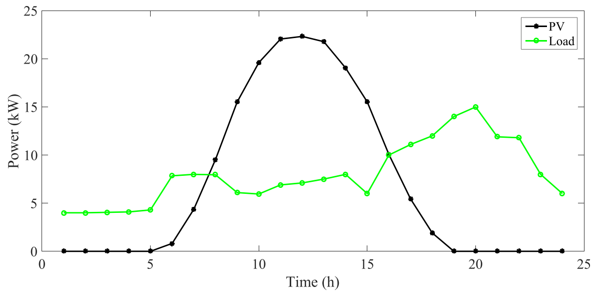

Fig. 8. The average daily curve of the generation power of the PV unit for Case II.

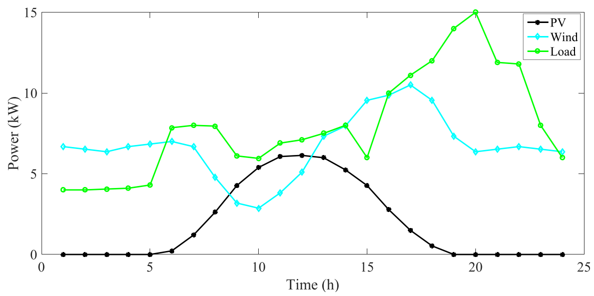

Fig. 9. The average daily curve of WT and PV unit generation power for Case III.

are off in most hours. So, there is no uncertainty caused by PV in most hours. In Case III, there is uncertainty caused by renewable resources in all hours, and in this case, the number of uncertainties is more than in Case II. So, the cost of modeling uncertainties is the highest in Case III. Of course, this cost corresponds to a cost to access the reliable planning of the islanded system. This shows the capability of the first and third innovations stated in subsection 1.4.

Table 6 shows the effect of battery degradation model on islanded system planning. In this table, the results of planning with/without battery degradation model are stated. Based on this table, considering the battery degradation model increases the planning cost of the islanded system, and the amount of this cost is reported in the last column of Table 6. Based on this table, the highest cost caused by the battery degradation model (difference in planning cost with/without battery degradation model) is seen in Case II because in this case, only PV produces electric energy and according to the results of Table 5, there is the largest number of batteries in Case II, so the cost due to battery degradation model is the highest in Case II. The amount of this cost is the lowest in Case I, because

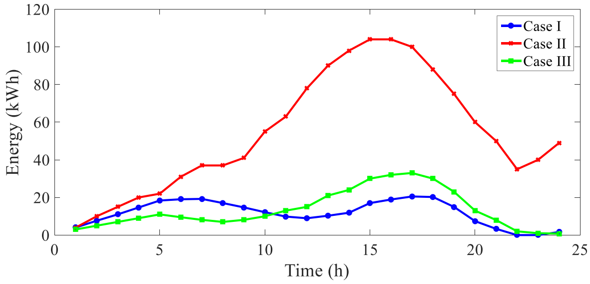

Fig. 10. Average daily curve of energy stored in the battery for Cases I-III

according to Table 3, the number of batteries in this case is the lowest. This represents the second innovation capability presented in subsection 1.4 in accessing a more reliable solution for islanded system planning.

B) Evaluation of optimal results of the system elements

This part of the paper provides the optimal performance results of the system elements as shown in Figs. 7–10. The daily curve of the generation power of WT and PV systems for cases I-III is shown in Figs. 7–9. Based on these figures, in some hours the RESs (WT and PV units) generation power is lower than the consumption load and in other hours it is higher. During the hours when the generation rate of RESs is greater than the consumption load, the excess generation will be stored within the battery. During the hours when the generation rate of RESs is less than the demand, the surplus consumption can be fed by batteries. Note that power generation by renewable sources is determined based on Eqs. (1) and (2). Fig. 10 depict the daily curve of energy stored in batteries for cases I-III. The increase/decrease in the amount of energy stored in batteries is corresponding to excess power of RESs and excess consumption, respectively. Finally, when Figs. 7–9 are compared with Fig. 10, the charging mode of the batteries is proportional to the excess generation output of RESs, and also the discharging mode of the batteries is proportional to the surplus consumption. Therefore, it can be said that batteries act as a flexible source for RESs and reduce output power changes of the RESs. In other words, the presence of the battery next to the RESs will smooth the output power profile of the system. It should be noted that in the performance of batteries, by comparing Figs. 7–9 with Fig. 10, when the power generation by RES is more than the power consumption, the batteries are in charging mode. In this case, the energy stored in the batteries increases. When the power generation by RES is less than the consumption power, the batteries are in discharge mode and inject active power into the islanded system. In this condition, the energy stored in the batteries decreases.

5. Conclusion

The present article discusses the problem of optimal sizing of independent hybrid RESs with uncertainties regarding power source and load, whose objective is minimizing the costs of construction and maintenance of RESs and batteries. Also, the constraints of the problem include the limitation of the number of constructed elements, the balance of supply and demand, and the specifications of the elements in the proposed scheme. The limitation of battery degradation was also taken into account. The mentioned problem was a MINLP problem, and the firefly algorithm was used to find a solution to the problem. According to the obtained results, the following cases can be mentioned: supplying the load by the PV system and battery will increase the cost of the scheme; the low cost of the proposed scheme if there are different RESs along with the battery; providing flexibility for the proposed scheme if the battery is used in the proposed scheme along with RESs, reliable responsiveness with strong stability for the proposed problem using firefly algorithm, the existence of high response time compared with genetic algorithms and particle swarm in firefly algorithm. Stochastic modeling, despite its higher planning costs, has proven to be a more dependable approach than deterministic modeling in addressing the uncertainties associated with load and renewable resources. It is important to mention that taking battery degradation into account results in a slight rise in planning cost, but this approach yields a more precise representation of battery performance. The benefits of this strategy encompass several aspects: 1) incorporating the uncertainties associated with load and renewable resources, 2) accounting for battery degradation, 3) access to a dependable solution based on the firefly algorithm, and 4) supplying the consumption energy using renewables, including wind, solar, and batteries.

It is noteworthy that, in addition to the consumption of electrical energy, thermal energy is also consumed at consumption points. Therefore, it is necessary to present thermal energy consumption and models of thermal sources and storage devices in the hybrid system. The proposed scheme is recommended as a future work considering the discussed topic. Also, the bio-waste energy unit is a type of renewable resource that can produce electrical and thermal energy from environmental waste. The proposed scheme will be considered in the future works by considering this energy source. Furthermore, the implementation of demand side management can effectively decrease planning expenses. Consequently, the proposed plan, which incorporates demand side management, was listed as a prospective undertaking. The proposed plan does not currently include an assessment of the reliability of the hybrid islanded system. However, it is acknowledged as a potential area of future investigation within the proposed plan. The proposed method utilized load and weather data from a single day. However, these numbers vary depending on the specific day. This matter is seen as a forthcoming task for the suggested proposal.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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