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# Intelligent energy management of microgrid including renewable resources and electric vehicle charging station using firefly algorithm

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## ABSTRACT

*As energy demand surges due to technological advancements and population growth, optimizing energy supply networks becomes critical. This study presents a novel approach to intelligent energy management in microgrids that incorporates renewable resources and electric vehicle (EV) charging stations. The primary innovation lies in the simultaneous application of the Firefly algorithm and the Monte Carlo method to enhance optimization speed and reduce operational costs, a strategy not previously explored in the literature. Despite existing research on microgrid management, significant gaps remain, particularly regarding the integration of EV charging infrastructure without active vehicle participation and the use of fuel cells as energy storage solutions. This paper addresses these gaps by proposing a framework that allows for future consumer integration while minimizing risks associated with operational uncertainties. Key findings indicate that utilizing the Firefly algorithm significantly outperforms traditional Particle Swarm Optimization (PSO) methods in identifying optimal solutions for energy management. The results demonstrate a marked reduction in operational costs over a 24-hour period while ensuring reliability in the energy supply. Furthermore, the study establishes a robust foundation for transforming passive distribution systems into active ones, aligning with smart grid concepts.*

## 1. Introduction

The expansion of the electric power grid and the increasing use of renewable energy sources have brought about challenges such as the need

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for expensive transmission lines and the issue of cascading blackouts that can negatively impact critical infrastructure. Microgrids have been recognized as a suitable solution for improving grid reliability and flexibility. Ahmad et al. [1], which is a review article, it discusses the challenges related to the expansion of the power grid and intermittent energy sources, referring to the techniques of EMCS in microgrids. This review covers various methods used for EM

optimization, including objective functions related to operating costs, energy storage degradation, revenue generation, and greenhouse gas emissions. Control systems are classified based on their application in microgrids for stable operation. This paper also highlights relevant IEEE standards to promote standard rules and enhance the interoperability of EMCS techniques.

Mazaheri Khamaneh et al. [2] propose a risk-aware multi-objective programming approach to optimize the operation of a renewable hybrid microgrid, taking into account both operational costs and environmental impact objectives. Uncertainties in wind speed, solar radiation, loads, and market price are modeled through scenario generation and reduction procedures. The conditional value-at-risk index is used to measure the risk of decisions. The epsilon constraint and fuzzy logic approaches are utilized to select the best solution in the Pareto set. A demand response program is implemented for electrical and heat loads to analyze the influence of responsive loads. The results indicate that a risk-averse strategy enhances robustness in worst-case scenarios but leads to higher operational costs and increased pollution. Conversely, utilizing responsive loads reduces operational costs but results in greater pollution under uncertain conditions. Babanezhaad [3] also explores co-production systems and their modeling, proposing a solution for operations planning and cost optimization in microgrid networks through the MILP method. This method has been successfully implemented in the MLEMS software, a tool designed for efficient planning and management of microgrid energy systems.

Ordoo and Arjmandi et al. [4] has used the SWOT-AHP model to investigate renewable energy development strategies and management solutions in Iran.

Factors have been assessed and evaluated in Weakness, Strength, Opportunity and Threat (SWOT) groups, and strategies have been divided based on critical priorities using the AHP model. The important strategies presented include increasing the guaranteed electricity purchase tariff, creating a renewable energy fund, improving financial security and electricity exports, and developing infrastructure for research and education. On the other hand, the

challenges and solutions related to the power balance of battery protection in EVs are very important in the field of renewable energy systems. In this regard, Li and Zhao et al. [5] emphasizes the importance of properly designed protection planning mechanisms to prevent rapid battery aging and reduced battery life when participating in vehicle management. Two-way network (V2G). The Tikhonov regularization method is used to update the parameters of the ELM model used in the study.

From the side of energy trading with other microgrids or the main grid, as a solution to reduce the costs of network operation, a three-stage energy trading framework is provided by Ahmed and Sindi et al [6], which, while maintaining the privacy of information for each microgrid, the prices, and the power to evaluate the hours It determines the optimum and allows the microgrid to perform its operations in an economical and feasible manner through the optimization of its resources as well as the exchange of power with neighboring microgrids and the main grid. By using energy sources, it is possible to deal with their uncertainties, so an adaptive scheduling algorithm for microgrids in systems consisting of multiple MMG microgrids is presented to provide operational costs over time, taking into account utilization constraints. In order to minimize consumption peaks and lower the cost of the electricity bill, a two-level program for energy management is described in Leung et al. [7] and Azzam et al.[8]. It blocks energy in these areas. Initially, customers can contribute to cost savings by modifying the times at which their appliances operate. In the second level, using a turn-based decentralized algorithm based on game theory, a power generation schedule for generators is obtained, where the constraints of the power system can be obtained. This program reduces economic problems for users and solves dynamic dispatch. As a result, with this program, users can reduce their bills while maintaining the power system's limitations.

Barco-Jiménez et al. [9], a distributed linear strategy for managing a microgrid by optimizing active and reactive power distribution is presented. Habib et al. [10] A joint optimization for the planning and optimal operation of residential complexes related to microgrids, including renewable energy sources

and electric vehicles, with regard to supply and consumption price plans to reduce peak load consumption and energy costs is provided. The MPC predictive control model accepts different system settings so that all three layers of hierarchical control in a microgrid solve the problems of power quality, power sharing, energy management, and economic optimization Shahzad et al. [11].

Kumar et al. [12] proposes a machine learning-based approach for energy management in renewable microgrids, considering the charging demand of hybrid electric vehicles. Ghatak et al. [13] examines the architectures, metrics, power converters, and control strategies of electric vehicle charging stations in microgrids. Shen and Wu et al. [14] presents a real-time energy management algorithm for a microgrid with an electric vehicle station and combined heat and power generation. Vujasinović and Savić [15] focuses on demand-side management and integration of a renewable energy station for charging electric vehicles into a smart grid. Overall, these papers provide insight into optimization and control strategies for energy management in microgrids with electric vehicle charging stations, considering renewable resources and charging demand.

In this paper, a 33-bus IEEE microgrid connected to its upper network is investigated with the aim of reducing operating costs. Due to the uncertainties associated with renewable energy sources and the need to use them, and the fact that in previous studies, reducing operating costs by creating infrastructure for the entry of future consumers has been ignored, In this research, the worm swarm algorithm and the Monte Carlo method are used simultaneously over a 24-hour period to increase the optimization speed and reduce costs. In addition, a fuel cell and an electric vehicle charging station are used as energy storage units, without the presence of electric vehicles, to provide suitable infrastructure for future studies. This allows the grid and individuals to enter the field of electric vehicle charging with less risk. The novelty of the article is as follows:

Simultaneous use of the Monte Carlo method and worm swarm algorithm to increase the speed of optimization and reduce costs, which has not been done in previous studies.

- Simultaneous use of an electric vehicle charging station without the presence of electric vehicles and a fuel cell as storage units, which has not been done in previous studies.
- Use of renewable sources to create a suitable foundation for transforming the passive distribution system into an active system and moving towards smart grid concepts.
- Achieving an efficient method to reduce costs and create suitable capacities in the network for future studies.

The article is categorized as follows: The problem statement is provided in the first section, including the definition of the objective function and constraints. The steady-state model is defined in the third section, and the fourth section examines four different operating scenarios. The Firefly algorithm is explained in the fifth section, followed by simulation results in the sixth section. Finally, the conclusion is presented in the seventh section.

## Nomenclature

| | |
|---|---|
| EMCS | Energy Management and Control Systems |
| PSO | Particle Swarm Optimization |
| PDO | Prairie Dog Optimization |
| MG | Micro Grid |
| MMG | Multi-Microgrid |
| MPC | Model Predictive Control |
| DRL | Deep Reinforcement Learning |
| TH | Thermal Heat |
| PEMFC-CHP | Proton Exchange Membrane Fuel Cell- Combined Heat and Power |
| WT | Wind Turbine |
| PV | Photo Voltaic |
| FA | Firefly Algorithm |
| EVCS | Electric Vehicle Charging Station |
| CS | Charging Station |
| EMCS | Energy Management and Control Systems |
| ELM | Extreme Learning Machine |
| EV | Electric Vehicles |
| AHP | Analytical Hierarchy Process |
| V2G | Vehicles to Grid |
| DG | Distributed Generation |
| PDF | Probability Density Function |

## 2. Methodology

The optimal energy management of a 33-bus IEEE microgrid is studied with the aim of reducing operating costs and related constraints. In this study, a base power of 10 MVA and a base voltage of 12.66 KV are considered, Baran and Wu [16], which will be discussed further.

### 2.1. Goal definition

In the first step, the microgrid tries to supply the required power for its load with its own products or to supply the energy it needs in hours when the price of energy is low. In this way, energy supply costs, charging station costs, and energy exchange costs with the upstream network are introduced as microgrid energy costs and are modeled further.

The cost- performance conditions can be divided into five parts: costs of purchasing electrical energy from the electricity market; The costs of electric energy produced by TH, PEMFC-CHP, WT and PV units were considered. Thus

$$Cost(s) = \sum_{t=1}^{24} C_{Buy,t,s} \times P_{Buy,t,s} + \sum_{t=1}^{24} \sum_{h=1}^{N_{TH}} f_{TH,h}\left(P_{TH,h,t,s}\right) \quad (1)$$

$$+ \sum_{t=1}^{24} \sum_{l=1}^{N_{PEMFC}} f_{PEMFC}\left(P_{PEMFC}\right) + \sum_{t=1}^{24} \sum_{j=1}^{N_{Wind}} f_{WT,j}\left(P_{WT,j,t,s}\right)$$

$$+ \sum_{t=1}^{24} \sum_{q=1}^{N_{PV}} f_{PV,q}\left(P_{PV,q,t,s}\right)$$

where $C_{Buy,t,s}$ is Cost of buying electricity from the market at time t in scenario s, $P_{Buy,t,s}$ is Power bought from the market at time t in scenario s, $f_{TH,h}(P_{TH,h,t,s})$ is cost function for thermal units, $f_{PEMFC}(P_{PEMFC})$ is cost function for Proton exchange membrane Fuel Cells, $f_{WT,j}(P_{WT,j,t,s})$ is Cost function for Wind Turbines, $f_{PV,q}(P_{PV,q,t,s})$ is cost function for Photovoltaic units.

The different parts of the above equation can be determined by:

$$f_{TH,h}\left(P_{TH,h,t,s}\right) = C_{TH,s}.P_{TH,h,t,s} \quad (2)$$

$$f_{PEMFC,l}\left(P_{PEMFC,l,t,s}\right) = C_{PEMFC,s}$$
$$P_{PEMFC,l,t,s} \quad (3)$$

$$f_{WT,j}\left(P_{WT,j,t,s}\right) = C_{WT,s}.P_{WT,j,t,s} \quad (4)$$

$$f_{PV,q}\left(P_{PV,q,t,s}\right) = C_{PV,s}.P_{PV,q,t,s} \quad (5)$$

### 2.2. Constraints

Microgrid energy management includes many constraints such as network balance (power balance), energy storage, production capacities, etc. This limitation limits the operation of the microgrid. Therefore, the microgrid must operate according to the constraints. The proposed optimization problem consists of several constraints, as follows:

$$P_{Buy,t,s} + \sum_{h=1}^{N_{TH}} P_{TH,h,t,s} + \sum_{l=1}^{N_{PEMFC}} P_{PEMFC,l,t,s} + \sum_{j=1}^{N_{WT}} P_{WT,j,t,s}$$

$$+ \sum_{q=1}^{N_{PV}} P_{PV,q,t,s} = Load_{t,s} + Loss_{t,s} \quad (6)$$

$$\forall t = 1:24$$

### Voltage Limits

For bus voltages remain within acceptable limits

$$V_{Min} \leq \left|V_i^t\right| \leq V_{max} \quad (7)$$

must be satisfied.

### Power Flow Equations

The active and reactive power flow are, respectively, given by

$$P_i = \sum_{i=1}^{N_{bus}} V_i V_j Y_{ij} \cos\left(\theta_{ij} - \delta_i + \delta_j\right) \quad (8)$$

$$Q_i = \sum_{i=1}^{N_{bus}} V_i V_j Y_{ij} \sin\left(\theta_{ij} - \delta_i + \delta_j\right) \quad (9)$$

where $Y_{ij}$ is the admittance between buses i and j, and $\theta_{ij}$ is the angle of this admittance.

### Generation Limits

The power generation units are set by

$$P_{Unit.i.t.s}^{min} \leq P_{Unit,i,t,s} I_t$$
$$\leq P_{Unit,i,t,s}^{max} \, . \quad (10)$$
$$\forall i \in S_{Unit} \quad t = 1:24$$

## Fuel Cell Constraints

The operational constraints for the Proton Exchange Membrane Fuel Cell (PEMFC) are defined by:

$$I_{PEMFC}^{min} \leq I_{PEMFC}^t \leq I_{PEMFC.}^{max} \tag{11}$$

$$0 \leq P_{H_{PEMFC}}^t \leq P_{MAX,PEMFC} - P_{PEMFC}^t \tag{12}$$

$$0 \leq P_{H_{PEMFCUsage}}^t \leq max \left\{ \begin{array}{l} \left( P_{MAX,PEMFC} - P_{PEMFC}^t \right), \\ \sum_{k=1}^{t-1} \left( P_{H_{PEMFC}}^t - P_{H_{PEMFCUsage}}^t \right) \end{array} \right\} \tag{13}$$

These equations limit the current and power output of the fuel cell.

## Line Flow Limits

The power flow through lines doesn't exceed their capacity when

$$S_{i-j,} \leq S_{i-j}^{max} \quad \forall i - j \epsilon S_b \quad t = 1:24 \tag{14}$$

## Energy Exchange Limit

The energy exchange with the main grid is limited by

$$E_{t,s} \leq S_{exch}^{max} \quad \forall \quad t = 1:24 \tag{15}$$

The above restrictions are stated according to the condition of production and consumption balance: the voltage is between maximum and minimum; active and reactive power limits; current passing through the lines; hydrogen station power and its flow; active and reactive losses; and charging station power. applied in simulation. Another function that should be checked is the function of minimizing the total costs associated with the charging stations that must be planned. which includes investment costs and operation costs of stations, maintenance costs during the planning period, and the relevant function is stated as follows:

$$\min f = \sum_{t=1}^{T} \frac{1}{\left(1+\eta\right)^t} \left[ \sum_{i=1}^{N_{EVCS}} \left( \begin{array}{l} C_{EVCS_i}^I \left(t\right) \\ +C_{EVCS_i}^O \left(t\right) \end{array} \right) \right] \tag{16}$$

In the above relationship, $C_{EVCS_i}^I$ is the cost of station investment and repairs, and $C_{EVCS_i}^O$ is the cost of station operation, η: Discount rate.

This function aims to minimize the total costs associated with EVCS over the planning period, including investment, operation, and maintenance costs.

## 3. Steady state model

### 3.1. Fuel cell

A fuel cell is a device that produces electricity through a chemical reaction. All fuel cells have two electrical poles (electrodes) called the anode and cathode. In fact, chemical reactions take place in these electrodes and lead to the production of electricity.

To better understand the operation of the fuel cell, it is better to get acquainted with the basic reactions and some terms in chemistry. In a fuel cell, the hydrogen combustion reaction is actually divided into two electrochemical half-reactions:

$$H_2 \leftrightarrow 2H^+ + 2e^- \tag{17}$$

$$\frac{1}{2}O_2 + 2H^+ + 2e^- \leftrightarrow H_2O \tag{18}$$
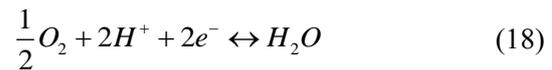
Oxidation has occurred in Eq.(17) because the reaction releases electrons, and reduction has occurred in Eq. (18) because electrons are consumed in the equation.

### 3.2. Wind Turbine

Using the Weibull probability density function to model the hourly wind speed is one of the conventional methods. In the following relations, the method of calculating the shape and scale parameters of the Weibull probability density distribution is given.

The shape and scale parameters of the Weibull probability density distribution can be computed using the mean values and standard deviation of the wind speed data, as shown in the following relationships, After calculating the shape and scale parameters of the Weibull probability density distribution, it is possible to calculate the probability of a specific wind speed according to

$$f\left(v\right) = \frac{k}{c} \left(\frac{v}{c}\right)^{k-1} \exp\left[\left(-\frac{v}{c}\right)^k\right] \tag{19}$$

where

$$k = \left(\frac{\sigma}{v_m}\right)^{-1.068} \tag{20}$$

$$c = \frac{v_m}{T\left(1+\frac{1}{k}\right)} \tag{21}$$

where $k$ is the shape parameter of the Weibull probability density function, c is the scale parameter of the Weibull probability density function, v is the wind speed in meters per second, f(v) is the Weibull probability density function, σ is the standard deviation of the practical wind speed data, and $v_m$ is the mean of the data. The practical ones are wind speeds. In the Monte Carlo simulation method, it is necessary to create a random variable based on real statistical data on random parameters such as wind speed and simulate real-state conditions.

One of the possible methods for generating a random variable based on statistical data is to use the inverse of the cumulative probability density function of wind speed. In the following relations, the cumulative Weibull probability density function for wind speed and how to generate the wind speed random variable based on it are described as

$$f(v) = 1 - \exp\left[\left(-\frac{v}{c}\right)^k\right] \tag{22}$$

$$V = -c\ln(1-u)^{1/k} = -c\ln(u)^{1/k}, \tag{23}$$

where u is a random number in a certain interval.

The output power of the wind-generating unit at any moment in time and wind speed are obtained from

$$P_v(v) = \begin{cases} 0 & 0 < v < v_{ci} \\ P_{rated} * \frac{(v - v_{ci})}{(v_r - v_{ci})} & v_{ci} < v < v_r \\ P_{rated} & v_r < v < v_{ct} \\ 0 & v_{ct} < v \end{cases} \tag{24}$$

With the wind speed that will be produced with the help of Eq.(24), it is sufficient for each hour of the Monte Carlo simulation. The relationships governing the wind production unit are applied to the wind speed of the simulation so that the power that can be delivered to the wind production unit to be determined. The output power of the wind generation unit is based on the wind speed and the power curve parameters of the wind turbine. Where $P_{rated}$ is the rated power of the wind

turbine, v is the turbine speed, $v_{ci}$ is the initial cut-off speed, $v_r$ is the rated speed, and $v_{ct}$ is the final cut-off speed. In Fig.1 , the box diagram of wind turbine power production is shown considering the Weibel density function. 2000 scenarios are produced; 10 scenarios are selected by the Monte Carlo method, which are the most probable states out of 2000 scenarios and are considered for wind turbine production energy.

### 3.3. Uncertainty of solar radiation

Simulating sunlight radiation in a probabilistic Monte Carlo simulation requires careful consideration of the resolution index probability density function, just as in wind speed modeling and random wind speed production. The requisite random solar radiation, which is the random variable corresponding to the resolution index, is then generated by taking the inverse of the cumulative probability density function that has been computed. The beta distribution is one of the probability distributions used in probabilistic analyses of solar radiation and the radiation clarity index. It is given by

$$K_t = \frac{G}{G_0} \tag{25}$$

$$\beta = \frac{\left(1 - \overline{K_t}\right)\left(\overline{K_t}\left(\overline{K_t}+1\right)\right)}{\sigma_{k_t}^2 - 1} \tag{26}$$

$$\alpha = \frac{\overline{K_t} * \beta}{1 - \overline{K_t}} \tag{27}$$

$$f(k_t) = \frac{T(\alpha+\beta)}{T(\beta)T(\alpha)} K_t^{\alpha-1}\left(1-k_t\right)^{\beta-1} \tag{28}$$

$$K_t = inverse \int_0^{K_t} f(K_t) \tag{29}$$

In above equations $K_t$ is the brightness index, G is the solar radiation, $G_0$ is the extraterrestrial solar radiation, $\overline{K_t}$ is the average brightness index, and α and β are constants of the beta probability distribution function. The output power of the solar cell module strongly depends on the solar radiation, ambient temperature, and structural characteristics of the module. By
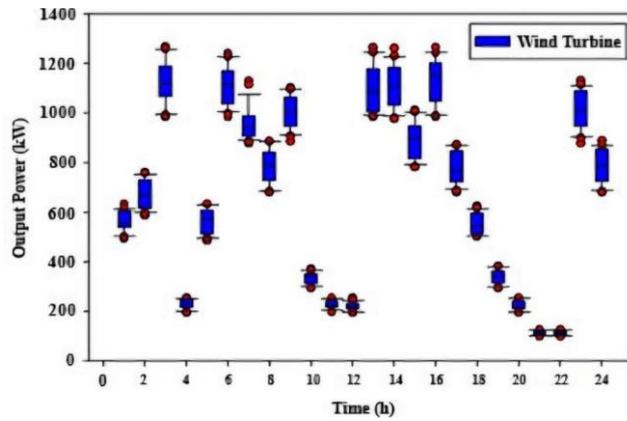
**Fig. 1.** Box diagram of wind turbine power generation.

changing the brightness index every hour, the output power changes with each time unit. The equations governing the output of solar cell units are presented below. With these equations and the generation of random variables such as the clarity index, the deliverable power of the solar cells in the system can be calculated at each step of the Monte Carlo simulation. It should be noted that during times when the sun does not shine (the solar radiation graph is shown in Fig. 10), the output power of the solar cells is considered to be zero. Thus,

$$T_c = T_a + \left( G * \frac{(N_{OT} - 20)}{800} \right) \quad (30)$$

$$I = k_t * (I_{sc} + (T_c - T_a) * K_I \quad (31)$$

$$I = k_t * \left( I_{sc} + (T_c - T_a) * K_I \right) \quad (32)$$

$$V = V_{oc} - k_V * T_c \quad (33)$$

$$PPV = N_{pv} * I * v * \eta \quad (34)$$

In the above equations, $T_c$ represents the temperature of the solar cell, $T_a$ is the ambient temperature, $N_{OT}$ is the nominal operating temperature of the solar cell, I is the output current of the solar cell, $I_{sc}$ is the short-circuit current of the solar cell, V is the output voltage of the solar cell, $V_{oc}$ is the open-circuit voltage of the solar cell, $K_I$ is the temperature coefficient of current, $k_V$ is the temperature coefficient of voltage, PPV is the output power of the solar cell, $N_{pv}$ is the number of solar cells, and η is the efficiency of the solar module.

Figure 2 shows a box plot of the power output of the solar cell, considering the beta probability density function. Since energy is only obtained from the solar cell during daylight hours and in the presence of light, the power output is zero during uncertain hours from 1-6 and 17-24.
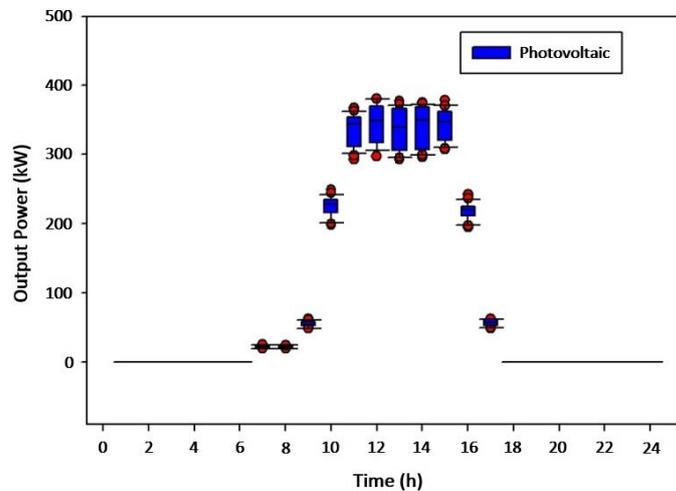


**Fig. 2.** Solar Power Generation Box Chart.

### 3.4. Network load uncertainty

To simulate the uncertainty of network load, a normal distribution function is used, which generates random scenarios with the Monte Carlo method and the most probable event is extracted from it. Figure 2 shows some of them with a standard deviation of 10%.

By evaluating the final answer, the final load distribution can be calculated in the presence of uncertainties in load, wind speed, and solar radiation. In an environment with uncertainties, initially, 2000 scenarios are generated for modeling the uncertainties of the three elements. Then, 10 scenarios with higher probabilities of occurrence are selected using the Monte Carlo method.

### 3.5. Charging station unit

Charging stations will be an important component of the network in the future of electric vehicles, providing the necessary electrical energy for charging electric and hybrid vehicles and exchanging energy with the grid. By optimizing their use and incorporating energy storage capabilities, not only can uncertainties in the grid be managed, but also operating costs can be reduced. The objective function for this is given in Eq. (16).

In this paper, considering that the design of an electric vehicle charging station is complex and costly, a simplified cost model is used to reduce costs and enable the establishment of stations. This allows for energy exchange with the microgrid and the main grid, as well as control of uncertainties arising from renewable sources, providing individuals and the grid with a lower-risk entry into the electric vehicle market. Alongside ease of use, it also allows for future development and expansion of the station. With experience and attracting more customers, it can gradually be upgraded to a more complex station with additional capabilities.

In this regard, four scenarios have been considered for operation, which will be discussed in the next section.

## 4. Scenarios

### 4.1. Utilization of microgrid with the aim of reducing the cost of power generation in the condition of load certainty

In this scenario, the proposed microgrid is used to reduce production costs associated with PEMFC as well as electricity generation from WT, PV, and TH. The objective function of this scenario is presented in Eq.(1). In this scenario, the power distribution among different energy sources in the microgrid is examined, and their responses are compared. Figure 11 illustrates the comparison between the results obtained from the Firefly Algorithm and the Particle Swarm Optimization algorithm, showing that the performance of the Firefly Algorithm is better. Figure 12 also depicts the power shares of energy sources with the aim of reducing exploitation costs.
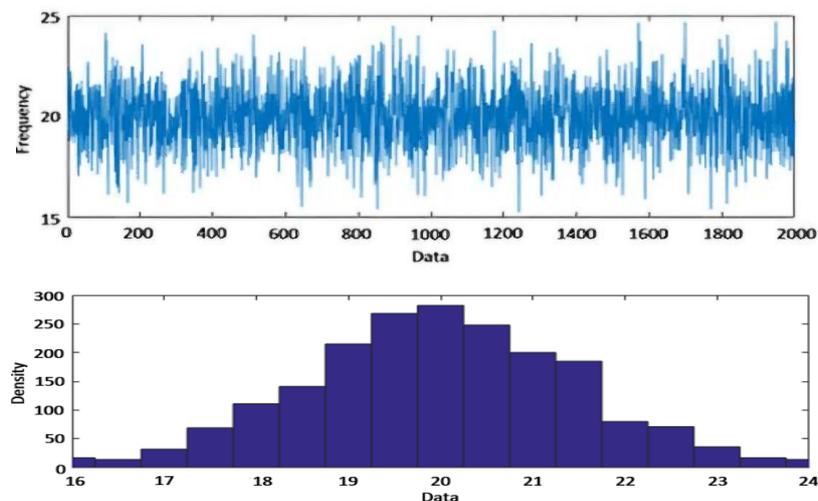


**Fig. 3.** Modeling of load uncertainty. A: Number of states with a standard deviation of 10; B: Normal distribution function.

## 4.2. Utilization of microgrid with the aim of reducing power generation in the condition of load certainty

To account for the uncertainty of load, wind power generation, and solar radiation in this design, a new algorithm has been utilized. The load is assumed to follow a normal distribution, wind power follows a Weibull distribution, and solar radiation follows a beta distribution.

The Monte Carlo method is employed to extract the highest probability of occurrence for each of these three elements. In the design conducted in this research, an estimation error of 10% is assumed for load, wind, and solar radiation for the designed network. In other words, the estimation errors for load, wind, and solar radiation are modeled with a normal, Weibull, and beta distribution, respectively, with an average value of zero and a standard deviation of 10%. The power shares of renewable energy sources (wind and solar), gas microturbines, and fuel cells for the objective of cost reduction are depicted in Fig. 14. The energy input, storage capacity, and utilization limit of the hydrogen storage system are presented in Fig. 15.

## 4.3. Adding a charging unit to the microgrid and redoing scenario one

In this scenario, a charging station is incorporated into the microgrid based on Ghahramani et al. [17] in Fig. 4. By integrating this unit into the microgrid and optimizing the operational costs over a 24-hour period using the Firefly Algorithm and Particle Swarm Optimization, as depicted in Fig.16, it is evident that the Firefly Algorithm outperforms.

## 4.4. Optimal management of the charging station according to the price and redoing scenario one

In this scenario, the microgrid has a CS, the goal is to optimize the operating costs of the microgrid in a 24-hour period by integrating this CS and using FA and PSO algorithms and comparing their results, as shown in Fig. 17. It is obvious that FA performs better than that. PSO in this field.
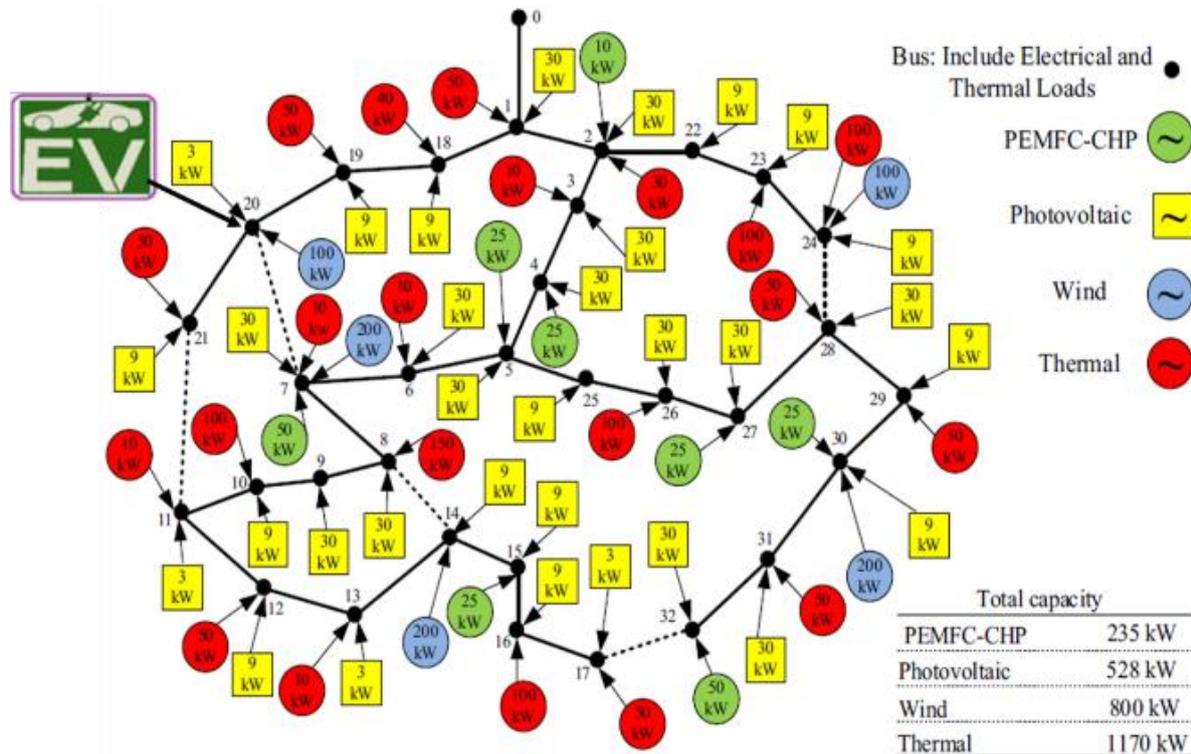


**Fig. 4.** Studied network with charging station in Shin 20, Bornapour et al [18].

To ensure the efficient use of the EVCS, a time-based charging and discharging strategy has been implemented. This strategy takes into account energy prices and peak demand. The station is divided into four operating cycles, including two charging cycles and two discharging cycles. The goal is to manage the charging and discharging time of the charging station in such a way as to minimize the overall operating cost of the microgrid.

Figure 6 shows the daily network load curve, while Fig. 7 shows the energy price. These figures provide valuable insight to optimize charging and discharging times of stations in order to achieve cost efficiency.

## 5. Firefly Algorithm

The Firefly Algorithm is an optimization algorithm inspired by the social behavior of fireflies. It is a path-independent optimization algorithm that exhibits high convergence speed, the ability to explore large solution spaces, parallelizability, and the potential for improving solutions compared to other deterministic methods.

To simulate the microgrid using the Firefly Algorithm, you first need to implement the microgrid model using the desired simulation programming language and define the system parameters. Then, you can execute the Firefly Algorithm for optimization purposes.

In this algorithm, each firefly can be viewed as a moving entity in the search space of the microgrid model. In each iteration of the algorithm, each firefly interacts with other fireflies and improves its own position. These interactions are based on the brightness of the fireflies, and the fireflies with higher brightness are considered superior. Subsequently, each firefly moves towards the superior fireflies to improve its position.

The Firefly Algorithm is a suitable optimization algorithm for complex microgrid models because microgrids involve numerous generation and consumption units, and the microgrid can be easily defined in the algorithm. Additionally, the Firefly Algorithm is well-suited for multi-variable optimization, and, due to its swarm behavior-inspired approach, it automatically contributes to improving the system's efficiency

Our objective is to minimize the power network costs while considering the relevant constraints mentioned above. These constraints are incorporated into the Firefly Algorithm to perform optimization. The flowchart of the Firefly Algorithm is provided below.
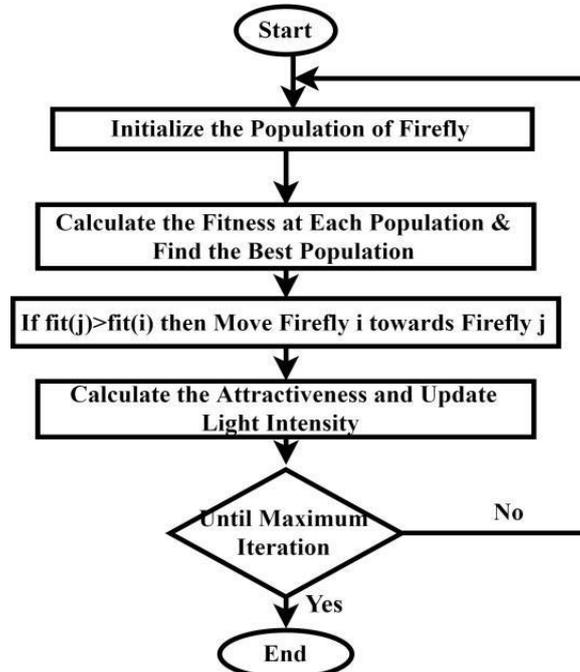


**Fig. 5.** Firefly Flowchart, Premkumar and Sowmya [19].

**Table 1.** Energy Generating Equipment Costs

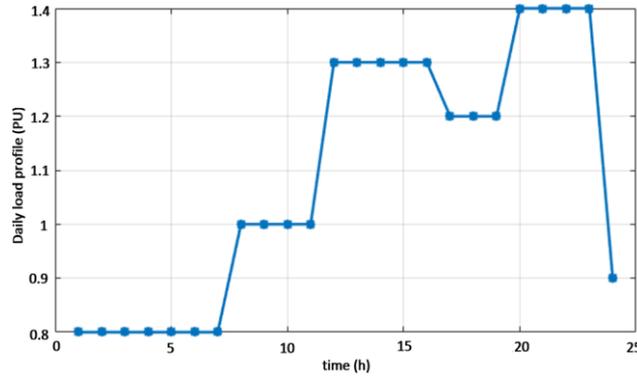| Parameter | Value($/kWh) |
|---|---|
| Cost of WT active power, $C_{WT}$ | 0.005 |
| Cost of PV active power, $C_{PV}$ | 0.005 |
| Cost of PEMFC active power, CPEMFC, $C_{HP}$ | 0.039 |
| Cost of TH active power, $C_{TH}$ | 0.039 |
| Cost of hydrogen $C_{pump}$ | 0.01 |
| Tariff of electrical energy selling to customer, $P_{Tariff}$ | 0.045 |
| Tariff of heat energy selling to customer, $P_{H, sell, t}$ | 0.045 |



**Fig. 6.** Daily grid load curve, Bornapour et al [18].
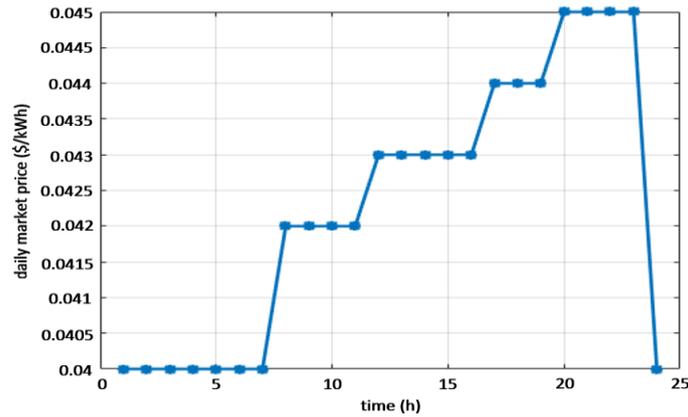


**Fig. 7.** Purchase price of energy from the upstream grid, Bornapour et al [18].
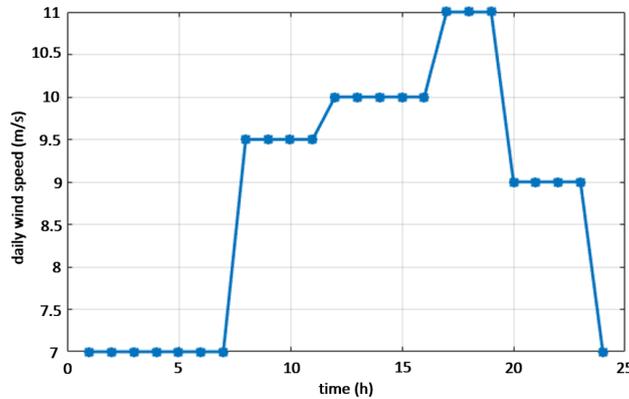


**Fig. 8.** Wind speed, Bornapour et al [18].
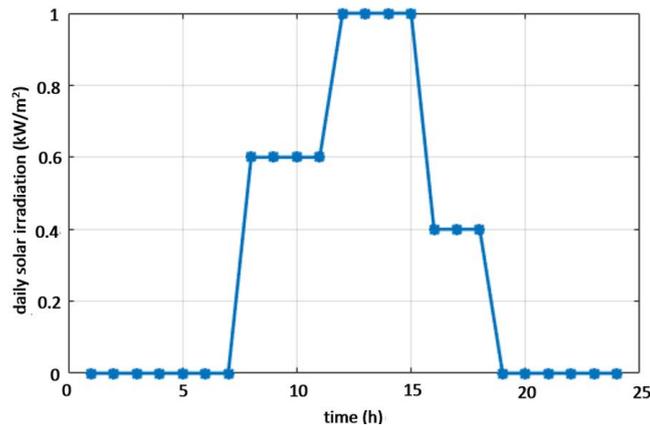
**Fig. 9.** Sunlight, Bornapour et al [18].
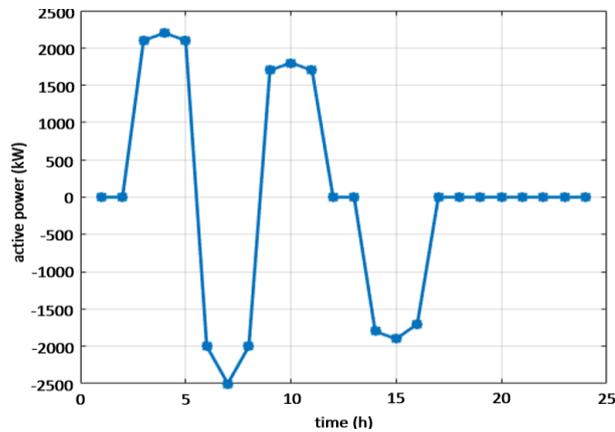


**Fig. 10.** Working cycles of a charging station connected to Shin20 network.
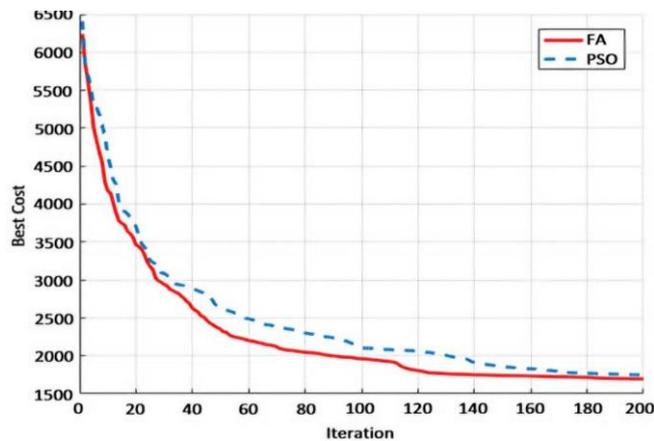


**Fig. 11.** Response of Firefly Algorithm to Solving Microgrid Exploitation Problem compared to PSO.

As previously mentioned, in this scenario, the distribution of power between different energy sources in the microgrid is examined, and their responses are compared. It is important to note that this scenario is single-objective. In other words, power distribution is done separately to reduce operating costs.

The contribution of renewable energy sources, including WT and PV, TH and PMFC to the objective of cost reduction is shown in Fig. 12.

The contribution of renewable energy sources, including wind and solar, gas microturbine, and fuel cell to the objective of cost reduction in Scenario 2 is shown in Fig. 14.
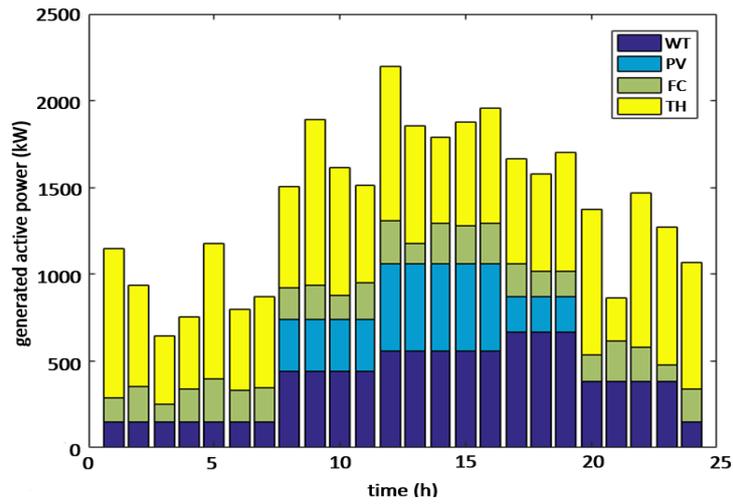
**Fig. 12.** Contribution of power of energy resources with the aim of reducing the costs of operation scenario 1.
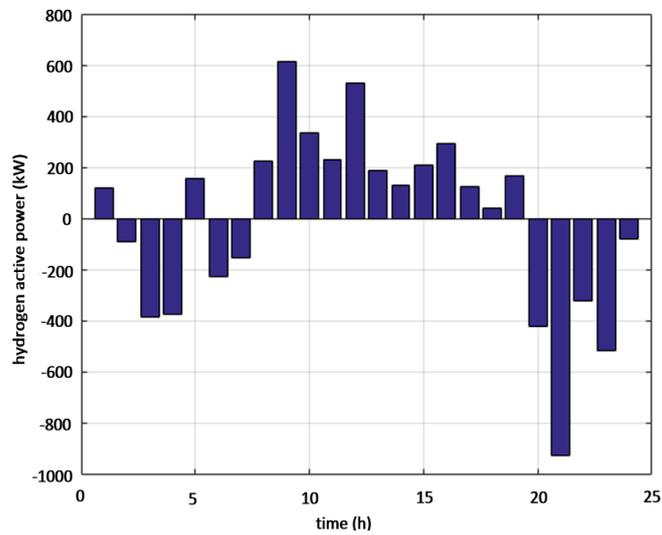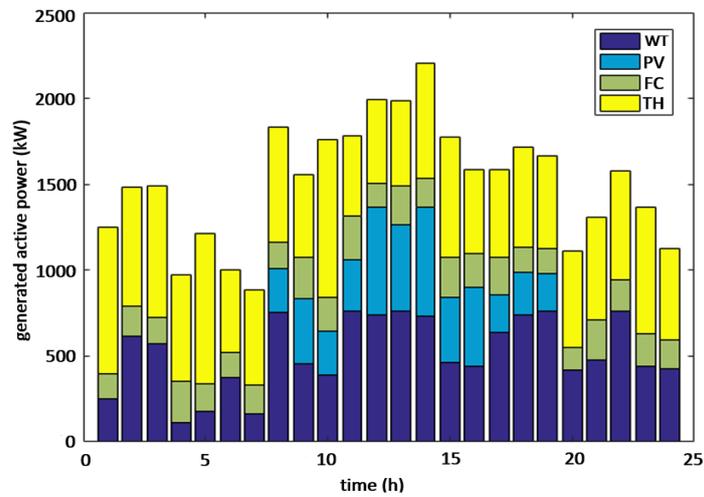


**Fig. 13.** Hydrogen storage function.
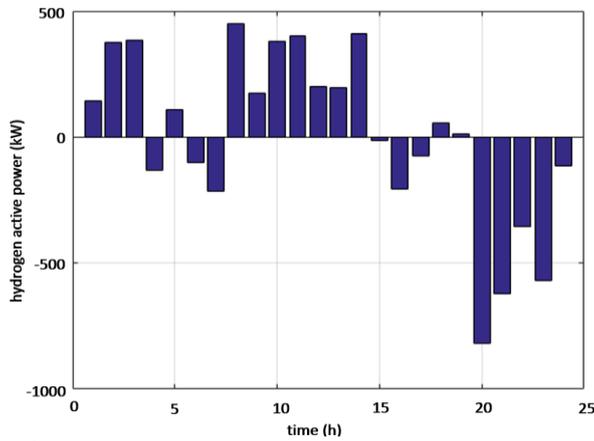


**Fig. 14.** Power Share of Energy Resources.

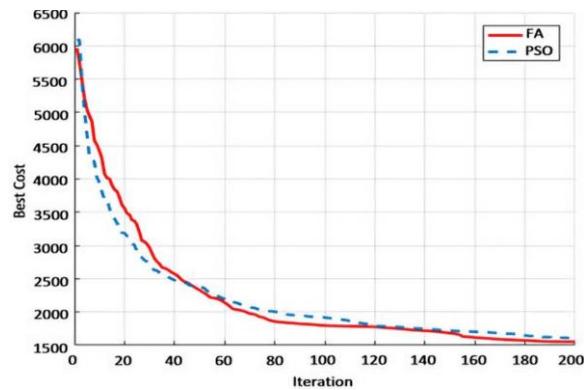**Fig. 15.** Input and output energy of hydrogen storage.



**Fig. 16.** Objective Function Minimization of Operational Costs Scenario 3.

In Scenario 3, with the addition of a charging station unit to the microgrid and the execution of a 24-hour operating cost optimization program using the Firefly Algorithm, the objective function is obtained as shown in Fig.11. As evident, the operating cost amounts to 1595 dollars per kilowatt per day, resulting in increased operating costs.

In the fourth scenario, similar to Fig. 19, we manage the charging and discharging times of the charging station to minimize the overall operating cost of the microgrid.

It should be noted that the objective function solutions for all four scenarios are presented in Table 2.
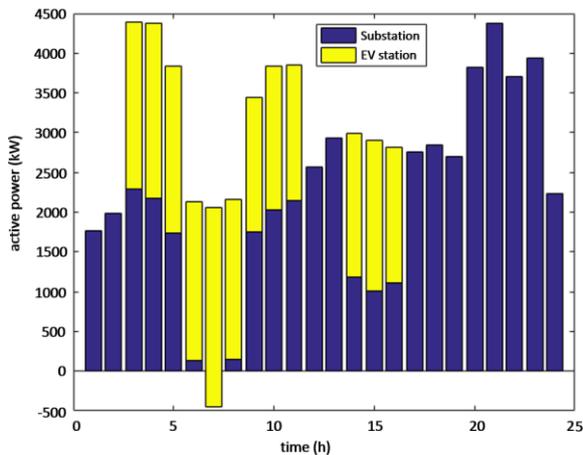


**Fig. 17.** Receiving power from upstream network with charge and discharging power
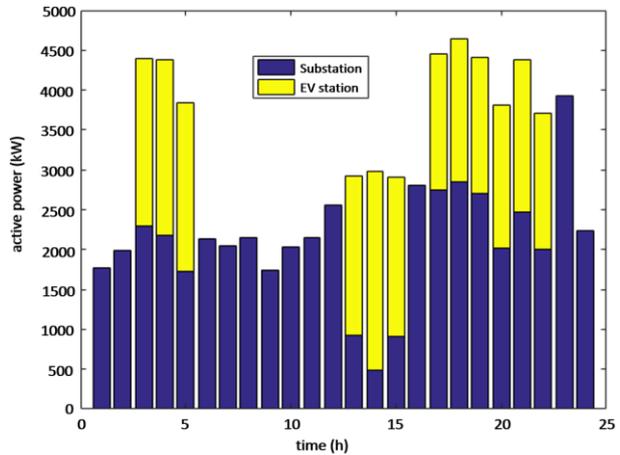


**Fig. 18.** Optimized charge and discharge power of charging station with energy received from upstream network
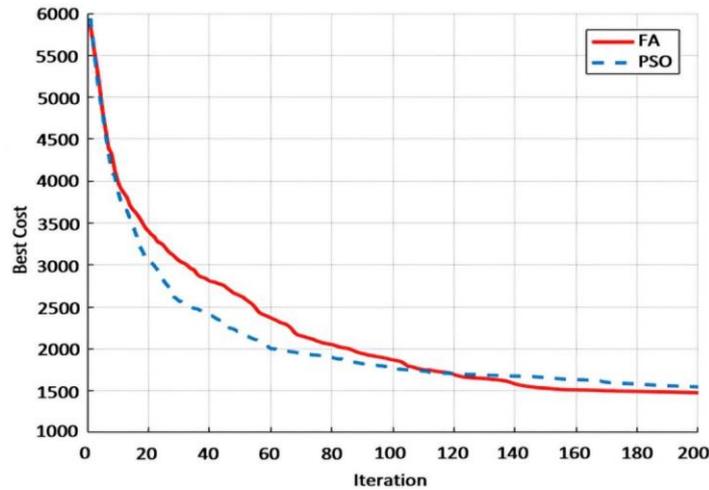
**Fig. 19.** Objective Function Minimizing Costs of Operation Scenario 4.

**Table 2.** Objective function response in scenarios

| Row | Scenario | operating cost ($/kWday) | |
|-----|----------|------|------|
| | | FA | PSO |
| 1 | 1 | 1690 | 1721 |
| 2 | 3 | 1595 | 1602 |
| 3 | 4 | 1476 | 1498 |

## 6. Conclusions

Due to the evolution of the electricity industry, the entry of electric vehicles into the grid has become inevitable. The limitation of fossil fuels also leads us to use renewable resources. Uncertainties related to renewable resources and the need to use them lead us to intelligentize the network and optimal use of resources. In addition to creating the necessary capacity and infrastructure for future power grids, this article has reduced operating costs in current conditions. In this regard, an IEEE 33-bus microgrid connected to its upper network was studied. To simultaneously reduce operating costs, the FireFly algorithm and the Monte Carlo method are used in a 24-hour period. The results are validated using the PSO algorithm, which shows the speed and convergence of the proposed method. In addition, fuel cells and electric vehicle charging stations, with energy storage capability, are used to exchange and exchange energy with the upstream grid based on energy pricing strategies, leading to significant cost reductions. At the same time, it has provided a capacity for the introduction of electric vehicles and their possible energy supply using renewable sources or purchasing energy from the grid. The availability of resources such as wind turbines, fuel cells, and solar panels not only provides a foundation for implementing a smart grid, but also reduces operating costs over the study period. Therefore, with the proposed strategies, not only the goal of cost reduction is achieved, but also suitable capacities are created in the network structure for future studies.

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