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A Novel Solution for Day-Ahead Scheduling Problems Using the IoT-Based Bald Eagle Search Optimization Algorithm

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Abstract: Advances in technology and population growth are two factors responsible for increasing electricity consumption, which directly increases the production of electrical energy. Additionally, due to environmental, technical and economic constraints, it is challenging to meet demand at certain hours, such as peak hours. Therefore, it is necessary to manage network consumption to modify the peak load and tackle power system constraints. One way to achieve this goal is to use a demand response program. The home energy management system (HEMS), based on advanced internet of things (IoT) technology, has attracted the special attention of engineers in the smart grid (SG) field and has the tasks of demand-side management (DSM) and helping to control equality between demand and electricity supply. The main performance of the HEMS is based on the optimal scheduling of home appliances because it manages power consumption by automatically controlling loads and transferring them from peak hours to off-peak hours. This paper presents a multi-objective version of a newly introduced metaheuristic called the bald eagle search optimization algorithm (BESOA) to discover the optimal scheduling of home appliances. Furthermore, the HEMS architecture is programmed based on MATLAB and ThingSpeak modules. The HEMS uses the BESOA algorithm to find the optimal schedule pattern to reduce daily electricity costs, reduce the PAR, and increase user comfort. The results show the suggested system's ability to obtain optimal home energy management, decreasing the energy cost, microgrid emission cost, and PAR (peak to average ratio).

Keywords: bald eagle search optimization algorithm; internet of things; renewable energy sources; battery energy storage system

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1. Introduction

An electric grid is a huge complex network designed for providing electricity to consumers to satisfy their growing energy demands. The International Energy Outlook in 2016 projected that there would be a notable increase in the overall energy demand of the world in the next 20 years. This growth in worldwide consumption has led to an immediate change in the conventional grid to meet the increasing demand. The conventional grid is the electricity network used for supplying and distributing electricity from the generation side to the consumer side. In other terms, it is used for connecting producers of electricity to consumers of electricity. However, the existing electric grid faces a few challenges [1]. These challenges vary from country to country based on the energy demand. The main challenges are to fulfill the required demand with the resources available and to provide accessibility to electricity with infrastructure utilities. The other challenges faced by the traditional grid are as follows: (a) It is a centralized grid in which the power is generated from a centralized location and carried to consumers. In addition, conventional grids are powered by non-renewable energy sources, i.e., natural gas, diesel, etc. (b) The grid consists of one-way communication where the consumer is just a receiver; it cannot provide any user preference, nor can a user state the required energy demand to the utility. (c) It is not well equipped to handle advanced technology and sensors. Thus, it fails to detect problems and anomalies. (d) The manual monitoring of energy distribution and the manual reading of metering infrastructure are required. All the aforementioned problems can lead to increasing grid vulnerability and power outage risks. Thus, it is necessary to overcome these challenges and make huge investments in the existing traditional grids. Additionally, owing to the worldwide rise in energy demand and significant changes in energy infrastructure, there is a need to evaluate/update the conventional grids into smart grids to address future energy demand. The smart grid (SG) represents one such solution that will make existing grids more responsive and intelligent. It is a relatively new concept with advanced information and communication technologies (ICT) and integrates two-way communication between a utility and its consumers [1]. SGs facilitate customer interactions with utilities in a bi-directional way to enhance the security, performance, reliability, and sustainability of the generation, transmission, and distribution of electricity.

One of the potential advantages of smart grids is the role they can play in making the electric grid more flexible and efficient, thanks to the integration of DER units and controlled loads. Distributed generators (DGs) and energy storage systems (ESSs) are DER units. Renewable energy sources (RES), such as solar (PV) and wind power, are commonly used in DG units [2–4].

The energy management of SGs has turned into a challenging topic in the literature [5]. In [6], a chance-constrained model was proposed for solving the probabilistic optimal energy management of MG systems. The authors have not yet investigated the efficiency of their model on the emission of greenhouse gases. The impact of the renewable energy sources (RESs) on the performance of islanded MG systems was studied in [7]. Though, cost allocation among MGs, the emission of greenhouse gases, and energy not supplied (ENS) were not investigated. The authors of [8] suggested the epsilon constraint method and a fuzzy model to define the best plan for the energy hubs in solving the multi-objective optimization for the water management of an MG system. Nevertheless, the uncertainties of RESs and demand response programs were not considered.

IoT-based EMSs are essential for managing problems and achieving energy savings. These systems must be able to prevent power peaks and maintain continuous energy in order to survive future trends [9,10].

Table 1 outlines the shortcomings and contributions of recent studies on demand management systems in a smart grid.

Table 1. Contributions vs. shortcomings of greatest recent studies concerning demand-side management systems.

Reference	Contributions	Shortcomings
[5]	Introduced a strategy for solving the problem of the optimal power management of a microgrid system.	• High computational complexity and a slow convergence rate.
[11]	The authors introduced the multi-objective scheduling of IoT-enabled intelligent houses for energy management based on the arithmetic optimization algorithm.	• The optimum cost-effective EMS process based on the bald eagle search optimization algorithm (BESOA) was not investigated.
[12]	Proposed a low-cost smart meter design that ensures power quality for consumers' appliances through smart monitoring and control with the help of IoT.	• Pollutant emissions, low efficiency, and expensive operating and maintenance costs.
[13]	Introduced a two-stage framework for demand-side management and energy savings for various buildings in a multi smart grid using the improved grey wolf optimization (IGWO) algorithm.	• Data storage and processing using the ThingSpeak platform were not considered.
[14]	Developed a home energy management system (HEMS) that included three novel demand response (DR) routines focused on peak clipping and demand-flattening strategies.	• These algorithms were lacking in terms of accuracy and computational time.

Table 1. *Cont.*

Reference	Contributions	Shortcomings
[15]	■ Based on the energy internet, the authors proposed a new robust intelligent energy management and demand reduction system for intelligent households.	• Data storage and processing on the ThingSpeak platform were not taken into account.
[16]	■ The authors proposed a residential energy management system using the main grid and selling electricity, as well as utilizing energy storage and renewable energy.	• The most cost-effective DSMS operation based on an AI optimization problem supplemented with ToU was not investigated.
[17]	■ The authors proposed a Raspberry Pi3-based supervisory control and data acquisition (SCADA)-controlled smart home.	• The most cost-effective DSMS operation based on an AI optimization problem supplemented with ToU was not investigated.
[18]	■ Risk assessment and price discrimination were considered as part of a cooperative Stackelberg game-based energy management proposal.	• Did not consider the trade-offs between user discomfort and minimizing electricity bills.
[19]	■ The authors proposed novel demand-side management of off-grid/on-grid, utilizing a neuro-fuzzy system.	• Data storage and processing using IoT were not considered.
[20]	■ The authors introduced a demand management scheme based on optimization for a multi microgrid.	• In this reference, a stable, accurate, and efficient performance was achieved at the cost of high execution time.
[21]	■ The authors suggested an artificial intelligence-based scheduling system for energy management in intelligent households.	• IoT data storage and processing were not taken into account.
[22]	■ The authors introduced an optimization procedure proposed based on integrated demand response (IDR) and degree of tolerance for home energy management.	• The researchers did not account for real-time changes in user demand.
[23]	■ For nano grid devices, the authors proposed a novel intelligent energy management as a cloud service.	• The most cost-effective DSMS operation based on an AI optimization issue supplemented with ToU was not investigated.
[24]	■ The authors proposed optimum power scheduling in microgrids combined with renewable energy sources for the demand management system.	• Did not consider the trade-offs between minimizing electricity bills and user discomfort.
[25]	■ The authors proposed a new IoT-enabled distributed energy management system with a high level of trust.	• The most cost-effective DSMS operation based on an AI optimization problem supplemented with ToU was not investigated.
[26]	■ For better microgrid stability and robustness, the authors implemented a new dynamic appliance clustering mechanism into the community household energy management system.	• Use of the cloud for energy management systems in the smart grid was not examined in this reference.
[27]	■ For smart microgrids, the authors presented an adaptive demand management strategy.	• Results were obtained with high computational complexity; • Data storage and processing using the IoT layer platform were not considered.
[28]	■ A 5G-based green and reliable communication system for a self-adaptive vehicular network in ITS is proposed to facilitate the end-users at cost-effective rates.	• The optimal cost-effective DSMS operation based on BESOA was not investigated.
[29]	■ Devised a dynamic application-partitioning workload task-scheduling secure (DAPWTS) algorithm framework consisting of different schemes including min-cut algorithm, searching node, energy-enabled scheduling, failure scheduling, and security schemes.	• The optimal cost-effective DSMS operation based on BESOA was not investigated.

Based on the knowledge gaps described in the previous section, this article has the following potential novelties.

- Firstly, the proposal of a new low-cost smart system design that ensures power quality for consumers' appliances through smart monitoring and control with the help of IoT;
- The implementation of a DSM program for smart microgrids with a variety of electrical loads. This load variation is rare in other articles;
- This paper solves the DSM problem by considering different objective functions, including reducing consumer bills and reducing power losses;
- This research proposes a bald eagle search optimization algorithm (BES)-based real-time optimal schedule controller for EMS;
- Two-layer hierarchical communication architecture is implemented based on the MQTT protocol, leveraging a cloud server named ThingSpeak to enable global and local communication for neighborhood device controllers;
- The utility authority will have control over individual consumers' electrical loads and peak demand through IoT and smart meters. Finally, consumers will be able to

track their real-time energy consumption, and related measures could be taken to reduce demand.

2. Problem Formulation

A home energy management system (HEMS) keeps track of household energy usage and controls appliance schedules and operations. It can be accomplished through demand-side management, which assists consumers in shifting their appliance consumption from peak to off-peak hours, lowering household electricity costs. To adjust the appliance usage pattern, it is crucial to schedule them in such a way that they meet all of the RASP's optimization goals. Researchers have been working on providing local energy (RES) that is easy to generate, less expensive, and environmentally beneficial for several decades. According to several studies, integrating renewable energy sources into the residential sector provides the most cost-effective alternatives. Residential appliance scheduling is formulated as an optimization problem which schedules smart home appliances in such a way that electricity cost is minimized, peak-to-average ratio is minimized, and consumer comfort is maximized. The aforementioned objectives are optimization objectives. Thus, to solve this problem, the methodologies employed for the scheduling techniques involve optimization techniques [1]. In this paper, we use the bald eagle search optimization algorithm (BES) technique for appliance scheduling in the residential sector.

As shown in Figure 1, the proposed smart microgrid system includes renewable energy sources, loads, a utility power grid, and energy internet connectivity.

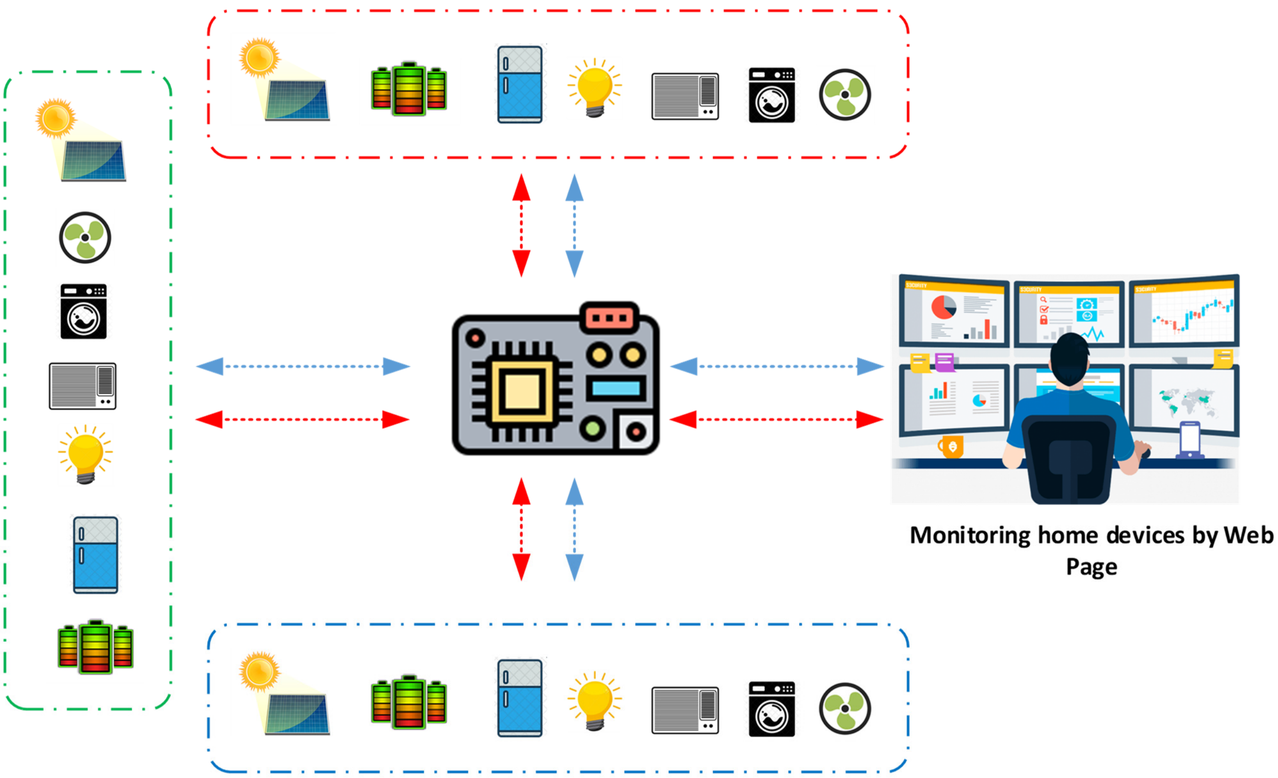

Figure 1. The components of the proposed smart grid scheme.

Data flow between MATLAB and ThingSpeak is used to model the suggested communication systems. ThingSpeak was chosen to imitate real-time cloud communication [30,31].

2.1. Modeling of the Renewable Resources and Energy Storage Devices

2.1.1. Photovoltaic

The power generated by the PV panels depends on the installed maximum power and weather conditions. Figure 2 shows an equivalent circuit based on the diode of a solar cell which can be represented as a parallel resistor, current source, diode, or as serial resistance. The current and voltage properties of solar cells are described by the standard mathematical equation [32]:

$$I = I_{ph,cell} - \underbrace{I_{o,cell}[\exp((q(V + IR\_(s,cell))/akT) - 1]}_{I_{d,cell}} - \frac{V + IR_{s,cell}}{R_{p;cell}} \quad (1)$$

where:

$I_{o,cell}$ is reversed leakage current;
$I_{ph,\ cell}$ is the photocurrent (A) of the photovoltaic cell;
k is the constant of Boltzmann's (1.38×10^{-23} J/K);
q is the electron charge (1.602×10^{-19} C);
$R_{p,cell}$ is parallel resistance (Ω).
$R_{s,cell}$ is the series resistance (Ω);
T is diode temperature.

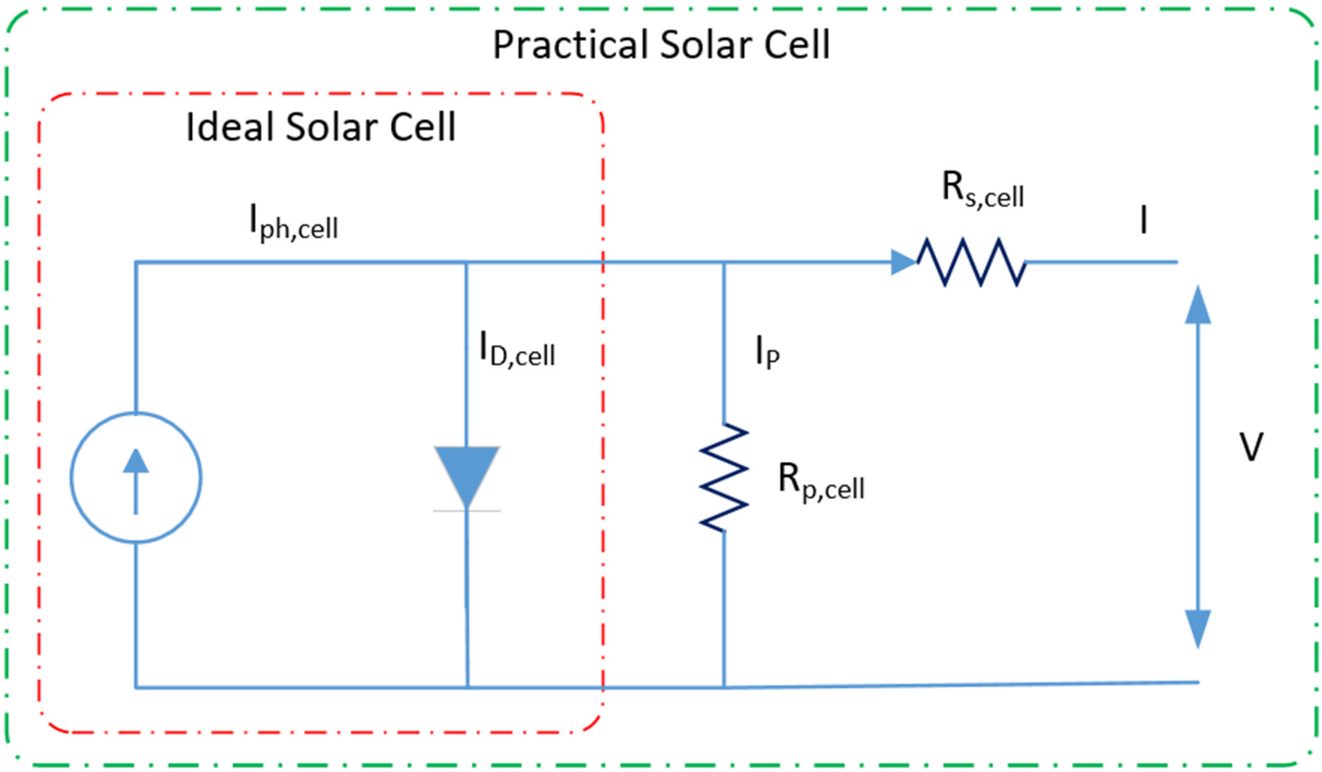

Figure 2. The circuit of a photovoltaic cell based on a single-diode mode.

The solar cell model is ideal if the parallel and series resistance of the solar cell are not taken into account. Figure 3 illustrates the ideal electrical current and voltage curves from Equation (1) [32]. Table 2 shows the electrical parameters of the SPR-305 E-WHT-D photovoltaic cell [32].

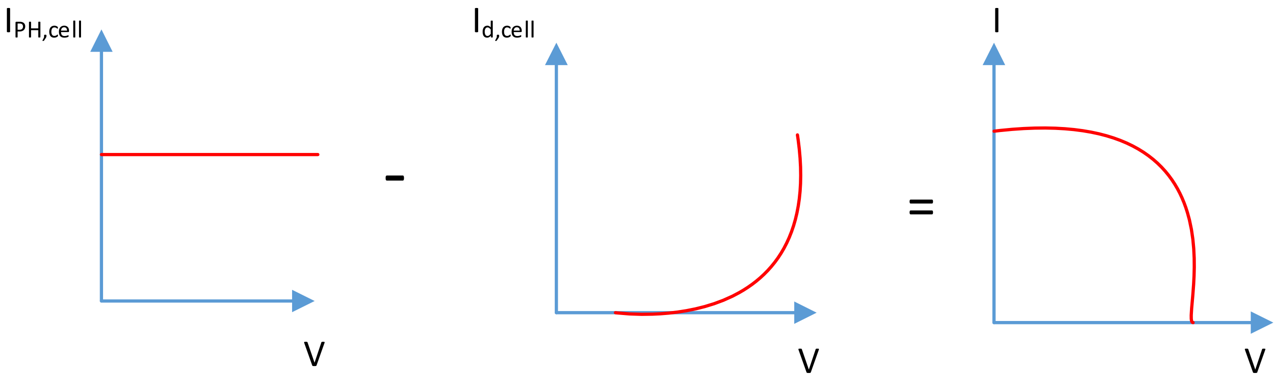

Figure 3. Typical current and voltage curves of a photovoltaic cell.

Table 2. Electrical parameters of the SPR-305 E-WHT-D photovoltaic cell [32].

Parameters	Value
Voltage of open circuit (V_{oc})	64.2 (V)
Maximum voltage (V_{mp})	54.7 (V)
Temperature coefficient of (V_{oc})	−0.27269 (%/°C)
Short − circuit current (I_{sc})	5.96 (A)
Maximum current I_{mp}	5.58 (A)
Temperature coefficient of (I_{sc})	0.061745 (%/°C)
Shunt resistance (R_{sh})	269.5934 Ω
Series resistance (R_s)	0.37152 Ω
Diode ideality factor	0.945
Diode saturation current I_o	6.3×10^{-1} (A)
PV type	SPR-305E-WHT-D

2.1.2. Battery

The energy supplied by the battery depends on its capacity and its state of charge (SOC). Moreover, the output power is limited to enhance the lifespan of energy storage devices. The SOC represents the ratio between the energy contained in the battery and its maximum capacity [33].

ESSs play an important role in achieving green energy goals and ensuring system reliability. Therefore, in our considered HEMS scheme, an ESS is used for storing excess available energy. The energy stored in the battery in any time instant, t, is denoted by $E_b(t)$ and given in (2). $E_b(t)$ has positive value in case of charging, while it obtains negative value during discharging. The charging and discharging efficiencies of the battery are denoted by η^c and η^d, respectively. The constraints given in (3) and (4) are considered for limiting the maximum charging and discharging states of the battery $\delta_b(t)$. The binary variable at time t determines battery discharging state ($\delta_b(t) = 0$) and charging state ($\delta_b(t) = 1$) at time t [34].

$$E_b(t)\& = \frac{E_b^c(t)}{\eta^c}\delta_b(t) - E_b^d(t)\eta^d(1 - \delta_b(t)) \tag{2}$$

$$0\& \leq \frac{E_b^c(t)}{\eta^c} \leq E_{b,max}^c(t)\delta_b(t) \tag{3}$$

$$0\& \leq E_b^d(t)\eta^d \leq E_{b,max}^d(t)(1 - \delta_b(t)) \tag{4}$$

$$SOC(t)\& = SOC(t-1) + \frac{E_b(t)}{C_b} \tag{5}$$

$$SOC_{max} \leq SOC(t) \leq SOC_{min} \tag{6}$$

The battery state of charge (SOC) characteristics are modeled in Equation (5). Equation (6) models the minimum and maximum SOC limits of battery at time t. C_b is battery-rated capacity. Figure 4 illustrates a flowchart of the suggested method.

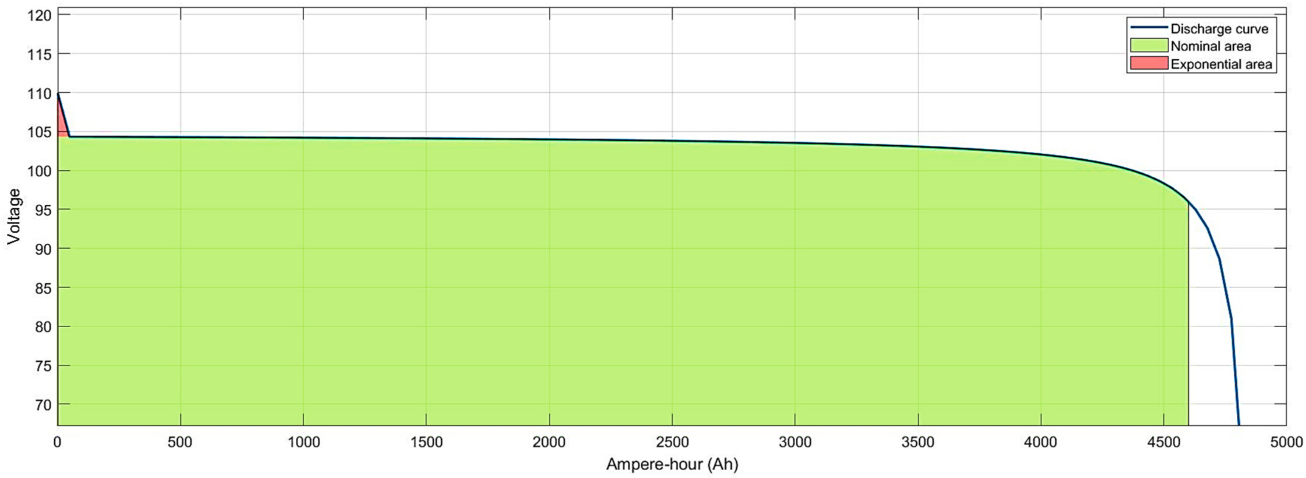

Figure 4. The battery current curves at 0.083333C (400A) [32].

2.2. Shifting of Loads

The suggested algorithm arranges devices to bring the load curve of the consumption schedule closer to the load curve of the desired load curve [35–38]:

$$\mathcal{C}_1 = \min\left(\mathcal{N}_{\mathcal{L}}^{\mathcal{S}^{\mathcal{H}}} - \mathcal{B}_{\mathcal{LC}}^{\mathcal{H}}\right) \tag{7}$$

The objective load curve $\mathcal{B}_{\mathcal{LC}}^{\mathcal{H}}$ has the inverse relation with $\mathcal{N}_{\mathcal{L}}^{\mathcal{S}^{\mathcal{H}}}$; this relation is established as:

$$\mathcal{B}_{\mathcal{LC}}^{\mathcal{H}} \propto \frac{1}{\mathcal{N}_{\mathcal{L}}^{\mathcal{S}^{\mathcal{H}}}} \tag{8}$$

where $\mathcal{N}_{\mathcal{L}}^{\mathcal{S}^{\mathcal{H}}}$ is the per-hour scheduled power load, and $\mathcal{N}_{\mathcal{L}}$ is the aggregated load of ON appliances during a particular time.

$$\mathcal{N}_{\mathcal{L}} = \sum_{\mathcal{A}=1}^{\mathcal{M}} \varsigma \times \mathcal{D}ev_{\mathcal{P}_{rate}^{\mathcal{A}}} \tag{9}$$

$\varsigma = 1; 0$ is the OFF/ON status of applinces during a particular hour.

The targeted $\mathcal{B}_{\mathcal{LC}}^{\mathcal{H}}$ is realized using constraints in Fitness Function ($\mathcal{F}_{\ell}$).

$$\mathcal{F}_{\ell} = \min(\mathcal{F}_{p}) \tag{10}$$

where $\mathcal{F}_{p}$ is calculated using:

$$\mathcal{F}_{p} = \begin{cases} \mathcal{N}_{\mathcal{L}}^{i\in p} \geq \mathcal{W}_{\mathcal{L}_1} & \text{when } hour_{p}^{off} \\ \mathcal{N}_{\mathcal{L}}^{i\in p} < \mathcal{W}_{\mathcal{L}_1} & \text{when } hour_{p}^{on} \end{cases} \tag{11}$$

$$\mathcal{W}_{\mathcal{L}imt_1} = sum\left(\mathcal{L}_{\mathcal{N}}^{h}\right) - std\left(\mathcal{N}_{\mathcal{L}}^{\mathcal{U}n\mathcal{S}^{\mathcal{H}}}\right) \tag{12}$$

$$\mathcal{W}_{\mathcal{L}imt_2} = \eta \times min\mathcal{N}_{\mathcal{L}}^{\mathcal{U}n\mathcal{S}} + std\left(\mathcal{N}_{\mathcal{L}}^{\mathcal{U}n\mathcal{S}^{\mathcal{H}}}\right) \tag{13}$$

$$\mathcal{W}_{\mathcal{L}imt_3} = mean\left(\mathcal{N}_{\mathcal{L}}^{\mathcal{U}n\mathcal{S}}\right) \tag{14}$$

$$\mathcal{L}_{\mathcal{N}orm}^{\mathcal{H}} = \left(\mathcal{N}_{\mathcal{L}}^{\mathcal{U}n\mathcal{S}} - min\mathcal{N}_{\mathcal{L}}^{\mathcal{U}n\mathcal{S}}\right) / \left(max\mathcal{N}_{\mathcal{L}}^{\mathcal{U}n\mathcal{S}} - min\mathcal{N}_{\mathcal{L}}^{\mathcal{U}n\mathcal{S}}\right) \tag{15}$$

The off-peak power limit ($\mathcal{W}_{\mathcal{L}imt_1}$) and on-peak power limit $\mathcal{W}_{\mathcal{L}imt_2}$ are calculated so that fair load distribution at the customer's end can be realized via a house load power-management scheduler [35–38].

3. Proposed Methodology

The bald eagle search optimization method is a meta-heuristic optimization algorithm inspired by bald eagle hunting behavior. There are three phases to this algorithm. The bald eagle chooses the best place in terms of food amount in the first step (selecting the space). The eagle seeks for prey inside the defined area in the second stage (searching in the space). In third stage, the eagle swings from the best position in the second phase to choose the best hunting place (swooping) [39].

In this stage, new positions will be generated using the equation below [39]:

$$\mathcal{S}_{new}(\imath) = \mathcal{S}_{\text{best}} + \alpha \cdot \mathcal{r} \cdot (\mathcal{S}_{\text{mean}} - \mathcal{S}(\imath)) \tag{16}$$

where $\mathcal{S}_{new}(\imath)$ is a newly generated position, $\mathcal{S}_{\text{best}}$ is the best position, $\mathcal{S}_{\text{mean}}$ is mean position, α is control gain [1.5, 2], and $\mathcal{r}$ is a random number [0, 1].

The algorithm adjusts the position of the eagle inside this search space after assigning optimal search space ($\mathcal{S}_{\text{best}}$). The model for updating it is as follows [39,40]:

$$\mathcal{S}_{\text{new}}(\imath) = \mathcal{S}(\imath) + \mathcal{n}(\imath) \cdot (\mathcal{S}(\imath) - \mathcal{S}(\imath+1)) + \mathcal{m}(\imath) \cdot (\mathcal{S}(\imath) - \mathcal{S}_{\text{mean}}) \tag{17}$$

where $\mathcal{m}$ and $\mathcal{n}$ are directional coordinates for an i_{th} position, they can be defined as:

$$\begin{gathered} \mathcal{m}(\imath) = \frac{\mathcal{mr}(\imath)}{max(|\mathcal{mr}|)}; \mathcal{mr}(\imath) = \mathcal{r}(\imath) \cdot \sin(\xi(\imath)) \\ \mathcal{n}(\imath) = \frac{\mathcal{nr}(\imath)}{max(|\mathcal{nr}|)}; \mathcal{nr}(\imath) = \mathcal{r}(\imath) \cdot \cos(\xi(\imath)) \\ \xi(\imath) = a \cdot \pi \cdot \text{ rand}; \mathcal{r}(\imath) = \xi(\imath) \cdot R \cdot \text{rand} \end{gathered} \tag{18}$$

where a is the control parameter that determines a corner between point searches in the center point and has a value of [5, 10], and R is the parameter that determines the number of search cycles and has a value of [0.5, 2]. The new positions' fitness will be assessed, and the $\mathcal{S}_{\text{best}}$ value will be adjusted in light of the findings.

Eagles approach target prey from the best-obtained position in this stage. The following is the hunting model [39,40]:

$$\mathcal{S}_{new}(i) = \text{ rand} \cdot \mathcal{S}_{\text{best}} + \mathcal{m}1(\imath) \cdot (\mathcal{S}(\imath) - c_1 \cdot \mathcal{S}_{\text{mean}}) + \mathcal{n}1(\imath) \cdot (\mathcal{S}(\imath) - c_2 \cdot \mathcal{S}_{\text{best}}) \tag{19}$$

where c_1 and c_2 are random numbers [1, 2]. $\mathcal{m}1$ and $\mathcal{n}1$ are directional coordinates, and can be defined as:

$$\begin{gathered} \mathcal{m}1(i) = \frac{\mathcal{mr}(\imath)}{max(|\mathcal{mr}|)}; \mathcal{mr}(\imath) = \mathcal{r}(\imath) \cdot \sinh(\xi(\imath)) \\ \mathcal{n}1(i) = \frac{\mathcal{nr}(\imath)}{max(|\mathcal{nr}|)}; \mathcal{nr}(\imath) = \mathcal{r}(\imath) \cdot \cosh(\xi(\imath)) \\ \xi(\imath) = a \cdot \pi \cdot rand; \mathcal{r}(\imath) = \xi(\imath) \end{gathered} \tag{20}$$

A flowchart of the proposed method is shown in Figure 5. The pseudocode of the bald eagle search optimization algorithm is shown in Table 3.

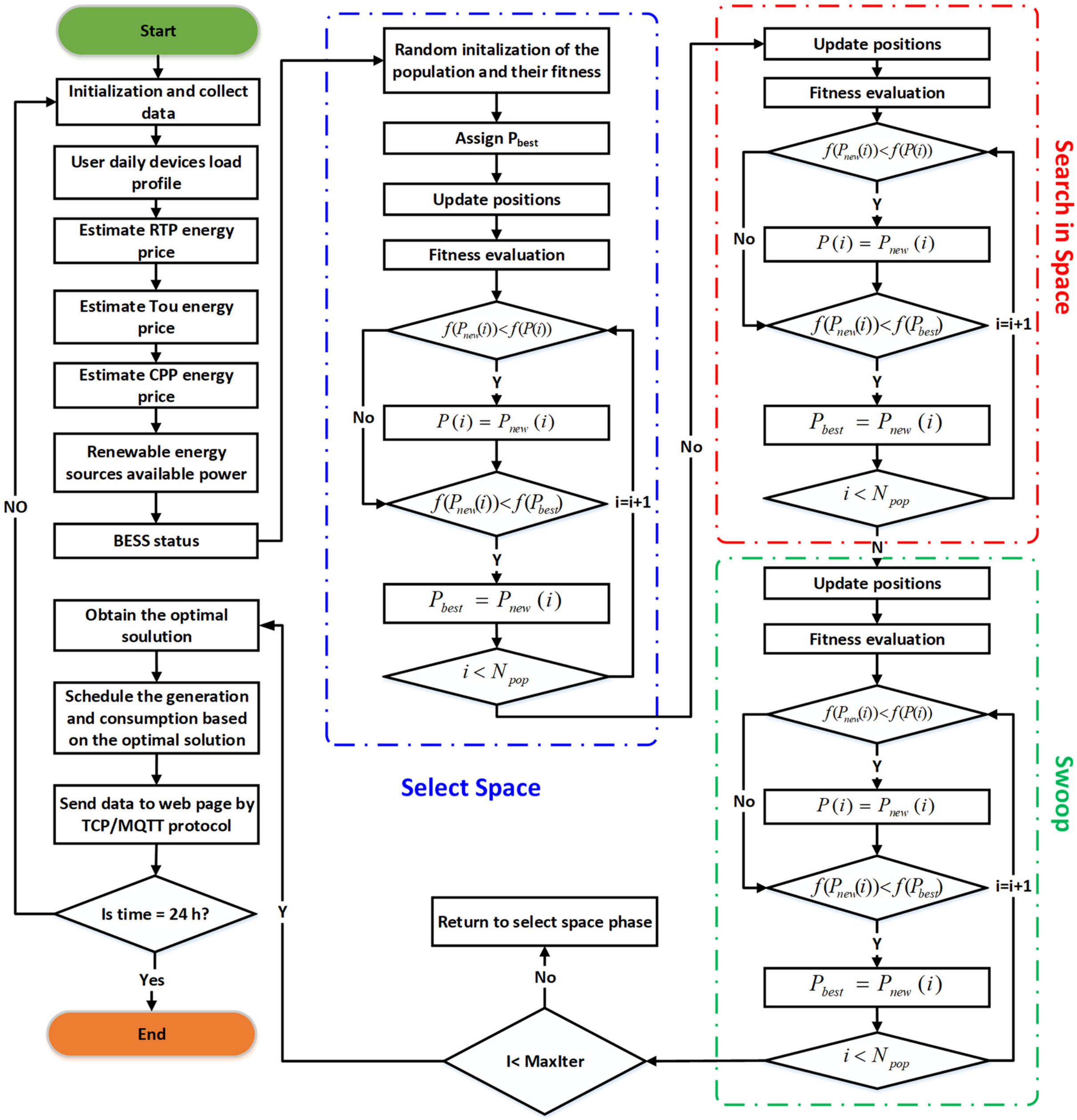

Figure 5. Flowchart of the proposed method.

Table 3. The pseudocode of the bald eagle search optimization algorithm [40].

1.	Random initialize point P_i for n-point
2.	Calculate the fitness values of initial point
3.	**While** (the termination conditions are not met)
	Select Space
4.	**For** (Each point *i* in the population)
5.	$\boldsymbol{P_{new} = P_{best} + \alpha \times rand(P_{mean} - P_i)}$
6.	$\boldsymbol{If\, f(P_{new}) < f(P_i)}$
7.	$\boldsymbol{P_i = P_{new}}$
8.	$\boldsymbol{If\, f(P_{new}) < f(P_{best})}$
9.	$\boldsymbol{P_{best} = P_{new}}$
10.	End IF
11.	End IF
12.	End For
	Search in space

Table 3. *Cont.*

13.	For (each point i in the population)
14.	$\boldsymbol{P_{new} = P_i + y(i) \times (P_i + P_{i+1}) + x(i) \times (P_i - P_{mean})}$
15.	$\boldsymbol{If\, f(P_{new}) < f(P_i)}$
16.	$\boldsymbol{P_i = P_{new}}$
17.	$\boldsymbol{If\, f(X_{new}) < f(P_{best})}$
18.	$\boldsymbol{P_{best} = P_{new}}$
19.	**End If**
20.	**End If**
21.	**End For**
	Swoop
22.	For (Each point i in the population)
23.	$\boldsymbol{P_{new} = rand \times P_{best} + x1(i) \times (P_i - c1 \times P_{mean}) + y1(i) \times (P_i - c2 \times P_{best})}$
24.	$\boldsymbol{If\, f(P_{new}) < f(P_i)}$
25.	$\boldsymbol{P_i = P_{new}}$
26.	$\boldsymbol{If\, f(P_{new}) < f(P_{best})}$
27.	$\boldsymbol{P_{best} = P_{new}}$
28.	End If
29.	End If
30.	**End For**
31.	Set k = k + 1
32.	**End While**

The objective function and the problem constraints are represented as follows:

$$minimize \Longrightarrow (C_E) \tag{21}$$

$$C_E = \sum_{t=1}^{T} \tau(t) P_{grid}(t) \Delta t \tag{22}$$

where C_E is cost of energy at time T. $P_{grid}(t)$ is grid power, Δt denotes interval time between two time instants, and $\tau(t)$ is the price of energy at time instant t [38,41].

The following are the equations for these constraints:

$$\sum_{t=1}^{T} \Big(P_{PV}(t) + P_{Wind}(t) + P_{grid}(t) \pm P_{BESS}(t) - P_{Load}(t) \Big) = 0 \tag{23}$$

$$P_{PV,min} \leq P_{PV}(t) \leq P_{PV,max} \qquad \forall t \in T \tag{24}$$

$$P_{Wind,min} \leq P_{Wind}(t) \leq P_{Wind,max} \quad \forall t \in T \tag{25}$$

$$0 \leq P_{grid}(t) \leq P_{grid,max} \qquad \forall t \in T \tag{26}$$

$$E_{BESS,min} \leq E_{BESS}(t) \leq E_{BESS,max} \quad \forall t \in T \tag{27}$$

$$E_{D,\ total} \leq E_{S,total} < E_{D,\ total} \tag{28}$$

The constraints state power balance equations at every time instant where $P_{PV}(t)$, $P_{Wind}(t)$, and $P_{grid}(t)$ are PV, wind, and grid output power at time instant t, respectively. $P_{Load}(t)$ and $P_{BESS}(t)$ are load demand power and the discharging/charging power of the battery, respectively. The minimum and maximum power output from the PV, wind, and utility grid are shown in Equations (24)–(28). $P_{PV,min}$ and $P_{PV,max}$ are the limits of a photovoltaic output power, $P_{Wind,min}$ and $P_{Wind,max}$ are the boundaries of the wind output power, and $P_{grid,max}$ is maximum power drawn from the utility grid in the case of a grid-connected mode. $E_{BESS,min}$ and $E_{BESS,max}$ are the capacity limits of the battery, as shown in Equation (27). The energy deficient is represented in Equation (28).

3.1. Suggested Communication Platform

Cloud-enabled IoT is used to communicate between agents in the microgrid and data storage. The data are transmitted between neighbors using the IoT platform, and then processed in a cloud computing layer. The proposed IoE communications network is made up of five layers: the agent layer, the IoT layer, the network layer, and the layer of processing data [38,41–44].

3.1.1. The MQTT Knowledge

The three primary participants in MQTT messaging are the MQTT broker, the MQTT subscriber, and the MQTT publisher. The MQTT publisher and subscriber do not have to run at the same time because they are not directly linked by IP address. The MQTT broker serves as a network hub, collecting messages from publishers and filtering, prioritizing, and distributing them to thousands of MQTT subscribers who are continuously connected. The MQTT broker is in charge of client authorization and a handshake procedure for communication initialization. MQTT publishers use adjustable topics to publish data, which clients must subscribe to. Metadata cannot be used to label messages in the MQTT protocol. These topics could be used to express routing information [15,45,46]. Figure 6a depicts the initialization of the connection via exchanging control packets between customers and the broker (a). CONNECT, CONNAC, PUBLISH, PUBACK, SUBSCRIBE, SUBACK, and other control packets communicate information about the quality of service (QoS), topic, and payload of the transmission. Figure 6b depicts the MQTT communication components [38].

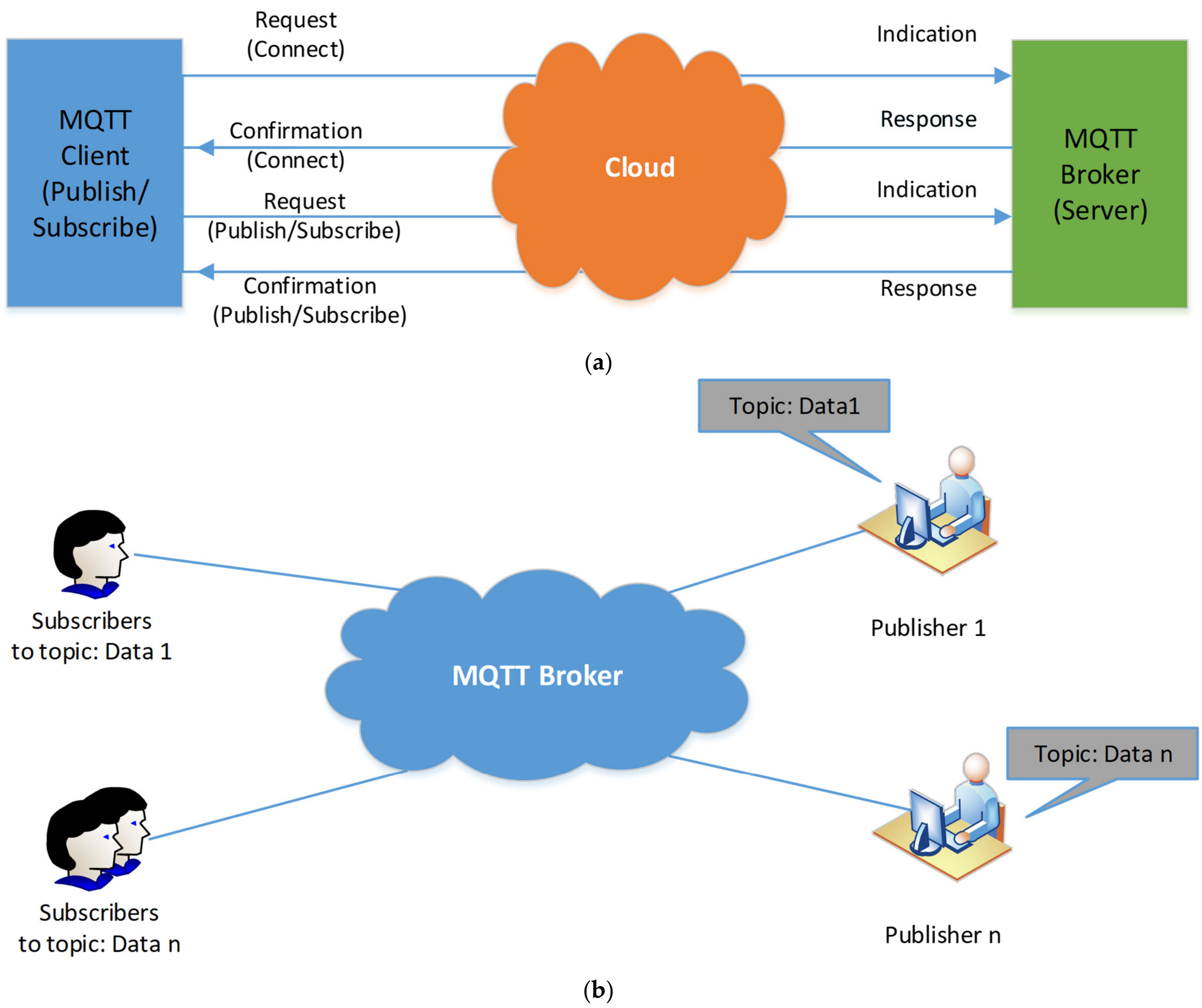

Figure 6. (**a**) Procedure of MQTT; (**b**) MQTT component and topic.

3.1.2. Proposed Architecture

Figure 7 depicts the suggested hierarchy of the cyber layer, physical layer, and regulating layer smart structures. There are two levels of communication in the proposed hybrid network. In the first layer, smart structure applications broadcast MQTT messages to consumers and subscribe to BMC's published MQTT messages for control and protection. The second (globe) layer, which is the HTTP POST/GET architecture, is how BMC communicates to the cloud. Each device is equipped with a Wi-Fi module, is connected to a local gateway, and regularly releases data on the subject. The BMC determines both topics and has them subscribe to a cloud channel. The aggregated cloud data can be accessed through a ThingSpeak-based cloud interface with a built-in device algorithm. The findings of the algorithm are transported from the cloud to the device through BMC [15,38,45,47].

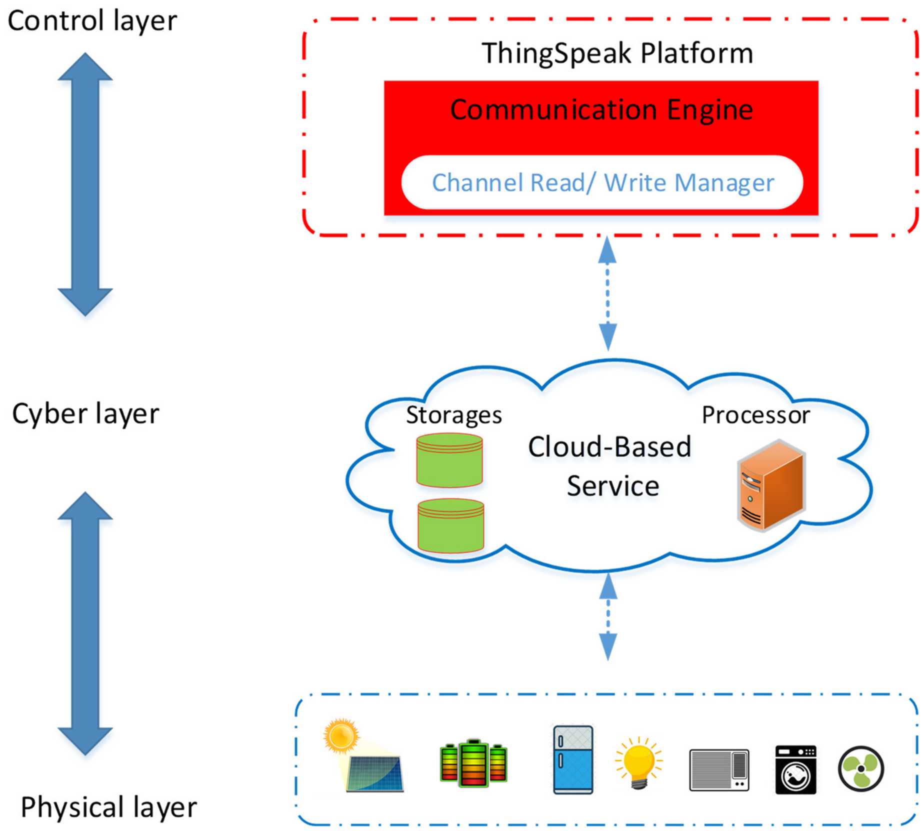

Figure 7. Communication building of the suggested system.

4. Results of the Proposed Method

In this section, the simulation results of the suggested approach for solving the problem of optimal power management of the studied microgrid system are presented. First, the single objective problem is solved to minimize the operational cost of the microgrid system. Afterwards, the minimization of emissions is considered as the objective function. In the next section, the two objective functions of the minimization of the total cost and emissions are considered simultaneously to solve the multi-objective optimal power management of the microgrid by implementing the suggested approach. Moreover, the results of the deterministic and stochastic optimal power management approaches for the microgrid components are compared.

The overall categorization of smart home appliances is presented in Table 4 [48].

This section discusses the impact of microgrid communication. The microgrid will exchange information such as load and energy generation when communication applications are present.

Table 4. Smart home appliance classification and parameters [48].

Categories	Type	Power (kW)	Length of Operational Time (hour)
Shiftable appliances	Washing machine	1.4	1–3
	Dish washer	1.32	1–3
	Hair straightener	0.0055	1–2
	Hair dryer	1.8	1–2
	Microwave	1.2	3–5
	Computer	0.15	6–12
	Oven	2.4	1–3
	Iron	2.4	2–4
	Toaster	0.8	3–5
	Electric kettle	2	1–2
	Printer	0.011	1–2
Non-shiftable appliances	TV	0.095	6–14
	Refrigerator	1.75	0–23
Controllable appliances	Air conditioner	1.14	6–8
	Lightning	0.1	12–20

The results of the smart EMS implemented with the proposed method over a cloud platform to govern devices in a microgrid are presented and discussed in this experiment. The microcontroller is a central command and control unit in this paper that organizes the ThingSpeak platform. MQTT acts as a middleman between the main control unit and the microgrid devices that subscribe to it. The ThingSpeak platform interface designed in this paper is a simple and straightforward user interface (UI) that allows a homeowner to engage with and obtain home energy management as a service over a cloud system. The dashboard and the UI flow architecture are demonstrated in Figure 8.

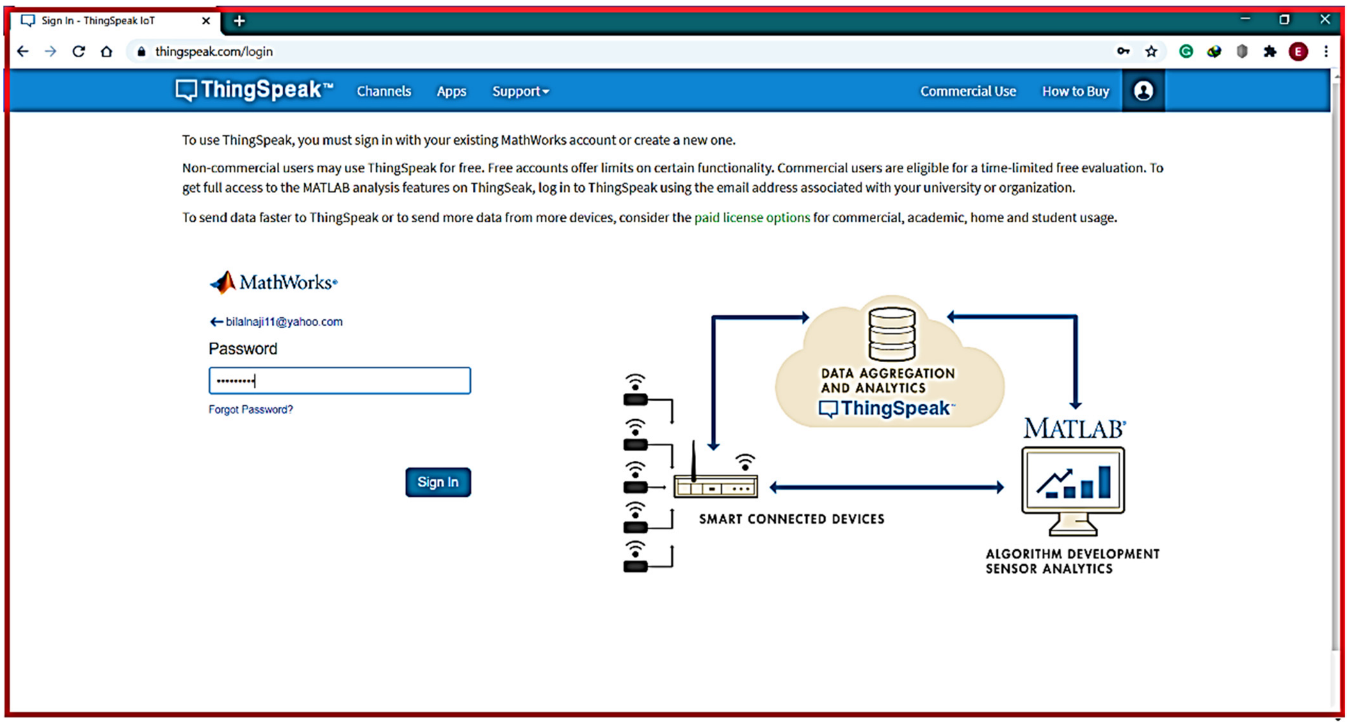

Figure 8. ThingSpeak platform.

The EMS includes a graphical user interface (GUI) to let consumers understand the total cost of microgrid devices and power consumption. Figures 9–13 show the power consumption of all loads without and with corrective methods.

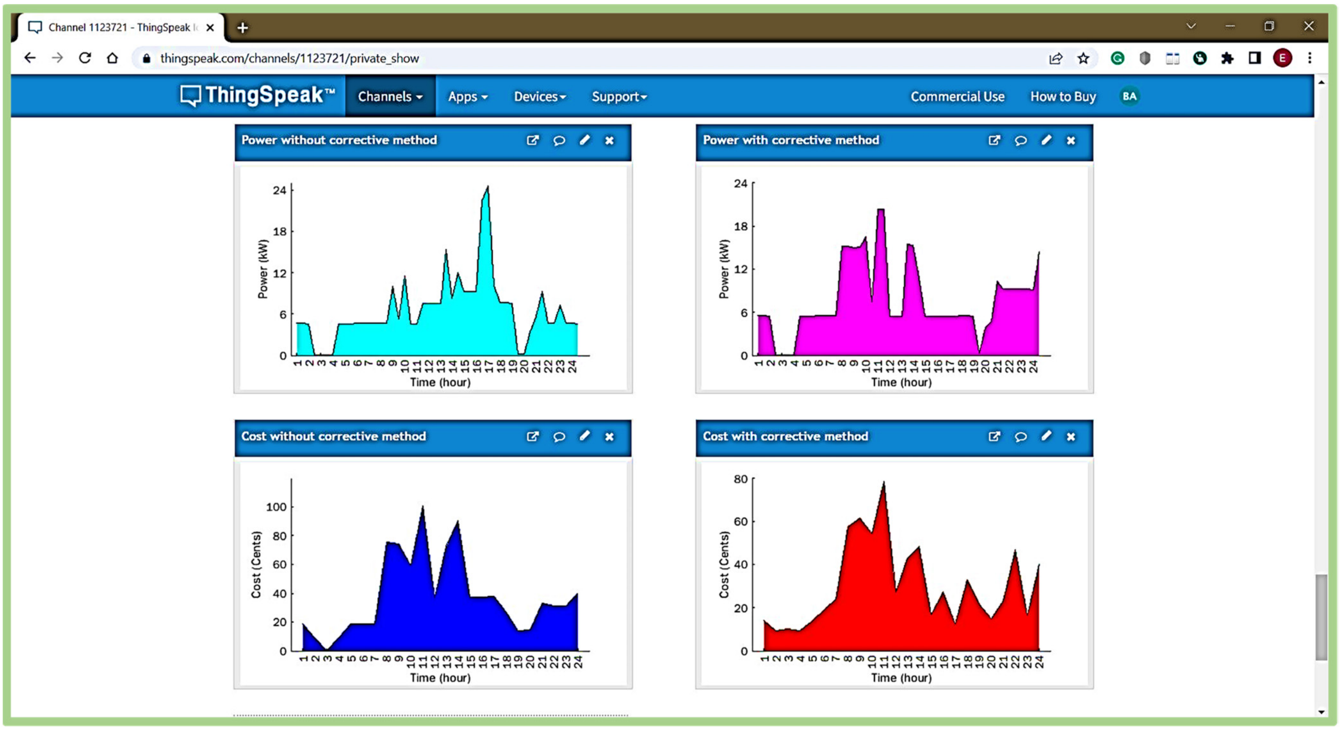

Figure 9. User interface design platform.

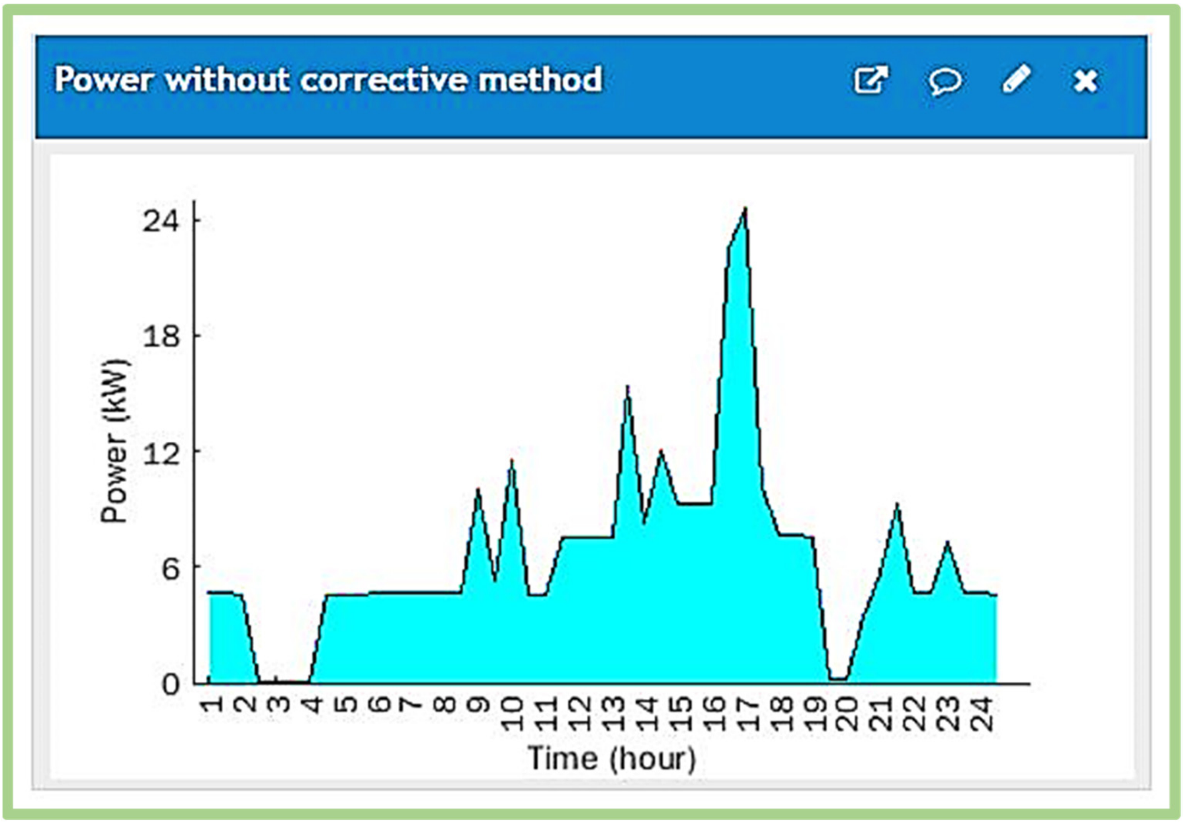

Figure 10. Power GUI of suggested EMS without the corrective method.

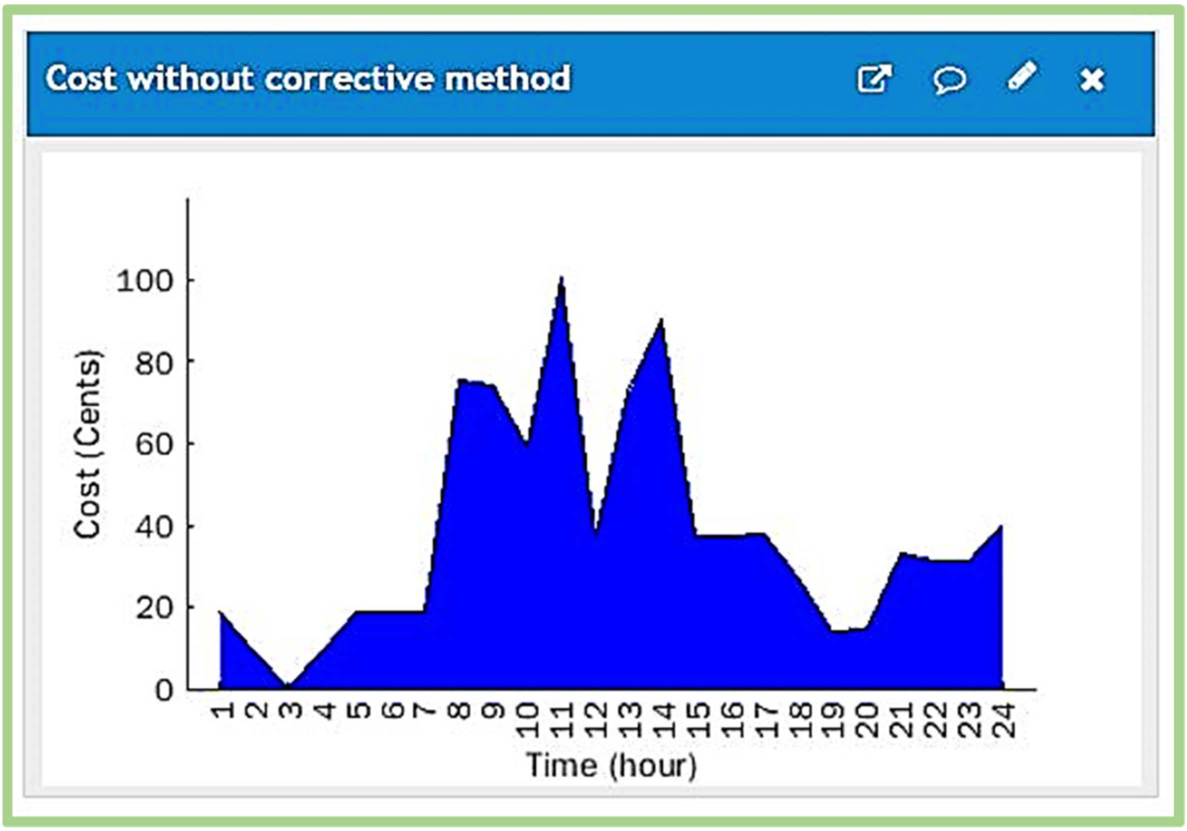

Figure 11. Cost GUI of suggested EMS without the corrective method.

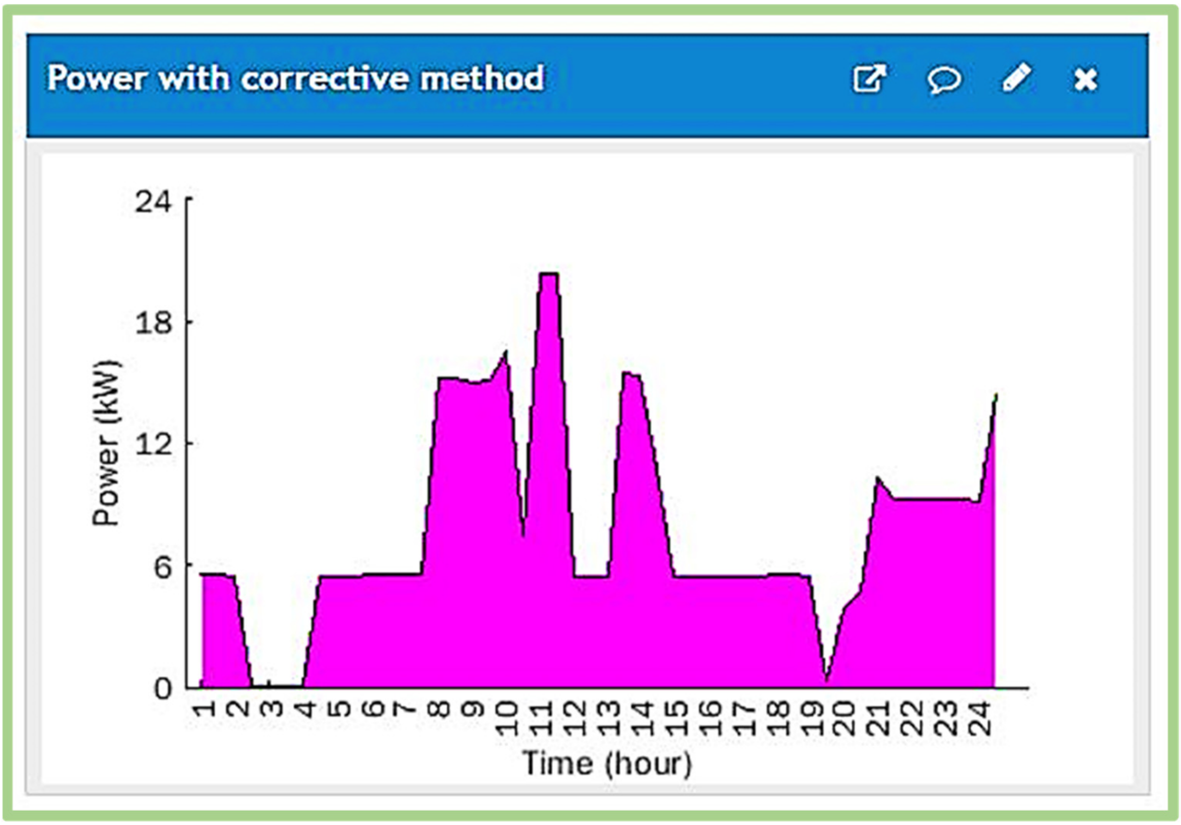

Figure 12. Power GUI of suggested EMS with the corrective method.

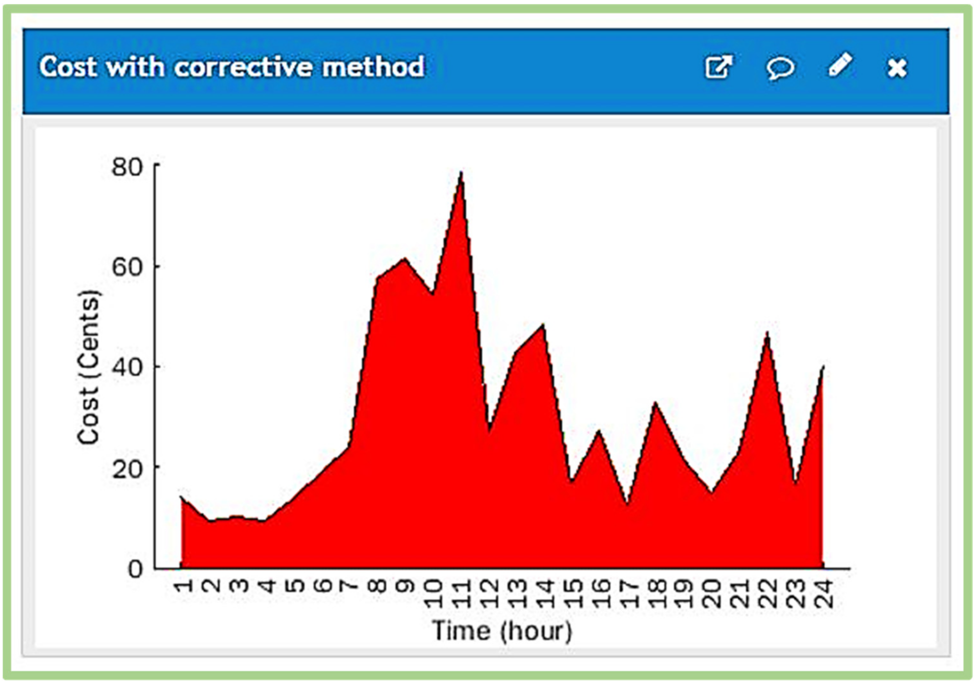

Figure 13. Cost GUI of suggested EMS with the corrective method.

Figure 10 shows the powerful GUI of the suggested EMS without the corrective method. Figure 11 shows the cost GUI of the suggested EMS without the corrective method. Figure 12 shows the powerful GUI of the suggested EMS with the corrective method. Figure 13 shows the cost GUI of the suggested EMS with the corrective method.

5. Discussion of Results

In addition to PAR, the cost of electricity emission reduction and cost savings were analyzed in a microgrid efficiency analysis. In the ToU case, the price before applying the suggested algorithm was 910.35 (cent). However, after applying the bald eagle search optimization algorithm, the cost was found to be 722.56. Comparing the proposed technique with the conventional method, the bald eagle search optimization algorithm saved 25.98% per day. Figure 14 shows a cost comparison of price without the proposed EMS and with the proposed EMS.

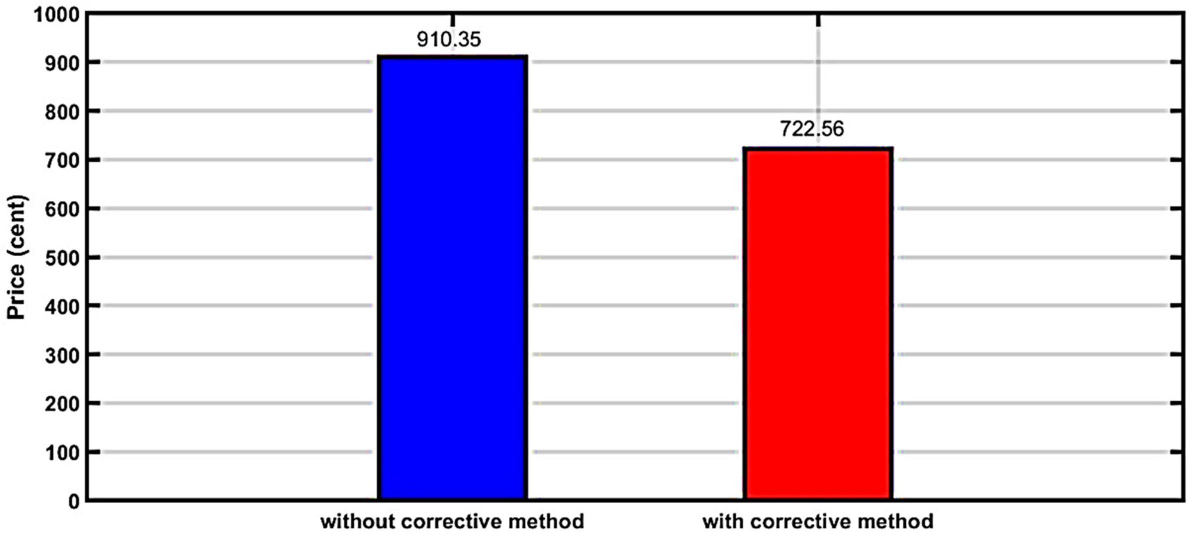

Figure 14. Cost comparison of price without the suggested EMS and with the suggested EMS.

6. Conclusions

The need for electricity is increasing on a daily basis. Power companies are unable to match this demand due to a scarcity of traditional energy resources and the deterioration of the current power grid. As a result, in this article, the concept of a smart grid is presented in which smart homes are built in such a way that home appliances can be coordinated with one another through an IoT-based home energy management system, and electricity consumption can be controlled by following an optimal consumption pattern. The integration of this ideal consumption pattern with renewable energy sources also minimizes waiting time, increasing customer comfort significantly. This paper presents a multi-objective version of the bald eagle search optimization algorithm (BESOA). The home energy management system architecture was investigated to analyze, control and monitor smart grid power consumption. Comparing the proposed method with the conventional method, the proposed method saved 25.98% per day.

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