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A Multi-Objective Improved Cockroach Swarm Algorithm Approach for Apartment Energy Management Systems

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Abstract: The electrical demand and generation in power systems is currently the biggest source of uncertainty for an electricity provider. For a dependable and financially advantageous electricity system, demand response (DR) success as a result of household appliance energy management has attracted significant attention. Due to fluctuating electricity rates and usage trends, determining the best schedule for apartment appliances can be difficult. As a result of this context, the Improved Cockroach Swarm Optimization Algorithm (ICSOA) is combined with the Innovative Apartments Appliance Scheduling (IAAS) framework. Using the proposed technique, the cost of electricity reduction, user comfort maximization, and peak-to-average ratio reduction are analyzed for apartment appliances. The proposed framework is evaluated by comparing it with BFOA and W/O scheduling cases. In comparison to the W/O scheduling case, the BFOA method lowered energy costs by 17.75%, but the ICSA approach reduced energy cost by 46.085%. According to the results, the created ICSA algorithm performed better than the BFOA and W/O scheduling situations in terms of the stated objectives and was advantageous to both utilities and consumers.

Keywords: multiple apartments loads; cockroach swarm algorithm; Bacterial Foraging Optimization Algorithm; energy storage systems; solar energy

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1. Introduction

Energy usage rises along with population growth. Traditional power grids are currently unable to meet the demand for electricity. SGs, or smart grids, are created to satisfy these requirements. Smart grids (SGs) include energy-efficient sources, intelligent controllers, smart meters (SM), renewable energy resources (RER), and intelligent gadgets. Through SMs in SGs, utilities and users are exchanging data. The data can be used to optimize the energy efficiency of smart apartments. Some demand-side management (DSM) techniques have been identified through research. These techniques optimize power usage patterns by shifting loads, filling valleys, clipping peaks, and other techniques. Such techniques can be used to balance supply and demand. Such strategies encourage consumers to switch their load from peak to off-peak times in this way. Demand response (DR) and load management (LM) are the two main responsibilities of DSM [1].

Consequently, there is an urgent need for a new generation of multi-energy demand response framework for a highly renewable building microgrid. Table 1 involves the contributions and shortcomings of the most recent research applied to energy-management-system-based optimization algorithms.

Table 1. Contributions vs. shortcomings of the most recent research concerning energy-management-system-based optimization algorithms.

References Groups	Reference	Contributions	Shortcomings
Price-Based Demand Response Programs	[2]	Utilizing a combination of bacterial foraging and genetic algorithm optimization techniques, the authors established demand side management.	Numerous appliances were taken into account in an extensive system, which made the system difficult.
	[3]	The authors proposed a dynamic coordination of household appliances utilizing multi-objective energy optimization.	Inelastic load is considered.
	[4]	The authors introduced a coalition-based game-theoretic energy management system for a building as a service over fog.	End-users' comfort was not considered.
	[5]	The authors used game theory to coalitional demand response management in community energy management systems.	The best, most cost-effective way to operate an energy management system based on ICSA was not looked into.
	[6]	The authors developed an optimal operation and stochastic scheduling of renewable energy for a microgrid.	Not compared with other techniques.
	[7]	An improved adaptive diffusion-kernel-density-estimation-based day-ahead interval scheduling approach for power systems was presented by the authors.	More computational time with the complex system.
	[8]	The authors presented real-time multi-energy demand response for highly renewable buildings.	Depended on random number for fewer generations.
	[9]	The authors presented metaheuristic optimization techniques for microgrid energy management.	Comfort concerns were not addressed, and peak-to-average ratio was ignored.
	[10]	Based on a multi-objective approach, the authors proposed energy management in microgrids, including smart homes.	Increased complexity.
Incentive-Based Demand Response Programs	[11]	The authors developed Benders decomposition-based stochastic planning and operation of energy hubs taking demand response programs into account	Increased operational cost.
	[12]	The authors introduced a two-stage demand response technique based on deviation compensation for numerous scenarios.	Execution time was high.
	[13]	The authors introduced scaling the economic impact of grid membership in a microgrid system using a unique metaheuristic method.	Proper implementation was not explored.
	[14]	The authors created a special metaheuristic method to scale the financial effects of grid involvement in a microgrid system.	Average waiting time (AWT) was not considered.

Table 1. *Cont.*

References Groups	Reference	Contributions	Shortcomings
Incentive-Based Demand Response Programs	[15]	The authors provided a real-time management of distributed multi-energy resources in multi-energy networks.	Complexity of the system was high.
	[16]	Energy consumption optimization and user comfort maximization in smart buildings using a hybrid of the firefly and genetic algorithms was discussed by the authors.	UC was not considered.
	[17]	The authors presented Fire-Fly-algorithm-based energy cost minimization using renewable energy sources.	End-users' comfort was ignored.
	[18]	A novel machine-learning-based price forecasting for energy management systems was introduced by the authors.	Neglected integration of RESs.
	[19]	An optimal energy management system for university campus using the hybrid Fire-Fly Lion Algorithm (FLA) was introduced by the authors.	UC was compromised and only passive appliances were considered.
	[20]	An optimal scheduling strategy for multi-energy microgrids considering integrated demand response was introduced by the authors.	Network loss and ESS capacity was decreased.
Price-Based Demand Response Programs	[21]	A coordinated control of hybrid ac/dc microgrids with PV wind battery under variable generation and load situations was introduced by the authors.	Implementation cost was not considered.
	[22]	The authors proposed a home energy management system based on reinforcement learning.	UC was compromised and only passive appliances were considered.
	[23]	The authors proposed peer-to-peer trading with demand response using smart bidding strategy	More computational time.
	[24]	The authors introduced the concept, architecture, and scheduling strategies for home energy management systems.	UC was compromised and only passive appliances were considered.
	[25]	The authors presented a coalition-game-theory-based consensus algorithm for demand management in smart microgrids.	Peak-to-average ratio was ignored.
	[26]	The authors presented an optimal energy management system (EMS) for residential and industrial microgrids.	To reduce cost, UC was compromised.
	[27]	Critical peak-pricing-based opportunistic home energy management for demand response was presented by the authors.	To reduce cost, UC was compromised.
	[28]	The authors introduced Optimal Energy Management Scheme of Battery Supercapacitor-Based Bidirectional Converter for DC Microgrid Applications.	UC was compromised and only passive appliances were considered.

Table 1. *Cont.*

References Groups	Reference	Contributions	Shortcomings
Price-Based Demand Response Programs	[29]	Energy Management System in Industrial Microgrids was presented by the authors.	Needed more accuracy.
	[30]	The authors suggested employing heuristic optimization techniques to schedule the Home Energy Management Controller (HEMC) effectively.	Ignored UC.
Incentive-Based Demand Response Programs	[31]	An optimization of demand-response-based intelligent home energy management system with binary backtracking search algorithm was presented by the authors.	More computational time.
	[32]	The authors introduced an energy storage management of a solar photovoltaic–biomass hybrid power system.	Peak-to-average ratio was not considered.
	[33]	The authors proposed a novel strategy for enhanced energy management systems, which includes an AC/DC hybrid microgrid system for industries.	PAR was ignored and system complexity increased.
	[34]	The authors developed a novel method for PV system-based SCADA to accomplish MPPT.	The best, most cost-effective way to operate an energy management system based on ICSA was not looked into.
	[35]	The authors proposed an efficient optimization-algorithm-based demand side management program for smart grid residential load.	More computational time.
	[36]	The authors presented an optimal scheduling of residential home appliances using a hybrid grey wolf genetic algorithm optimizer.	The best, most cost-effective way to operate an energy management system based on ICSA was not looked into.
	[37]	The authors introduced energy consumption optimization and user comfort management in residential buildings using a bat algorithm and fuzzy logic.	More computational time.
	[38]	The authors presented a smart energy management system for minimizing electricity costs and peak-to-average ratio in residential areas with hybrid genetic flower pollination algorithm.	The best, most cost-effective way to operate an energy management system based on ICSA was not looked into.
	[39]	The authors suggested a control strategy for inverters used in environmentally friendly applications.	Nevertheless, the best, most cost-effective way to operate an energy management system based on ICSA was not looked into.
	[40]	A demand response program (DRP) for renewable-based microgrids (MGs) has been put up in [40] that considers the high penetration of solar and tidal energy as significant, pervasive renewable resources in the power networks.	User comfort was compromised.
Price-Based Demand Response Programs	[41]	The authors suggested a residential energy management system while taking into account reliable demand response tactics and uncertainties.	Delay, user comfort, and PAR were ignored.

Table 1. *Cont.*

References Groups	Reference	Contributions	Shortcomings
Price-Based Demand Response Programs	[42]	For microgrids with renewable energy sources, the authors presented an Internet-of-Energy-based optimal multi-agent control system.	System complexity increased.
	[43]	The authors introduced a demand side management strategy for multi-objective day-ahead scheduling considering wind energy in smart grids.	The best, most cost-effective way to operate an energy management system based on ICSA was not looked into.
	[44]	The authors introduced renewable energy effects on energy management based on demand response in microgrid environments.	Cost increased with increased comfort.
	[45]	The authors put forth a deep-reinforcement-learning-based energy management system for microgrids.	Daily PAR increased.
	[46]	The authors presented a particle swarm optimization model predictive control for microgrid energy management.	User comfort and privacy issues.
	[47]	The authors presented a centralized neighborhood energy management with coordinated smart home energy sharing model for neighborhood smart homes, which are integrated within house renewable energy resources and energy storage systems.	System complexity increased.
	[48]	An energy management of microgrids with a smart charging strategy for electric vehicles using an improved RUNge Kutta Optimizer (RUN) was introduced by the authors.	AWT for UC was not taken into account.
	[49]	The authors proposed four new, more useful research models in four situations to evaluate peak demand. The recommended system is based on the assumption that there are a finite number of devices in the study area, and it expresses arrivals or power needs through a quasi-random process.	System complexity increased.
	[50]	The authors suggested a distributed method that focuses on organizing the demand management problem of planning the problem of smart devices for sparing load change. Customers' discomfort was decreased through the load shifting approach of sparsity.	Real-time forecasting was not considered.
Incentive-Based Demand Response Programs	[51]	The IoT-based bald eagle search optimization algorithm was used by the authors to suggest solutions for day-ahead scheduling issues.	Daily PAR increased.
	[52]	The authors proposed to develop the residential microgrid (RMG) cloud-based Multi Agent Framework (MAF) for smart grid culture. The presented MAS is composed of intelligent home agents and a microgrid designed to alleviate peak load and reduce energy costs of intelligent households.	RES not integrated.

Table 1. *Cont.*

References Groups	Reference	Contributions	Shortcomings
Incentive-Based Demand Response Programs	[53]	The authors introduced a coordinated optimization scheduling operation of integrated energy system considering demand response and carbon trading mechanism.	System complexity increased.
	[54]	The author implemented an islanded microgrid framework P2P construction. The multi-layered and multi-agent procedures and designs that achieve this P2P construction are several goals. The agent with communication and computation capabilities can simultaneously run these multi-layer control-related processes.	Requirements of the customers for reliable power grids were not considered.
	[55]	The authors looked at effective DSM methods for reducing the peak-to-average energy consumption ratio from the grid. To find the most effective load control strategy to level the load curve, they examine the trend of energy use, power costs, weather, and other factors. It offers a genetic method for controlling energy.	Computational time was not practical.
	[56]	The authors introduced a SCADA-controlled smart home utilizing a Raspberry Pi3, but they did not look into the most advantageous way to operate an energy management system based on ICSA.	The user did not have ways of handling the constraints.
	[57]	Utilizing both cloud servers and fog nodes, the authors created a hybrid cloud and fog system. Using the free and open source Constricted Application Protocol (CoAP) and the cloud service ThingSpeak, they put their framework into use on a Wi-Fi IoT board.	Daily PAR increased.
	[58]	The authors introduced EMS of on-grid/off-grid utilizing ANFI scheme; however, they did not take into account data processing and storage using the Thing-Speak platform.	Cost minimization was not considered.
	[59]	The architecture framing, design, and implementation of an IoT and an electronic Cloud computer were provided by the authors. This computer gives a consumer recharge profile for remote access by utilities and users. Companies may manage and provide incentives and persuade customers to change their energy usage thanks to consumer load profiles.	Cannot be applied to different building types involving a higher number of appliances.
	[60]	Demand response was used to create and implement a multi-agent network control system for delivery networks. In order to promote transactions between DSOs (distribution network operators) and distribution network operators, this project aims to provide dynamic boards as a helpful and effective tool.	Daily PAR increased.

Table 1. *Cont.*

References Groups	Reference	Contributions	Shortcomings
Price-Based Demand Response Programs	[61]	The authors introduced hierarchical EMS based on optimization.	Expensive for small-scale residential users.
	[62]	The flexibility possibilities of commercial and residential contexts were combined by the authors through the creation of a brand-new agent-based framework. This concept calls for a central demand response provider (DRP) to coordinate the demand aggregators' response plans for the commercial and residential sectors (IDRA, RDRA).	System complexity increased.
	[63]	A multi-objective issue was provided by the authors, and its resolution was based on an evolutionary algorithm and a task management technique. One of the many goals in the issue is a real-time pricing (RTP) response to demand. The reduction of customer annoyance and daily energy costs were two goals that were taken into account.	Only RTP was used.
	[64]	The authors established dynamic coordination between appliances and dwellings to maximize energy efficiency in smart buildings.	The authors did not use the Improved Cockroach Swarm Algorithm Approach to minimize the cost.
	[65]	The authors proposed hierarchical model predictive control for islanded and grid-connected microgrids with wind generation and hydrogen energy storage systems.	The authors did not use the Improved Cockroach Swarm Algorithm Approach to minimize the cost.
	[66]	The authors have launched a smart homes Energy Management Framework (EMS). This device communicates with a specific IP address IoT module leading to a large network of wireless appliances on every home computer.	Daily PAR increased.
	[67]	The authors introduced a new IoT-enabled trust-distributed EMS; however, optimization based on ICSA was not investigated.	More computational time.
	[68]	A Binary Backtracking Search Algorithm (BBSA) was recommended as a real-time, optimal time schedule controller for HEMS to manage energy consumption. BBSA provides optimal schedules for domestic equipment to reduce overall demand and schedule household appliances operating at specific times of the day.	Neglected theUC.
	[69]	The authors proposed an optimal load-shedding scheme using a grasshopper optimization algorithm for islanded power systems with distributed energy resources.	Depended on random number for fewer generations.
	[70]	The authors suggested a strategy based on Q-Learning algorithms called "home energy management as a service." However, optimization based on ICSA was not examined.	More computational time.

Table 1. *Cont.*

References Groups	Reference	Contributions	Shortcomings
Incentive-Based Demand Response Programs	[71]	The authors presented a ground-breaking real-time electricity scheduling for a home energy management system using the Internet of Energy.	Ignored the electricity cost and PAR.
	[72]	The authors introduced a brand-new power management system as a fog computing network service. The fog computing platform's implementation satisfied requirements for flexibility, interoperability, accessibility, data protection, and real-time energy management.	System complexity increased.
	[73]	The authors introduced a paradigm for self-learning home administration. The IoT concepts were implemented on a multi-agent system platform for agent communication and interaction.	Numerous appliances were taken into account in an extensive system, which made the system difficult.
	[74]	An efficient energy management in smart grid considering demand response program and renewable energy sources was introduced by the authors.	They did not address the UC.
	[75]	A sophisticated energy management technique for microgrids with a real-time monitoring interface was introduced by the authors.	More computational time.
	[76]	The authors introduced consensual negotiation-based decision making for connected appliances in smart home management systems.	UC was compromised.
	[77]	The authors introduced a new communication platform for smart EMS using mixed-integer linear programming.	An energy management system based on ICSA was not looked into.
	[78]	The authors introduced demand response program for efficient demand-side management in smart grid considering renewable energy sources.	The authors did not use the Improved Cockroach Swarm Algorithm Approach to minimize the cost.
	[79]	The authors introduced the real-time opportunistic energy-efficient scheduling of home appliances for demand side management using evolutionary techniques.	The best, most cost-effective way to operate an energy management system based on ICSA was not looked into.
	[80]	The authors presented an enhancing demand side management using evolutionary techniques in smart grid.	The authors did not use the Improved Cockroach Swarm Algorithm Approach to minimize the cost.
	[81]	The authors presented an idea on optimizing energy consumption with combined operations of microgrids for demand side management in smart homes.	The best, most cost-effective way to operate an energy management system based on ICSA was not looked into.
	[82]	The authors introduced a novel economic dispatch in the stand-alone system using an improved butterfly optimization algorithm.	An energy management system based on ICSA was not looked into.

Table 1. *Cont.*

References Groups	Reference	Contributions	Shortcomings
	Most significant contributions of our work	1. Outlining a methodology for optimization for the MG's hourly day-ahead scheduling. 2. Using real data to evaluate the optimization framework's performance in estimating the output power of PV and wind turbines. 3. Introducing an optimization technique using the Improved Cockroach Swarm Algorithm to reduce the cost of supplying the load. 4. The goal of this work was to reduce energy consumption expenses, raise the Peak-Average Ratio (PAR), and improve user comfort.	Investigating a secure cloud-based platform for a multi-agent hybrid AC/DC MG is considered our future work.

Energy management system programs are further classified into two types, i.e., incentive-based (IB) and price-based (PB) DR programs. Price-based demand response programs are classified into three types, i.e., time of use (TOU), real-time pricing (RTP), and critical peak pricing (CPP), and incentive-based demand response programs are classified into three types, i.e., direct-load programs, demand bidding, and interruptible programs. The first column in Table 1 represents the classification reference groups of energy management system programs.

2. Proposed System

The Figure 1 shows typical smart apartments with an energy management system. The system model used in the research is also depicted in this graphic, along with the paper's flow. The suggested system model includes RESs, such as solar and wind energy, as well as power companies that draw electricity from the main grid. Electricity from the power grid is directly communicated to the smart meter, as opposed to renewable energy, which is first transported to the planned Energy Management Controller (EMC) and then stored in the storage system installed in the smart dwellings. The suggested EMC system, which is connected to all the schedulable appliances in a typical smart apartment, best scheduled their operation to switch them over to renewable energy and the power grid to lower costs while preserving user comfort levels. Conversely, non-schedulable appliances that are fixed to run or based on their demands also directly communicate with the proposed EMC system to switch their operation to the RES system or power grid in order to reduce the cost and PAR values. This is completed while preserving user comfort levels.

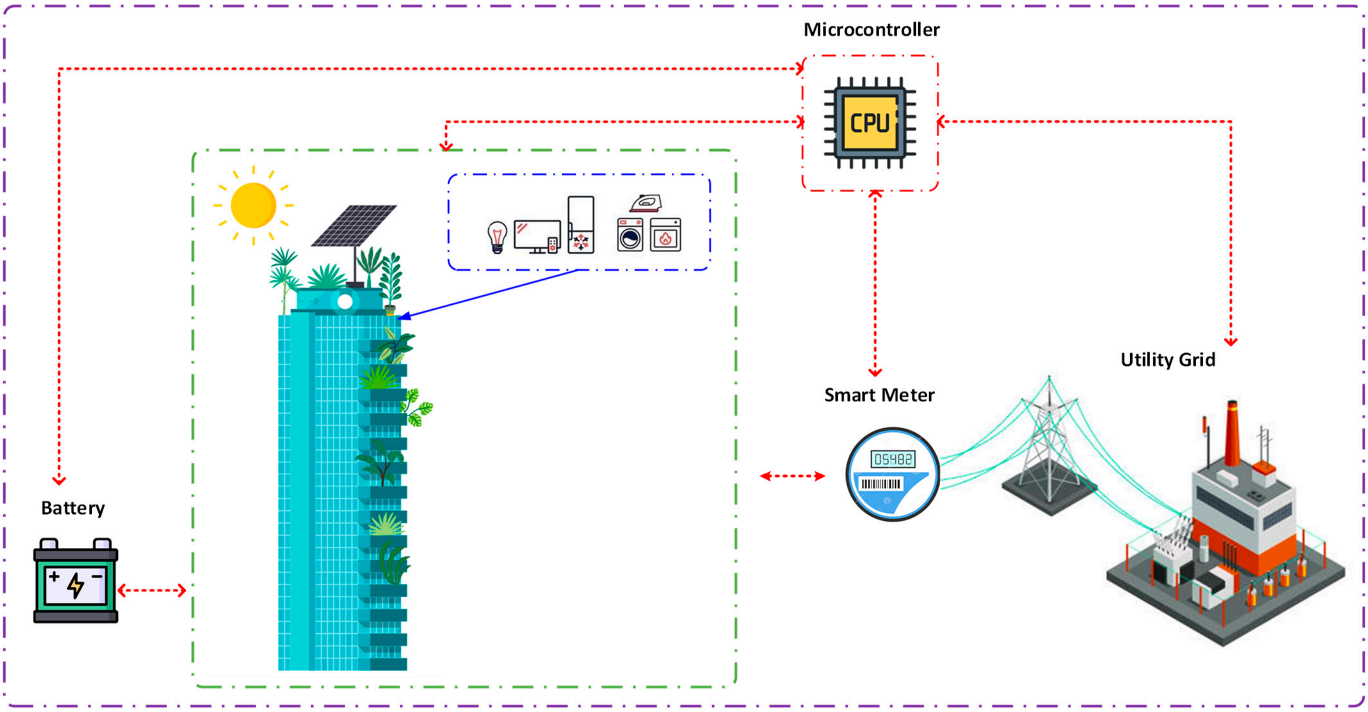

Figure 1. Proposed microgrid system structure of multiple apartments.

3. Problem Formulation

Different power ratings of appliances are taken into account during the scheduling process, which can be divided into two categories: schedulable (SA) and non-schedulable (NSA) appliances. The power rating of each device utilized in scheduling is listed in Table 1. Equations (1) and (2) illustrate how the running time of the appliance is divided into equal time slots (1 h for each slot) throughout the day (K):

$$K = k_1, k_2, k_3, \ldots, k_n \tag{1}$$

where n is the number of time intervals $per\ day = (1, 2, 3, \ldots, N)$ and K is the total number of time intervals in a day (24 h), as follows.

$$n = \frac{\text{24 h of the day}}{\text{no. of intervals}} = \frac{\text{24 h of the interval}}{\text{24 intervals}} \tag{2}$$

According to Equation (3), the group of appliances that are taken into account for scheduling is designated as G and includes both schedulable and non-schedulable equipment [83]:

$$G = g_1, g_2, g_3, \ldots, g_n \tag{3}$$

where $g_1, g_2, g_3, \ldots, g_n$ specifies the individual appliance.

3.1. Photovoltaic System

The photovoltaic system's output power, $\mathcal{W}_{\mathcal{PV}}$(kW), is depicted in a microgrid as [84]:

$$\mathcal{W}_{\mathcal{PV}}(t) = \xi_{\mathcal{PV}} \times \mathcal{A}_{\mathcal{PV}} \times \mathcal{I}_r(t)\left[1 - \mathcal{T}emp_f(\mathcal{T}emp_a(t) - \mathcal{T}emp_{amb})\right] \tag{4}$$

$$\mathcal{W}_{min} \leq \mathcal{W}_{\mathcal{PV}} \leq \mathcal{W}_{max} \tag{5}$$

where $\mathcal{T}emp_f$ is the temperature, $\mathcal{T}emp_a$ is the outdoor room temperature (°C), $\mathcal{T}emp_{amb}$ is the ambient room temperature (°C), $\mathcal{A}_{\mathcal{PV}}$ is the photovoltaic area (m^2), $\mathcal{I}_r(t)$ is the photovoltaic irradiance ($\frac{\text{kW}}{\text{m}^2}$) at a certain time t, and $\xi_{\mathcal{PV}}$ is the photovoltaic efficiency (%).

The Weibull Probability Density Feature (WPDF) is used to model a solar output power hourly distribution and assess its potential. The WPDF is listed as:

$$\mathcal{f}(\mathcal{W}_{\mathcal{PV}}(t)) = \frac{k}{c} \times \left(\frac{\mathcal{I}_{rr}(t)}{c}\right)^{k-1} \times e^{-\left(\frac{I_r(t)}{c}\right)^k} \tag{6}$$

$$k = \left(\frac{\eta}{\overline{\mathcal{A}}}\right)^{-1.086}, \text{ and } c = \frac{\overline{\mathcal{A}}}{\Gamma\left(1+\frac{1}{k}\right)} \tag{7}$$

where Γ is gamma function, η is data standard deviation, $\overline{\mathcal{A}}$ is data athematic mean, and are all present. The Levelized Photovoltaic Cost of Energy ($\mathcal{S}_s$) ($\frac{\$}{kWh}$) and Photovoltaic Operating Cost ($\mathcal{S}_{\mathcal{PV}}$) are shown as [84]:

$$\mathcal{S}_s = \frac{\mathcal{S}_{sinv} + \sum_{i=1}^{n} \mathcal{S}_{som}(1+\mathcal{E}_r)^{-i}}{\sum_{i=1}^{n} \mathcal{N}_{\mathcal{PVAN}}(1-\eta_{\mathcal{s}})^{i-1}} \tag{8}$$

$$\mathcal{S}_{\mathcal{PV}} = \sum_{t=1}^{\mathcal{T}} \mathcal{S}_s \times \mathcal{W}_{\mathcal{PV}}(t)\mathcal{f}(\mathcal{W}_{\mathcal{PV}}(t)) \tag{9}$$

where $\mathcal{N}_{\mathcal{PVAN}}$ is the photovoltaic energy output (kWh), $\mathcal{S}_{som}$ is the photovoltaic operating and maintenance cost, $\mathcal{S}_{sinv}$ is the photovoltaic investment cost ($), $\eta_{\mathcal{s}}$ is the photovoltaic degradation factor, and n is the lifetime of the photovoltaic system.

3.2. Utility Grid

The demand is met privately from RESs and ESSs connected to the utility during the SMG's peak demand period. On the other hand, at off-peak times and when SMG generation is in excess, the energy is delivered to the utility at the utility rate. The utility and SMG owner must enter into a contract before the utility can purchase the extra energy from the SMG. This will lower the energy cost of the generation units and reduce the CO_2 emissions cost. Moreover, the contract allows the utility to sell its energy to SMG to cover the demand and improve reliability. Based on the price signal, the utility energy cost $\mathcal{S}_{\mathcal{g}}$($) is given as [84].

$$\mathcal{S}_{\mathcal{g}} = \sum_{t=1}^{\mathcal{T}} [\mathcal{W}_{\mathcal{gc}}(t) - \mathcal{W}_{\mathcal{gs}}(t)]\varrho(t) \tag{10}$$

$\mathcal{W}_{\mathcal{gc}}(t)$ is the microgrid power purchased from the utility at a specific time, where $\mathcal{W}_{\mathcal{gs}}(t)$ is the surplus microgrid generation power sold to the utility (kW), and (t) is ToU utility price ($\frac{\$}{\text{kWh}}$). The predicted generator's expected utility emission cost, $\mathcal{N}_{\mathcal{g}}$($), is described as:

$$\mathcal{N}_{\mathcal{g}} = \sum_{t=1}^{\mathcal{T}} \left[\sigma(\mathcal{W}_{\mathcal{gc}}(t))^2 + \varsigma\mathcal{W}_{\mathcal{gc}}(t) + \tau\right] \tag{11}$$

where τ is the emission coefficients of the utility generators.

3.3. Batteries

In this study, the BESS is employed to cover the hours of greatest demand shaving and to lessen the variations brought on by RESs. Li-ion batteries are employed because of their high energy density. The utility pricing signal is used to determine whether to charge or discharge the BESS. The BESS will discharge during the ToU if the energy price is higher than a predetermined amount, and vice versa. The SMG's efficient operation, the PAR, and the utility's peak load will all be improved through BESS. Additionally, any time the storage level is lower than the upper charge level, the BESS is employed to store the excess generated electricity from the PV and wind systems. Consequently, the stored energy in the BESS can be stated as follows [85]:

$$\mathcal{N}_s(t) = \mathcal{N}_s(t-1) + \mathcal{H}_s \xi_{\mathcal{C}} \mathcal{W}_{ch}(t) - \frac{\mathcal{H}_s \mathcal{W}_{dch}(t)}{\xi_{\mathcal{D}}} \tag{12}$$

where $\mathcal{N}_s(t)$ is the amount of energy stored in the battery (kWh), $\mathcal{W}_{dch}(t)$ and $\mathcal{W}_{ch}(t)$ are the battery's charging and discharging powers at that time (kW), $\xi_{\mathcal{D}}$ and $\xi_{\mathcal{C}}$, are the battery's discharging and charging efficiencies (%), and Ts is the length of the time slot (hour).

$$0 \leq \mathcal{W}_{ch}(t) \leq \mathcal{W}_{ch}^{max} \tag{13}$$

$$0 \leq \mathcal{W}_{dch}(t) \leq \mathcal{W}_{dch}^{max} \tag{14}$$

$$\mathcal{N}_s^{min} \leq \mathcal{N}_s(t) \leq \mathcal{N}_s^{max} \tag{15}$$

$\mathcal{W}_{dch}^{max}$ and $\mathcal{W}_{ch}^{max}$ are the maximum battery discharging and charging power, respectively, where $\mathcal{N}_s^{max}$ and $\mathcal{N}_s^{min}$ are the maximum and minimum stored energy in the batteries, respectively, in (kWh). The battery's levelized operational and degradation cost is shown as:

$$\mathcal{S}_{\mathcal{B}} = \frac{\left[\mathcal{S}_{binv} + \sum_{i=1}^{n} \mathcal{S}_{bom}(1+\mathcal{E}_r)^{-i}\right](1+\mathcal{E}_r)^{-n} - \mathcal{V}_s}{(1+\mathcal{E}_r)^{-n} \mathcal{Z}_{\mathcal{T}f} \mathcal{Z}_{\mathcal{T}c} \mathcal{Z}_{\mathcal{D}c} \mathcal{B}_{\mathcal{R}c} \mathcal{N}_{\mathcal{R}b}} \tag{16}$$

where $\mathcal{Z}_{\mathcal{T}c}$ is the fading coefficient of normalized capacity, $\mathcal{N}_{\mathcal{R}b}$ is the BESS-rated capacity, $\mathcal{Z}_{\mathcal{T}f}$ is the normalized temperature-dependent power fading coefficient, $\mathcal{B}_{\mathcal{R}c}$ is the battery-rated cycle life, and $\mathcal{Z}_{\mathcal{D}c}$ is depth of discharge (DoD). $\mathcal{S}_{bom}$ is the BESS investment cost in dollars. $\mathcal{V}_s$ is the battery salvage value.

$$\mathcal{S}_{bop} = \sum_{t=1}^{\mathcal{T}} \mathcal{S}_b \left(\xi_c \mathcal{W}_{ch}(t) + \frac{\mathcal{W}_{dch}(t)}{\xi_{\mathcal{D}}} \right) \tag{17}$$

3.4. Smart Device Classification

Future users of smart household appliances such washing machines, boilers, dishwashers, refrigerators, TVs, heating and refreshment systems, and lighting devices are carrying out the activities to assure usability for consumers. Below are the main categories of appliances: appliances that can be scheduled for shifts are managed via EMS ($\mathcal{T} = 24$).

These gadgets are made to lower the energy charge transferred from one slot to another. Devices with the ability to shift have a certain energy load profile where configurable delays happen across guaranteed consumption periods. Vacuum cleaners, washing machines, dryers, and dishwashers are a few examples of shiftable devices. Consider the controllable interface set to be $\mathcal{D}_{m,n}$ and $d_m = 1, \ldots, \mathcal{D}_{m,n}$ for $n \in \mathcal{N}$ for each user [86].

$$\mathcal{L}_{m,n} = \sum_{d_m \in \mathcal{D}_m} \mathcal{L}_{\mathcal{D}_{m,n}} \tag{18}$$

Manageable appliance sets are represented by $\mathcal{D}_{m,n}$ and manageable appliance loads by $\mathcal{L}_{m,n}$.

The amount of energy used by non-shiftable appliances remains constant during the working time $t \in \mathcal{T}$. Devices that cannot be moved cannot be scheduled during off-peak hours to save money. Electric appliances including lamps, refrigerators, fans, and TVs have energy consumption profiles. Let a collection of user $n \in N$ non-shiftable gadgets be represented as:

$$\mathcal{L}_{nm,n} = \sum_{d_{nm} \in \mathcal{D}_{nm}} \mathcal{L}_{\mathcal{D}_{nm,n}} \tag{19}$$

In the community microgrid (photovoltaic), renewable energy sources are used to provide electricity that is owned by the community. The optimization model aims to plan the scarce energy resource for the operation of the devices based on their preferred time of operation and electricity cost. The ToU electricity tariff allows for the 24 h operation of electrical equipment. $\mathcal{L}^{n,t}$ represents the total amount of power used by customers during the time slot of $n \in \mathcal{N}$ in $t \in \mathcal{T}$.

$$\mathcal{L}_d^n = \mathcal{L}_{m,n} + \mathcal{L}_{nm,n} \tag{20}$$

$$\mathcal{L}_d^{n,t} = \sum_{t=1}^{\mathcal{T}} \mathcal{L}_d^{n,t} \tag{21}$$

$\mathcal{L}_\mathcal{T}$ is the overall power profile of the community of $\mathcal{N}$ users. Users' $n \in \mathcal{N}$ at $t \in \mathcal{T}$ power profiles are indicated by $\mathcal{L}^{n,t}$.

$$\mathcal{L}_\mathcal{T} = \sum_{n \in \mathcal{N}} \sum_{t \in \mathcal{T}} \sum_{d \in \mathcal{D}} \mathcal{L}_d^{n,t} \quad \forall t \in \mathcal{T} \tag{22}$$

To lower expenses and demand peaks at different times throughout the day, each consumer has software for tracking their personal energy usage. The aggregated power profile is used to calculate the PAR ratio [86]. This is a universal device demand form factor. Equations (23)–(25) define PAR:

$$\mathcal{L}_{peak} = max \mathcal{L}_\mathcal{T} \tag{23}$$

$$\mathcal{L}_{avg} = \frac{1}{\mathcal{T}} \sum\nolimits_{n=1}^{\mathcal{N}} \sum\nolimits_{t=1}^{\mathcal{T}} \mathcal{L}^{n,t} \quad \forall t \in \mathcal{T} \tag{24}$$

$$PAR = \frac{\mathcal{L}_{peak}}{\mathcal{L}_{avg}} \tag{25}$$

3.5. Peak Average Ratio

The ratio of the customer's peak demand in a certain time slot (t) to the average of the entire load consumed during the given time horizon $t = \{1, 2, \ldots, 24\}$ is known as the PAR. The clients' energy use is measured using PAR. The utility peak plants' operations are impacted by the PARs of the users. The PAR of the consumers must be decreased in order to preserve the supply–demand power balance. The PAR can be calculated as follows for M users [84]:

$$\mathcal{PAR} = \frac{max(\mathcal{N}_{Total}(t, m))}{\frac{1}{\mathcal{H}} \sum_{m=1}^{\mathcal{M}} \left(\sum_{t=1}^{\mathcal{H}} \mathcal{N}_{Total}(t, m) \right)} \tag{26}$$

3.6. Energy Consumption Model

Microgrid loading apparatus comes in three different varieties. The first category includes non-shiftable appliances such as washing machines, clothes dryers, $\mathscr{b} = \{\mathscr{b}_1, \mathscr{b}_2, \ldots, \mathscr{b}_u\}$. Users are unable to halt this type of device function until it is finished. The second category focuses on shiftable devices such vacuum cleaners, water pumps, and $a = \{a_1, a_2, \ldots, a_s\}$. Users can switch to a cheaper time zone and, if necessary, stop their operation once it has begun in this manner. The third kind includes fixed devices like air conditioners, refrigerators, and $\mathcal{F} = \{c_1, c_2, \ldots, c_f\}$. Device operating times in this category cannot be changed. The following equations list these types of energy use [87]:

$$\mathcal{N}_a(t) = \sum_{s=1}^{\mathcal{S}} \mathcal{N}_s^a(t) \mathcal{Z}_s^a(t) \tag{27}$$

$$\mathcal{N}_{b}(t) = \sum_{u=1}^{\mathcal{U}} \mathcal{N}_{u}^{b}(t)\mathcal{Z}_{u}^{b}(t) \tag{28}$$

$$\mathcal{N}_{c}(t) = \sum_{f=1}^{\mathcal{F}} \mathcal{N}_{f}^{c}(t)\mathcal{Z}_{f}^{c}(t) \tag{29}$$

where $\mathcal{Z}_{s}^{a}(t)$, $\mathcal{Z}_{u}^{b}(t)$, and $\mathcal{Z}_{f}^{c}(t)$ are the ON/OFF states of shiftable, non-shiftable, and fixed devices, respectively, and $\mathcal{N}_{s}^{a}(t)$, $\mathcal{N}_{u}^{b}(t)$, and $\mathcal{N}_{f}^{c}(t)$ are the energy consumed (kWh) by shiftable, non-shiftable, and fixed devices during time t, respectively. The daily total energy usage can be represented as:

$$\mathcal{N}_{Total} = \sum_{t=1}^{24} (\mathcal{N}_{a}(t) + \mathcal{N}_{b}(t) + \mathcal{N}_{c}(t)) \tag{30}$$

3.7. Tariff of Time of Use (ToU)

The revised ToU rate is based on escalating customer load demand and escalating generation costs. Adjustments are applied for on-peak and shoulder-peak hours per hour:

$$\xi_h = \begin{Bmatrix} \mathcal{TOU}_h & when\ \hbar_{off} \\ \delta_h & other\ wise \end{Bmatrix} \tag{31}$$

where $\hbar_{off}$ is the off-peak hour, h is the number of hours, and ξ_h is the modified ToU pricing signal. The values of δ depend on additional expenses.

When electricity prices are higher during periods of high energy demand (on-peak hours) and lower during periods of low power demand (off-peak hours), the utilities establish market-specific prices [88].

3.8. Model of Energy Pricing

The appliances' energy consumption is multiplied by the pricing signal to determine the price of energy. There are a number of electrical tariffs, including ToU pricing, day-ahead pricing (DAP), real-time pricing (RTP), and critical peak pricing (CPP), that can be used to lower the cost of electricity over the course of a day. The ToU pricing plan is used in this study because it offers incentives to users who reduce their consumption during peak hours. Because it divides the day into three blocks—off-peak, mid-peak, and peak—ToU is regarded as a static pricing approach. The cost of daily energy consumption can be expressed as:

$$\mathcal{S}_{\mathcal{T}} = \sum_{t=1}^{24} [\mathcal{N}_{a}(t) + \mathcal{N}_{b}(t) + \mathcal{N}_{c}(t)]\varrho(t) \tag{32}$$

3.9. Model of Demand Response

Participants may receive rewards from the microgrid operators for keeping an eye on responsive shifting devices. The ratio of total load, the collection of available time slots, and all responsive shifting device data are recovered and sent to the microgrid control center. A forward shift, a backward shift, or both may be possible with the responsive shifting devices' available shifting time slots. Demand response, which includes responsive shifting devices' active power $\mathcal{E}_{\mathcal{RP}}$ and reactive power $\mathcal{E}_{\mathcal{RQ}}$, can be illustrated as [89]:

$$\mathcal{E}_{\mathcal{R}} = \mathcal{E}_{\mathcal{RP}} + j\mathcal{E}_{\mathcal{RQ}} \tag{33}$$

Using (34) and (35), it is possible to plan the shifted active/reactive power of responsive shifting devices (RSA) from instant i to t and vice versa (forward $\mathcal{E}_{\mathcal{RP}f,t}$ and backward $\mathcal{E}_{\mathcal{RP}b,t}$).

$$\mathcal{E}_{\mathcal{RP}f,t} = \sum_{i,t \in \mathcal{T}} \mathcal{E}_{\mathcal{RP}i,t} \tag{34}$$

$$\mathcal{E}_{\mathcal{RP}b,t} = \sum_{i,t \in \mathcal{T}} \mathcal{E}_{\mathcal{RP}i,t} \tag{35}$$

In contrast, the number of shiftable time slots τ_{sh} is indicated in (36):

$$|\tau_{sh}| \leq t_f - t_s \tag{36}$$

where (t_f) stands for the ending time and (t_s) for the beginning. An illustration of the microgrid incentive cost operator is:

$$\mathcal{S}_\ell = \sum \mathcal{S}_{dr} \mathcal{E}_{\mathcal{RP}f,t} \tag{37}$$

where $\mathcal{S}_{dr}$ is the customer incentive rate for RSA shifting (\$/kW). The definition of the incentive cost rate for off-peak, mid-peak, and peak times is:

$$\mathcal{S}_{dr} = \begin{cases} \gamma_1 \alpha_s t \in \mathcal{H}_1 \\ \gamma_2 \alpha_s t \in \mathcal{H}_2 \; \mathcal{H}_1 \cup \mathcal{H}_2 \cup \mathcal{H}_3 = \mathcal{H} \\ \gamma_3 \alpha_s t \in \mathcal{H}_3 \end{cases} \tag{38}$$

where γ_1, γ_2, and γ_3 values are between 0 and 1, and are defined as a ToU-based scaling factor for the off-peak, mid-peak, and peak periods $\mathcal{H}_1$, $\mathcal{H}_2$, and $\mathcal{H}_3$, respectively.

The first level of optimization involves reducing costs associated with operating solar systems (9), battery energy storage systems (19), daily energy costs (23), microgrid incentive costs, and grid emissions as specified by the following equation:

$$minimize \Longrightarrow \mathcal{S}_{Total} = \mathcal{S}_g + \mathcal{N}_g + \mathcal{S}_{\mathcal{PV}} + \mathcal{S}_{\mathcal{O}w} + \mathcal{S}_{bop} + \mathcal{S}_{\mathcal{T}} \tag{39}$$

The following should be completed to reduce the PAR to improve microgrid performance:

$$minimize \Longrightarrow \{\mathcal{PAR}\} \tag{40}$$

3.10. User Comfort Maximization

In order to reduce the cost of electricity, the load for appliances has been moved to off-peak times. The waiting time of appliances has been assessed in order to determine end-user comfort U_C during appliance scheduling. It is believed that g_α represents the respective beginning times of the appliances. $\widehat{W}$ is the appliance waiting time, which is expressed as [90]:

$$\widehat{W} = abs(g_\alpha - R_T) \tag{41}$$

where R_T stands for an appliance's request time. The following is an example of the average appliance waiting time ($\widehat{W}_A$):

$$U_C = \widehat{W}_A = \frac{\sum_{g=1}^{B_N} abs(g_\alpha - R_T)}{B_N} \tag{42}$$

B_N displays how long each appliance was operating throughout various time windows throughout the day.

Also, the normalized waiting time of appliances $\widehat{W}_N$ can be expressed as:

$$\widehat{W}_N = \frac{\sum_{s=1}^{T} \widehat{W}_A(s)}{max\left(\sum_{s=1}^{T} \widehat{W}_A(s)\right)} \tag{43}$$

4. Optimization Algorithm

4.1. Improved Cockroach Swarm Optimization Models

The population-based global optimization technique known as the Cockroach Swarm Optimization Algorithm (CSOA) has been used to solve a variety of issues in the literature, including [91]. The following are the models for the Cockroach Swarm Optimization Algorithm (CSOA).

4.1.1. Swarming-Chase Behavior

$$x_i = \begin{cases} w.x_i + \text{step} \cdot \text{rand} \cdot (p_i - x_i), & x_i \neq p_i \\ w.x_i + \text{step} \cdot \text{rand} \cdot (p_g - x_i), & x_i = p_i \end{cases} \tag{44}$$

where p_i is the individual best position and p_g is the overall best position; x_i is an inertial weight that is constant; step is a fixed value; and rand is a random number between [0, 1]:

$$p_i = \text{Opt}_j\{x_j, |x_i - x_j| \leq \text{ visual } \} \tag{45}$$

where, $j = 1, 2, \ldots, N$, $i = 1, 2, \ldots, N$ are constants for the perception distance of the visual.

$$P_g = Opt_i\{x_i\} \tag{46}$$

4.1.2. Behavior of Hunger

$$x_i = x_i + (x_i - ct) + x_{\text{food}} \tag{47}$$

x_i represents the cockroach's position, $(x_i - ct)$ represents its migration from that position, c controls the speed of migration at time t, x_{food} represents the location of food, thunger represents the hunger threshold, and hunger is a random value between [0, 1].

4.1.3. Dispersion Behavior

$$x_i = x_i + \text{rand}(1, D), i = 1, 2, \ldots, N \tag{48}$$

A D-dimensional random vector with a settable range is called rand (1,D).

4.1.4. Ruthless Behavior

$$x_k = p_g \tag{49}$$

p_g is the overall best location and k is a random number from the range $[1, N]$. Algorithm 1 provides an illustration of the ICSO algorithm [91].

4.2. Bacterial Foraging Optimization Algorithm (BFOA)

Passsino originally presented the Bacterial Foraging Optimization Algorithm (BFOA) in the year 2002. *Escherichia coli* (*E. coli*) bacteria's chemotactic and foraging behavior served as its primary inspiration. The bacteria can migrate in both directions, from the toxic area to the nutritional area, through tumbling and smooth flowing. The first is chemotaxis, the second is reproduction, the third is elution—dispersal, and the fourth is swimming. These four mechanisms are crucial to the BFOA.

If the bacterium discovers a new point in the chemotactic step where the nutritional medium is higher than current position, the bacteria moves one step further in that direction. Up until the worst nutrient medium is reached, this process is repeated. The bacteria are organized in declining order during the reproduction step according to the nutrient content they picked up during the chemotaxis process. Each bacterium divides into two, with the first half of the population that has gathered adequate nutrition reproducing. As the other half of the population gradually passes away, their presence in the population is eliminated while keeping the original population constant. The population and behavior of bacteria will change as the environment changes; an elimination and dispersal stage is used to study this phenomenon. Each bacterium is given a random number between 0 and 1 in this step. If the value of the random number is smaller than the value of the predefined parameter, it survives; otherwise, it is deleted from the environment. Below is a list of the BFOA equations and the fitness function [92].

$$[\theta]^i[j+1,k,l] = [\theta]^i[j,k,l] + c[i]\frac{\Delta[i]}{\sqrt{\Delta^i[i].\Delta[i]}} \tag{50}$$

Algorithm 1: Improved Cockroach Swarm Optimization Algorithm (CSOA)

$Input: fitness\ function: f(x), x \in R^D$
$set\ parameters\ and\ generate\ an\ initial\ population\ of$
$cockroach$
$set\ p_g = x_1$
$for\ i = 2\ to\ N\ do$
$if\ f(x_i) < f(p_g)\ then$
$p_g = x_i$
$end\ if$
$end\ for$
$if\ p_i == x_i\ then$
$x_i = w.x_1 + step.rand.(p_g - x_i)$
$else$
$x_i = w.x_1 + step.rand.(p_i - x_i)$
$end\ if$
$if\ f(x_i) < f(p_g)\ then$
$p_g = x_i$
$end\ if$
$end\ for$
$if\ Hunger == t_{hunger}\ then$
$x_i = x_1 + (x_t - c_t) + x_{id}$
$hunger_i = 0$
$incremant\ hunger_i\ counters$
$end\ if$
$for\ i = 1\ to\ N\ do$
$x_i = x_i + rand(1, D)$
$if\ f(x_i) < f(p_g)\ then$
$p_g = x_i$
$end\ if$
$end\ for$
$k = rand[1, N]$
$x_k = p_g$
$end\ for$

At the chemotactic step j, reproduction step k, and elimination step i, its bacterium expresses itself as $\theta^i[j,k,l]$. This results in a step of size $c[i]$ in the bacterium, and Δ denotes a vector in the random direction whose elements lie in the range $[-1, 1]$:

$$J_{cc}[\theta, P[j,k,l]] = \sum_{i=1}^{S} J_{cc}\left[\theta, \theta^i[j,k,l]\right] \tag{51}$$

where S is the total number of bacteria, p is the number of variables in each bacterium that need to be optimized, and $J_{cc}[\theta, P[j,k,l]]$ is the value of the objective function that should be added to the real objective function in order to obtain a time-varying objective function.

$$\theta = [\theta_1, \theta_2, \theta_3 \ldots \theta_p] \tag{52}$$

$$J[i,j,k,l] = J[i,j,k,l] + J_{cc}[\theta^i[j,k,l], P[j,k,l]] \tag{53}$$

$$\text{Fitness} = \frac{1}{1 + \sum_{t=1}^{24} [[\text{ PLoad } [t] - \text{ Objective } [t]]^2]} \tag{54}$$

To achieve a final load curve that is extremely similar to the desired load curve, the aforementioned fitness function is chosen for the BFOA. The following Figure 2 displays the BFOA flow chart [92].

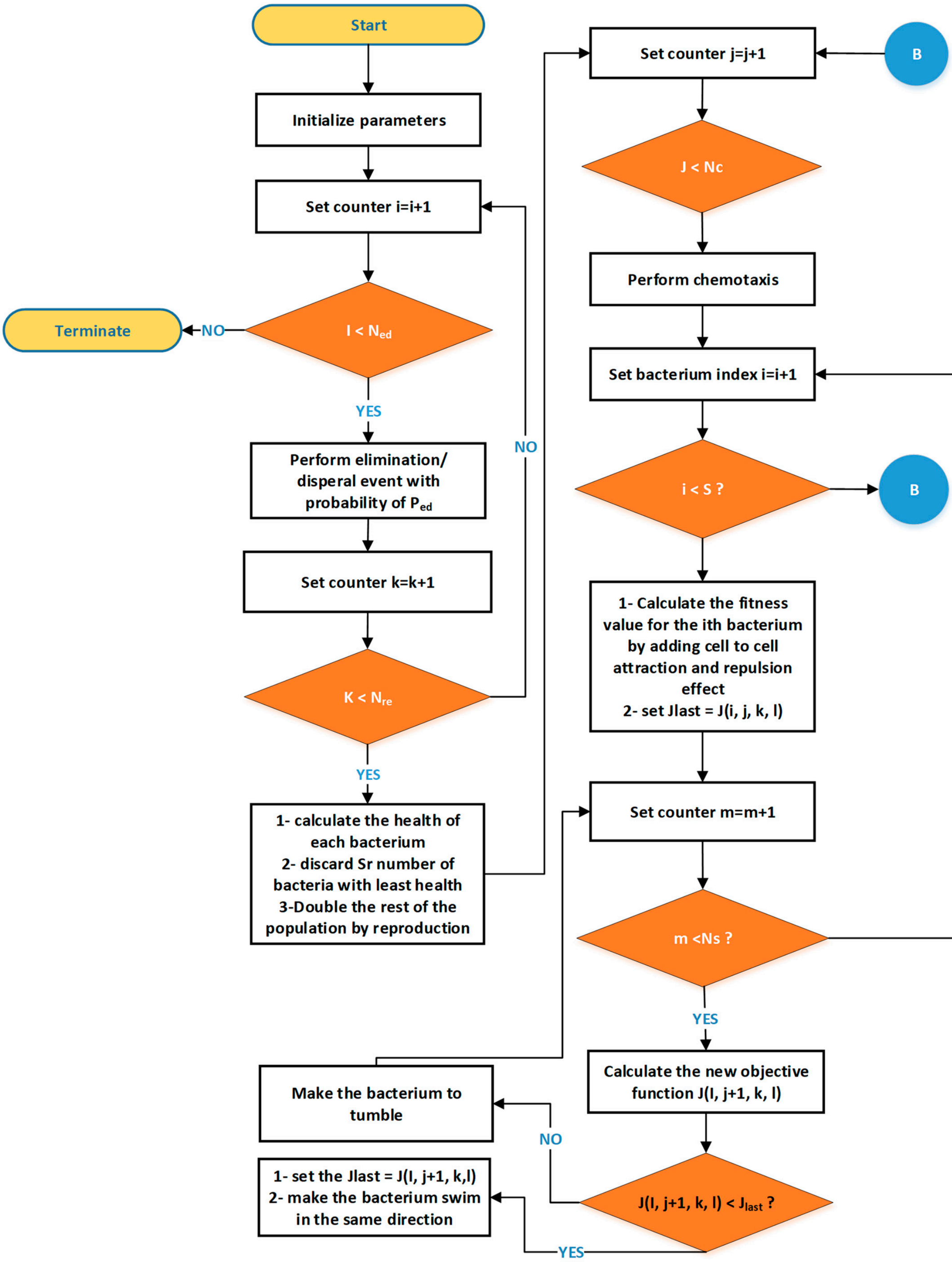

Figure 2. Bacterial Foraging Optimization Algorithm.

5. Simulations Results

The outcomes of the suggested EMS simulation are provided in this section. The major objectives of this effort are to lower the cost of electricity use, lower the PAR, and raise user comfort (UC) based on lowering waiting times. We offer an effective 24 h scheduling plan that strikes a balance between these objectives.

To confirm the accuracy of the system, the results obtained with the Improved Cockroach Swarm Algorithm (ICSA) are compared with the results obtained with the Bacterial Foraging Optimization Algorithm (BFOA) in reference [92]. Figure 3 illustrates the power of suggested apartments' demand side management without the corrective method. Figure 4 shows the power of suggested apartments' demand side management with the BFOA method. Figure 5 illustrate the power of suggested apartments' demand side management with the ICSA method.

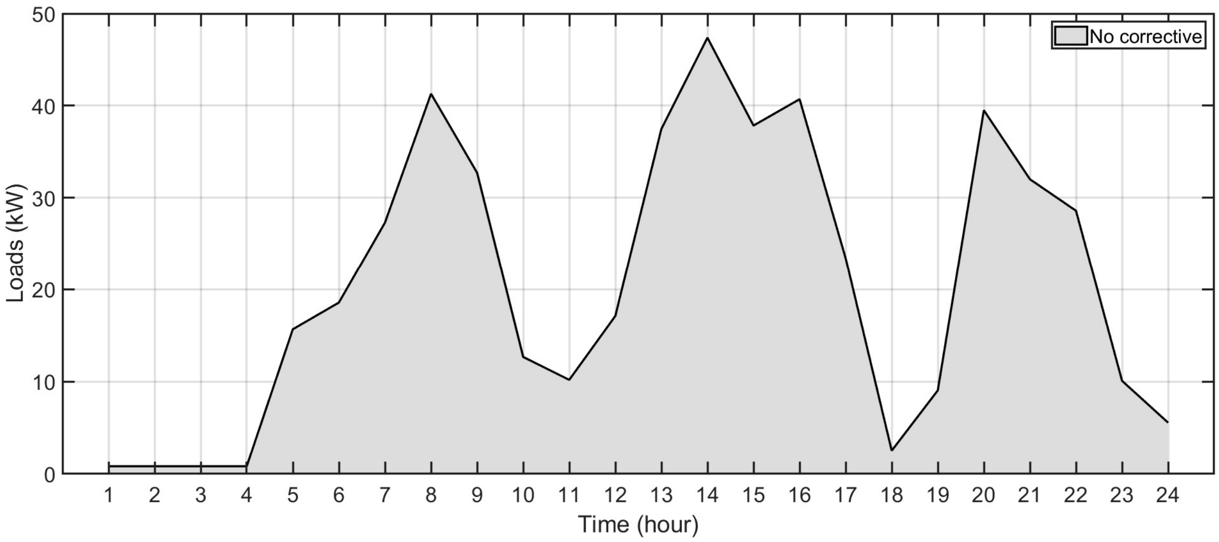

Figure 3. Power of suggested apartments' demand side management without the corrective method.

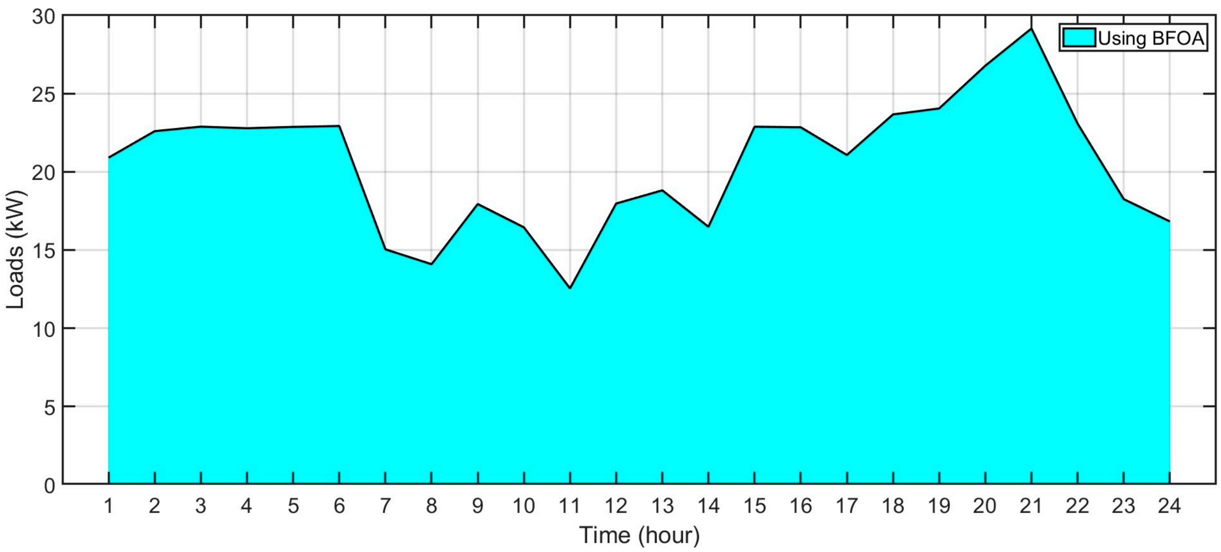

Figure 4. Power of suggested apartments' demand side management with the Bacterial Foraging Optimization Algorithm method [92].

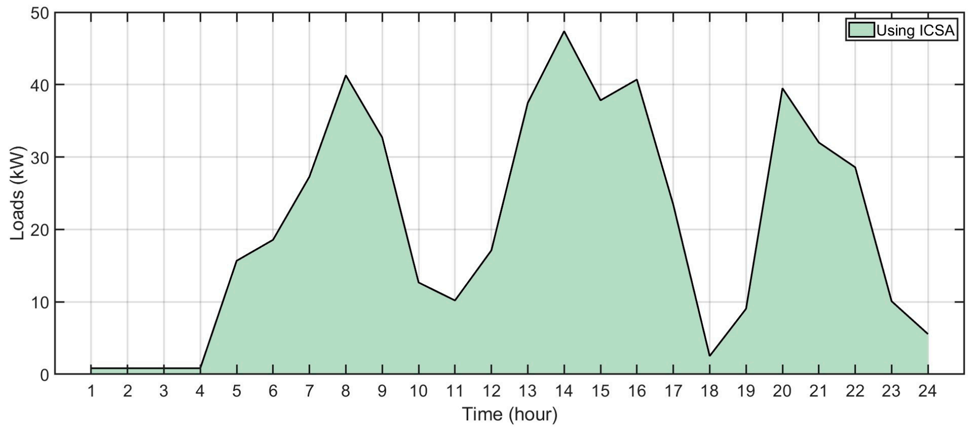

Figure 5. Power of suggested apartments' demand side management with the Improved Cockroach Swarm Algorithm method.

Figure 6 shows the cost of suggested apartments' demand side management without the corrective method. The results of Figure 6 show that the unscheduled pattern forces the customer to pay more for electricity consumption at different times of the day, especially during peak hours. Figure 7 shows the cost of suggested apartments' demand side management using the BFOA method. Figure 8 shows the cost of suggested apartments' demand side management using the ICSA method.

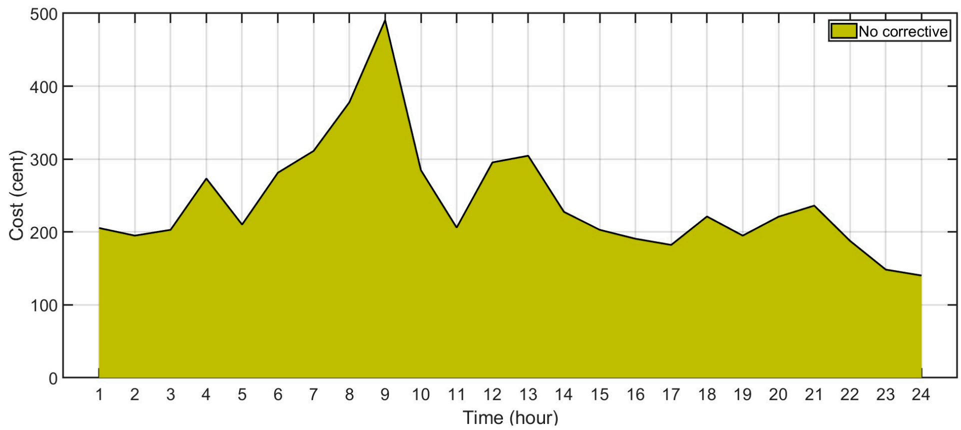

Figure 6. The cost of suggested apartments' demand side management without the corrective method.

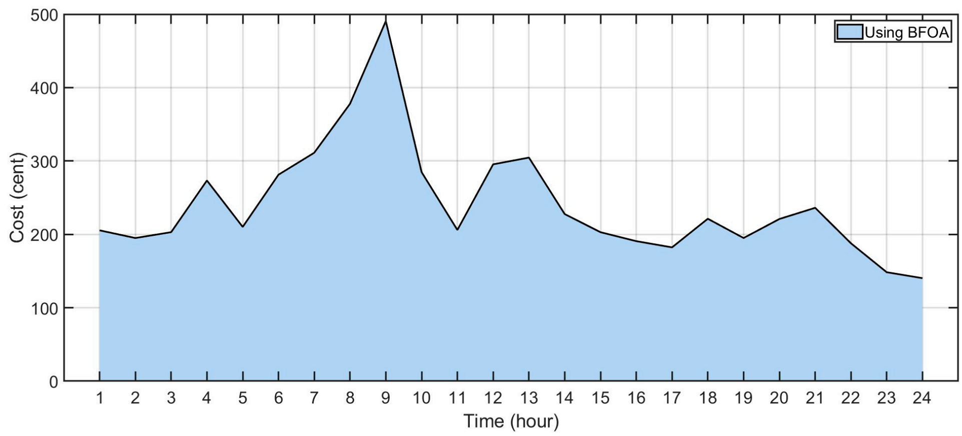

Figure 7. Cost of proposed apartments' demand side management using the Bacterial Foraging Optimization Algorithm method [92].

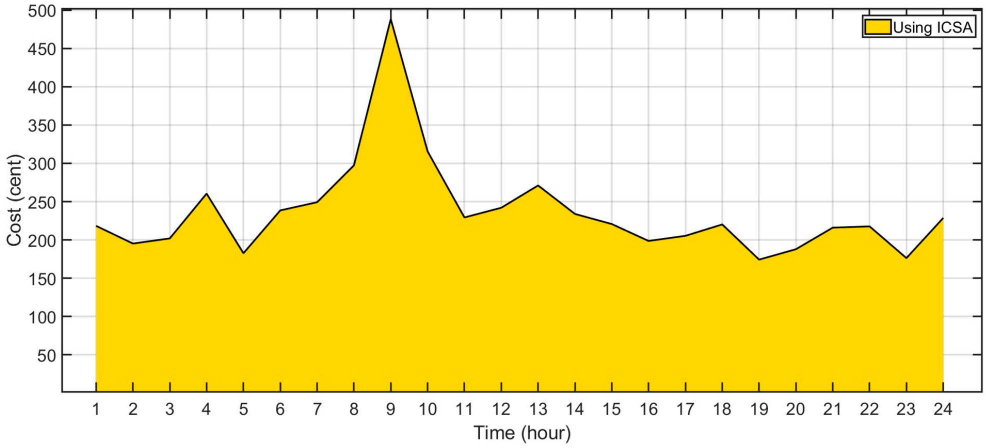

Figure 8. The cost of suggested demand side management using the Improved Cockroach Swarm Algorithm method.

The proposed ICSA scheme's maximum periodic energy usage is more optimal when compared to optimal schemes with unscheduled patterns.

The outcomes also demonstrate that the best plans attempt to schedule the loads outside of peak times in each simulated scenario such that the consumer pays less during peak times.

As can be seen in Figures 6–8, the total daily electricity bill for the unscheduled pattern is 6820.690 cents using ToU signals as the electricity tariffs. In the first scenario, the BFOA was able to reduce the cost of daily electricity consumption by 17.75%. But, the cost reduction using the ICSA was 46.08%, using ToU tariffs.

Accordingly, it can be inferred from the simulations that the EMS, which is based on an optimal scheduling scheme employing the ICSA, performs well in obtaining the solution that sets the best trade-off between the goal functions.

Table 2 shows the hourly energy consumption without the corrective method using the Bacterial Foraging Optimization Algorithm and using the Cockroach Swarm Algorithm. Table 3 shows the hourly electricity bill without the corrective method using the Bacterial Foraging Optimization Algorithm and using the Improved Cockroach Swarm Algorithm.

Table 2. Hourly energy consumption without the corrective method using the Bacterial Foraging Optimization Algorithm and using the Cockroach Swarm Algorithm.

Hours	Without Correction	Bacterial Foraging Optimization Algorithm [92]	Improved Cockroach Swarm Algorithm
1	0.8325	20.90278	22.20814
2	0.8325	22.5959	22.62476
3	0.8325	22.8845	22.7661
4	0.8325	22.7809	21.7005
5	15.6732	22.86822	19.86826
6	18.5666	22.92446	19.43832
7	27.2875	15.04272	12.0435
8	41.2883	14.09256	11.0852
9	32.7043	17.9376	17.84806
10	12.6725	16.45168	18.22842
11	10.1898	12.54522	13.96528

Table 2. *Cont.*

Hours	Without Correction	Bacterial Foraging Optimization Algorithm [92]	Improved Cockroach Swarm Algorithm
12	17.1088	17.9709	14.71786
13	37.4662	18.8145	16.7425
14	47.3785	16.4835	16.93712
15	37.8325	22.88228	24.8825
16	40.7	22.84306	23.78804
17	23.4173	21.07372	23.73846
18	2.516	23.6652	23.54976
19	9.0465	24.0463	21.4896
20	39.4975	26.77986	22.7698
21	32.005	29.15674	26.66738
22	28.5825	23.0769	26.73694
23	10.0825	18.2521	21.682
24	5.55	16.8239	27.417

Table 3. Hourly electricity bill without the corrective method using the Bacterial Foraging Optimization Algorithm and using the Improved Cockroach Swarm Algorithm.

Hours	Without Correction	Bacterial Foraging Optimization Algorithm [92]	Improved Cockroach Swarm Algorithm
1	8.183475	205.4743274	218.3060162
2	7.184475	195.002617	195.2516788
3	7.384275	202.985515	201.935307
4	9.99	273.3708	260.406
5	144.036708	210.1589418	182.5893094
6	227.812182	281.2831242	238.5081864
7	564.578375	311.2338768	249.180015
8	1107.352206	377.9624592	297.305064
9	894.462605	490.59336	488.144441
10	219.360975	284.7785808	315.5339502
11	167.316516	205.9925124	229.3098976
12	281.268672	295.441596	241.9616184
13	606.577778	304.606755	271.061075
14	654.297085	227.637135	233.9016272
15	335.574275	202.9658236	220.707775
16	339.845	190.739551	198.630134
17	202.559645	182.287678	205.337679
18	23.5246	221.26962	220.190256
19	73.367115	195.015493	174.280656
20	325.854375	220.933845	187.85085

Table 3. *Cont.*

Hours	Without Correction	Bacterial Foraging Optimization Algorithm [92]	Improved Cockroach Swarm Algorithm
21	259.2405	236.169594	216.005778
22	232.66155	187.845966	217.6386916
23	81.970725	148.389573	176.27466
24	46.287	140.311326	228.65778

The comparison of the total daily electricity bill for the W/O, BFOA, and ICSA algorithms is shown in Figure 9.

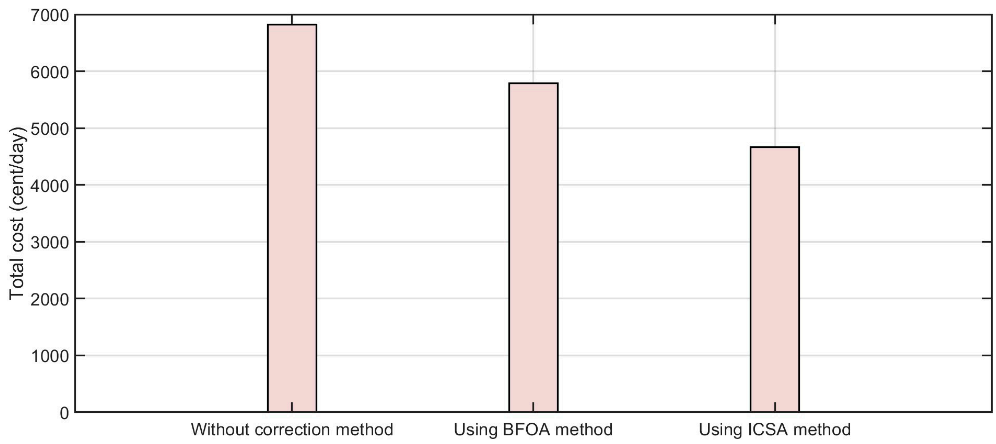

Figure 9. Cost comparison without proposed method of the Bacterial Foraging Optimization Algorithm in reference [92] and the Improved Cockroach Swarm Algorithm.

Prior to using the suggested approach, the cost was 6820.690112 (cent). However, the cost is discovered to be 5792.45007 after using the BFOA algorithm, and the cost was discovered to be 4668.968446 after using the BOA algorithm. The BFOA algorithm saved 17.75% per day and the ICSA algorithm saved 46.085% per day when compared to the suggested approach and the conventional method. Figure 9 illustrate a cost comparison of price without the corrective method, with the BFOA method and with the ICSA method. Table 4 shows the cost comparison of price without the corrective method, using the BFOA method and using the ICSA method

Table 4. Cost comparison of price without the corrective method, using the BFOA method and using the ICSA method.

	Total Cost (cent/day)	Improvement (%)
Without corrective method	6820.690112	
Using BFOA method in reference [92]	5792.45007	17.751%
Using ICSA method	4668.968446	46.085%

Consumer Comfort

In this study, we also took into account consumer comfort, which is calculated in terms of electricity bill and electrical device waiting time. Electrical equipment has to wait longer because the load is switched from high-peak hours to low-peak hours in order to lower energy utilization costs. Therefore, there is a trade-off between the cost of energy usage and the waiting time for electrical devices. We introduced the Improved Cockroach Swarm Algorithm (ICSA) to reduce the trade off, and the outcome is shown in Figure 10 clearly.

These graphs show that electrical devices without the suggested approach have a longer waiting time than in the case of the suggested approach. The comfort of the consumer is increased because the Improved Cockroach Swarm Algorithm (ICSA) of electrical devices allows the user to generate an interruption and operate the device as needed while disobeying the schedule set by the DSM system for that device, as shown in Figure 10. The heuristic algorithms BFOA and ICSA show a reduction in waiting time as compared to without the corrective method. Moreover, the ICSA has a minimum waiting time in both scenarios.

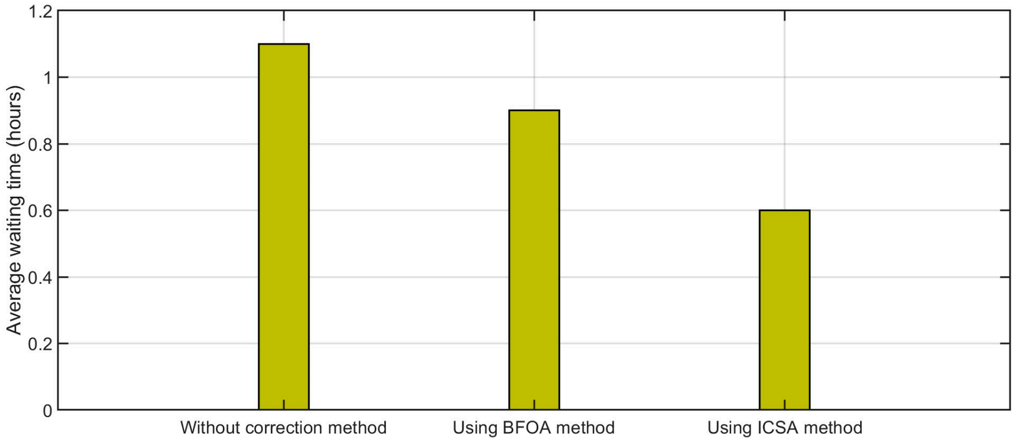

Figure 10. Average waiting time (consumer comfort) of apartment appliances comparison between no proposed method, the Bacterial Foraging Optimization Algorithm, and with the Improved Cockroach Swarm Algorithm.

6. Conclusions

For off-grid and on-grid systems combined with solar PV generation and batteries, a cost-effective microgrid-based energy management system was developed. On a daily basis, the off-grid and on-grid models for the cost analysis were developed using an Improved Cockroach Swarm Optimization technique. The proposed framework was evaluated by comparing it with the BFOA and W/O scheduling cases. The BFOA algorithm reduced energy costs by 17.75% as compared to the W/O scheduling case, whereas the ICSA reduced energy costs by 46.085% as compared to the W/O scheduling case. The created ICSA performed better than the BFOA and W/O scheduling situations in some areas of the desired objectives, according to the results, and is advantageous to both the utility and consumers. The results provided in the last section conclude that the Improvement Cockroach Swarm Optimization Algorithm (ISCOA) performs best among all techniques due to its real-time and distributed characteristics.

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