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A novel economic dispatch in the stand-alone system using improved butterfly optimization algorithm

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ABSTRACT

Distributed renewable energy systems are now widely installed in many buildings, transforming the buildings into 'electricity prosumers'. Additionally, managing shared energy usage and trade in smart buildings continues to be a significant difficulty. The main goal of solving such problems is to flatten the aggregate power consumption-generation curve and increase the local direct power trading among the participants as much as possible. This study provides a coordinated smart building energy-sharing concept for smart neighborhood buildings integrated with renewable energy sources and energy storage devices within the building itself. This neighborhood energy management model's primary objective is to reduce the total power cost of all customers of smart buildings in the neighborhood by increasing the use of locally produced renewable energy. In the first stage, a group of optimum consumption schedules for each HEMS is calculated by an Improved Butterfly Optimization Algorithm (IBOA). A neighborhood energy management system (NEMS) is established in the second stage based on a consensus algorithm. A group of four smart buildings is used as a test system to evaluate the effectiveness of the suggested neighborhood smart building energy management model. These buildings have varying load profiles and levels of integration of renewable energy. In this paper, the proposed framework is evaluated by comparing it with the Grey Wolf optimization (GWO) algorithm and W/O scheduling cases. With applying GWO, the total electricity cost, peak load, PAR, and waiting time are improved with 3873.723 cents, 21.6005 (kW), 7.162225 (kW), and 87 s respectively for ToU pricing and 11217.57 (cents), 18.0425(kW), 5.984825 (kW), and 98 s respectively for CPP tariff. However, using the IBOA Improves the total electricity cost, peak load, PAR, and waiting time by 3850.61 (cents), 20.1245 (kW), 6.7922 (kW), and 53 s respectively, for ToU and 10595.8 (cents), 17.6765(kW), 5.83255(kW), and 74 s for CPP tariff. Also, it is noted that the run time is improved using GWO and IBOA by 13% and 47%, respectively, for ToU and 2% and 26% for CPP. However, the number of iterations required to obtain the optimal solution is reduced using the GWO and IBOA by 60% and 81% for ToU and 55% and 80% for CPP tariffs. The results show significant improvements obtained by applying just intelligent programming and management.

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Abbreviations & acronyms

CMG	Community Microgrid
IBOA	Improved Butterfly Optimization Algorithm
DERs	Distributed Generation Resources
DR	Demand Response
GWO	Grey Wolf Algorithm
W/O	Without
PAR	Peak-to-Average Ratio
RES	Renewable Energy Sources
FPS	Flat Pricing Scheme
AC/DC	Alternating Current/Direct Current
MPPT	Maximum Power Point Tracking
SCADA	Supervisory Control and Data Acquisition
DRP	Demand Response Program
IoE	Internet of Energy
BPSO	Binary Particle Swarm Optimization
BSA	Backtracking Search Algorithm
IoT	Internet of Things
MAF	Multi-Agent Framework
P2P	Peer to Peer
BOA	Butterfly Optimization Algorithm
CoAP	Constricted Application Protocol
ANFIS	Adaptive Neuro-Fuzzy Inference System
EMS	Energy Management System
DSO	Distribution Network Operators
DRP	Demand Response Provider
RTP	Real-Time Pricing
SEMS	Smart Energy Management System
DSMS	Demand Side Management System
SHEMF	Smart Homes Energy Management Framework
IP	Internet Protocol
BBSA	Binary Backtracking Search Algorithm
MAS	Multi-Agent System
DSM	Demand Side Management
HEMS	Home Energy Management Systems
PV	Photovoltaics
MGs	Micrograms
RMG	Residential Microgrid
MGCC	Microgrid Central Controller

1. Motivation and relevant background

Fossil resources like coal and oil have run out due to the rise in load demand. As a result, the ecosystem has been significantly harmed, and global warming is intensified. The world has resorted to using both small- and large-scale Renewable Energy Sources (RES), including solar, wind, and wave power, to address the challenges raised. It is necessary to re-evaluate power generating near residential and industrial locations that require more energy due to the issues of the energy process transmission and the ongoing rise in load demand. RES, especially solar and wind energy, which have become increasingly competitive due to the low prices, are used to produce electricity in these areas [1].

The most effective strategy to improve the stability and dependability of the electrical microgrid is to integrate RESs. As a result, numerous studies are carried out every-day to enhance the efficiency of the integrated sources in the hybrid microgrid. The following exemplification of studies is and cannon be exhaustive. It represents only a selection which provide a suitable context of this study. Safamehr and Rahimi-Kian [2] proposed a cost-efficient and reliable micro-grid energy management using the intelligent demand-response program-based Artificial Bee Colony algorithm and quasi-static technique. Huang et al. [3] presented a coordinated control to improve performance for a building cluster with energy storage, electric vehicles, and energy sharing considered. The authors introduced self-governed online energy management and trading for smart micro/nano-grids in Ref. [4]. Furthermore, a new three-layer real-time scheduling framework embedded with an information feedback mechanism has been proposed for Community Microgrids (CMGs) energy management by Md Juel Rana et al. [5]. Khajehzadeh et al. [6] presented a novel approach for planning Distributed Generation Resources (DERs) to provide loads within a Microgrid (MG), regardless of whether there is a power outage. Using a Flat Pricing Scheme (FPS) in the microgrid, the authors of [7] suggested a methodology to systematically schedule energy consumption to address the Demand-Side Management (DSM) problem. In Ref. [8], Faran et al. proposed a novel solution for optimized energy management systems comprising an Alternating Current/Direct Current (AC/DC) hybrid microgrid system for industries. The authors of the study presented in Ref. [9] proposed a novel method to accomplish Maximum Power Point Tracking (MPPT) for Supervisory Control and Data Acquisition (SCADA) based on photovoltaic systems. In Ref. [10], Jasim et al. proposed efficient optimization algorithm-based demand--side management program for smart grid residential load. In Refs. [11–14], the authors proposed a control approach for parallel-operated inverters in green applications; however, the optimal cost-effective energy management system based on BOA is not studied. A Demand Response Program (DRP) for renewable-based Microgrids (MGs) has been presented by Li et al. [15] that considers the significant, widespread use of solar energy and tidal energy as renewable resources in power networks. The authors introduced a HEMS in Ref. [16] while considering effective demand response tactics and uncertainties. The authors proposed a novel, Internet of Energy (IoE) based optimal multi-agent technique for microgrids that utilize renewable energy sources in references [17–19]. Zhang et al. [20] proposed microgrid energy management based on deep reinforcement learning with expert knowledge. Authors in Ref. [21] developed represented a stochastic bottom-up model for generating electrical loads for residential buildings in Canada. Tezde, Okumus and Savran [22] presented a new two-stage hybrid optimization algorithm for scheduling households' power consumption with distributed energy generation and storage. Alhasnawi [23] proposed a novel decentralized control method for microgrids in the internet of energy paradigm.

Vardakas, Zorba and Verikoukis [24] proposed four new, more useful research models to evaluate peak demand in four situations. The assumed finite number of devices in the research area is expressed by a quasi-random process for arrivals or power demands, forming the suggested system's foundation. In Ref. [25], authors suggested an algorithm that focuses on planning the problem of smart devices for sparing load change in demand management. The sparse strategy for load shifting reduces customers' discomfort. The authors of [26] employed the IoT-based bald eagle search optimization technique to offer a fresh approach to day-ahead scheduling problems. In Ref. [27], Vagdoda et al. proposed to develop the Residential Microgrid (RMG) cloud-based Multi-Agent Framework (MAF) for smart-grid culture. The presented MAS comprises intelligent home agents and a microgrid designed to alleviate peak load and reduce the energy costs of intelligent households. The authors of [28] developed multi-objective scheduling of IoT-enabled smart homes for energy management based on arithmetic optimization methods. In Ref. [29] author implemented an islanded microgrid framework Peer to Peer (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. Wang et al. [30] examined effective DSM methods for reducing the grid's peak-to-average energy consumption ratio. 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. The authors of [31] introduced a SCADA-controlled smart home utilizing a Raspberry Pi3. Still, they did not look at the most advantageous way to operate an energy management system based on Butterfly Optimization Algorithm (BOA). Moghaddam and Leon-Garcia [32] built a hybrid cloud and fog system that uses both cloud servers and fog nodes. Utilizing the free and open-source Constricted Application Protocol (CoAP) and the cloud service ThingSpeak, they put their architecture into use on a Wi-Fi-IoT board.

The Adaptive Neuro-Fuzzy Inference System (ANFIS)-based Energy Management System (EMS) for On-grid/Off-grid systems was introduced in Ref. [33]. Hashmi, Ali and Zafar provided the architecture framing, design, and implementation of an IoT and an electronic cloud computer [34]. 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. Using demand response, a multi-agent system for active network control of delivery networks was created and used [35]. This project aims to provide a dynamic board as an effective and useful tool to support the transaction between DSO (Distribution Network Operators) and distribution network operators. In Ref. [36], Alhasnawi and Jasim introduced hierarchical EMS based on optimization. The authors of [37] designed a brand-new agent-based framework to merge the flexibility capabilities of business and residential settings. According to this strategy, a central Demand Response Provider (DRP) would coordinate the response strategies for demand aggregators serving the industrial and residential sectors. The authors in Ref. [38] presented a multi-objective problem with an evolutionary algorithm and a task management technique. A Real-Time Pricing (RTP) reaction to demand is one of the multiple objectives of the problem. Two objectives were considered: daily energy costs and decreased customer annoyance. The authors of [39] developed a Smart Energy Management System (SEMS) as a service on a cloud computing platform for nano-grid equipment; however, they didn't research the most beneficial BOA-based Demand Side Management System (DSMS) operation. The authors of [40] suggested an adaptive power management technique for the grid-connected and isolated modes. To meet demand, a hybrid system that combines power distribution, photovoltaics, and batteries is employed in the residential area of the customer in this study. The suggested approach enables coordinated energy delivery services to offer the appropriate active power and service whenever necessary. Al-Ali et al. [41] launched a Smart Homes Energy Management Framework (SHEMF). This device communicates with a specific Internet Protocol (IP) address IoT module leading to a large network of wireless appliances on every home computer. In Ref. [42], the authors introduced a new IoT-enabled trust-distributed EMS; however, optimization based on BOA is not investigated. Ahmed et al. [43] suggested a Binary Backtracking Search Algorithm (BBSA) to handle energy consumption for a real-time optimum time schedule controller for HEMS. To minimize overall demand and arrange household appliances operating at particular times of the day, BBSA offers optimum schedules for domestic equipment. In Ref. [44], the authors proposed an optimal load-shedding scheme using a grasshopper optimization algorithm for islanded power system with distributed energy resources. A proposal of an approach called home energy management as a service based on Q-Learning algorithms was introduced in Ref. [45]. Using the Internet of Energy, the authors of [46] proposed a revolutionary real-time electricity scheduling for EMS; however, optimization based on BOA is not investigated. In Ref. [47], the authors introduce a new power management system as a fog computing network service. The implementation of the fog computing platform supports flexibility, interoperability, accessibility, data protection, and real-time energy management needs. Li et al. [48] introduced a self-learning domestic administration framework. The communication and interactions between agents were implemented on the IoT concepts on a Multi-Agent System (MAS) platform. A new, trustworthy EMS and control method for a hybrid microgrid system powered by green energy was introduced by the authors of [49]. The authors introduced a sophisticated energy management technique for microgrids with real-time monitoring interface [50]. In Ref. [51], the authors introduced consensual negotiation-based decision-making for connected appliances in smart home management systems. An efficient energy management in smart grids considering demand response programs and renewable energy sources was introduced in Ref. [52]. While Kamboj, Bath and Dhillon [53] presented a non-convex economic load dispatch problem solution using Grey Wolf Optimizer, a follow-up study [54] introduced a solution to small-scale power systems' non-convex economic load dispatch problem using an ant lion optimizer. Furthermore, authors presented demand response-integrated economic dispatch incorporating renewable energy sources using ameliorated dragonfly algorithm [55] and an optimal generation scheduling and dispatch of thermal generating units considering the impact of wind penetration using the hGWO-RES algorithm was introduced in Ref. [56]. In Ref. [57], the authors presented a solution to the non-convex/convex and dynamic economic load dispatch problem using a moth flame optimizer and an optimal operation model for a microgrid-based multi-agent system is proposed in Ref. [58].

In this study, a coordinated energy management approach for smart neighborhood buildings is developed, featuring local energy trading between the neighborhood community's smart buildings. This model primarily aims to reduce the total combined electricity bill for all smart home users by increasing RER energy utilization in the neighborhood region with neighborhood power sharing. This model considers a group of four smart buildings a neighborhood community. All buildings are integrated with different levels of solar power, wind power, and battery capacities. The proposed neighborhood energy management scheme is developed with the help of the Improved Butterfly Optimization Algorithm (IBOA).

1.1. *Contributions and novelties*

Even while the studies discussed have certain advantages, it is important to note that they also have several drawbacks and disadvantages, some of which are listed below. There hasn't been a reliable approach in the research that can provide the best outcome. A comprehensive model that fully considers the coordination between renewable resources, the storage system, and the demand-side management strategy is also lacking in the research that has been provided. This research is restricted to middle-stage component optimization; however, most of this optimization shares a number of DGs. A mechanism is required for the MG to be synchronized. The multi-agent system used in this study can achieve the required optimization objective. Or, to put it another way, the multi-agent, three-layered system (MAS) is the starting point of this study. Then, the model's load and DR mechanisms are developed. A developed Improved Butterfly Optimization Algorithm (IBOA) is proposed to address this issue. Consequently, a quick summary of this paper's key advantages and breakthroughs is provided below.

1. Introducing a new optimization technique using an improved butterfly optimization algorithm (IBOA) to reduce the cost of supplying the load; in this regard, the coefficients are not constant and will change as the simulations go.
2. The suggested framework is assessed in terms of energy cost, carbon emission, and PAR (Peak to Average Ratio) by comparison with a framework based on the Grey Wolf Algorithm (GWO) and without (W/O) scheduling case.
3. This research suggests the neighborhood energy management approach to maximize the use of locally produced renewable energy.
4. All smart neighborhood buildings aim to reduce their combined electricity costs.

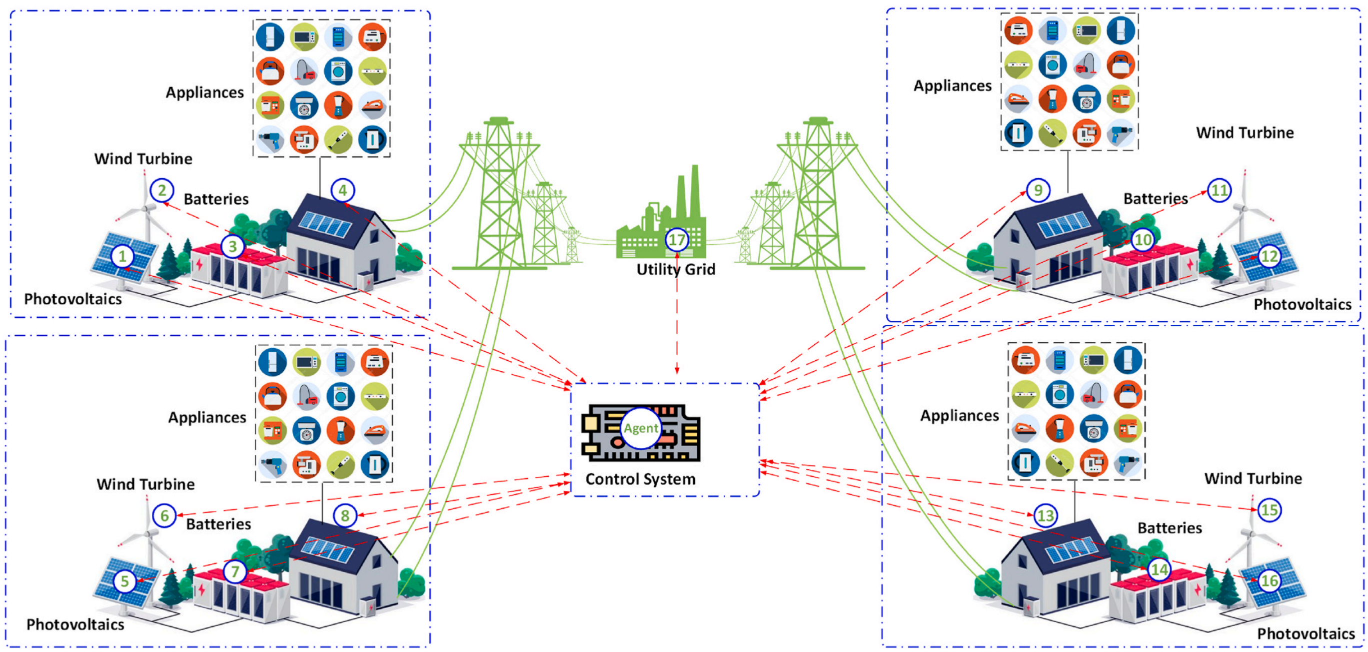

Fig. 1. Proposed energy management system model.

5. With the help of the agents DMS, and Building Central Controller (BGCC), this work develops a layered MAS optimization model. It also considers the MG's real-time energy management and optimizes the cost of an MG in the MGCC agent.
6. In this paper, a neighborhood community with a collection of four smart buildings is used as a test system to assess the performance of the suggested model. All smart buildings have installed different RER energy capacities, representing the test system.

2. Problem formulation

It is thought of how central control equipment might use in an energy management situation. All intelligent electrical equipment is programmed and controlled via the building's network's central control. The objective function is shown in the equation below [59]:

$$\text{Objective Function Min} = \frac{\text{SP}}{\text{LF}} \tag{1}$$

LF represents the load factor, and the running cost of a smart house is represented by SP. To calculate SP, one must subtract the cost of acquiring energy from the upstream grid (CEP), the profit made from selling that energy (CES), and the profit made from participating in a program to cut back on consumption (CDM).

$$\text{SP} = C_{\text{EP}} - C_{\text{ES}} - C_{\text{DM}} \tag{2}$$

$$\text{LF} = \frac{\text{Average of load}}{\text{Peak of load}} \tag{3}$$

The load factor can be raised in two ways: by lowering a peak consumption or raising an average consumption via filling a load profile's dips. Water heaters, dishwashers, vacuum cleaners, and water pumps are examples of replacement equipment used in this study. However, after the working time is determined, they are interrupted and moved to different time periods. As was already said, many gadgets lack this capability out of necessity and are not adjustable. Since the user controls how long these gadgets are in use, incentive programs are considered to encourage consumers to use them as effectively as possible [59].

$$X_i = \sum_{t=1}^{T}\left(\sum_{i\epsilon[I,D,B]} p_i \times \sigma_i(t)\right) \tag{4}$$

The cost of all devices at interval t is determined as follows:

$$\varsigma_i = \sum_{t=1}^{T}\left(\sum_{i\in[I,D,B]} p_i \times \delta(t) \times \sigma_i(t)\right) \tag{5}$$

where T is the total time gap, p_i represents the appliance electricity rates, and $(\delta(t)$ represents the power price.

$$\sigma_i(t) = \begin{cases} 0, \text{if appliance is off} \\ 1, \text{if appliance is off} \end{cases} \tag{6}$$

2.1. User discomfort

Reduced user discomfort is the third goal. Appliance startup time instant α_a and closure time instant b_β are assumed to be $(\alpha_a < b_\beta)$ to estimate the waiting time. The device's waiting period is computed as [60]:

$$W = |(\alpha_a - T_r)| \tag{7}$$

where W stands for the waiting period in hours and T_r for the appliance request time. The determined average appliance waiting time is displayed [51]:

$$W_{avg} = \frac{\sum_{y=1}^{Y_n} a_\alpha - T_r}{Y_N} \tag{8}$$

where Y_N is the group of appliances and W_{avg} represents the overall average waiting time for all appliances. The following mathematical

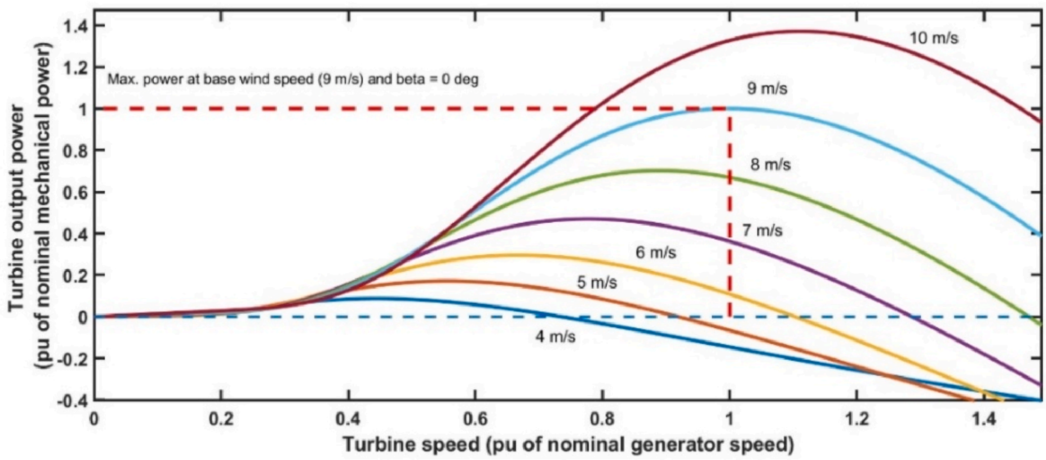

Fig. 2. Turbine power characteristics (Pitch angle beta = 0 deg).

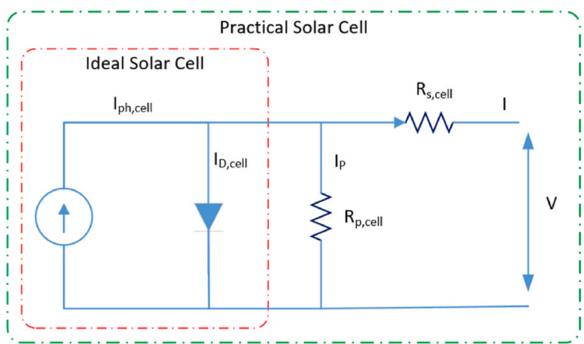

Fig. 3. A solar cell's single-diode mode-based circuit.

illustration can be used to express the third goal:

$$min\ W_{avg} = \frac{\sum_{y=1}^{Y_n} a_\alpha - T_r}{Y_N} \tag{9}$$

2.2. Environmental emissions

Minimizing environmental emissions, including CO_2, NO_x, and SO_2, is the fourth goal. The emissions are considered to address concerns about environmental protection and climate change. These emissions are calculated as follows and quantified in kg/h [60]:

$$F_E = \sum_{i=1}^{ng} \left(a_i + b_i P_{g_i} + c_i P_{g_i}^2 + d_i^{(e_i P_{g_i})} \right) \tag{10}$$

where P_{g_i} is the grid's power in kW and F_E is the amount of environmental emissions in kilograms per hour. The emission coefficients are a_i , b_i , c_i , d_i and e_i:

$$min\ F_E = \sum_{i=1}^{ng} \left(a_i + b_i P_{g_i} + c_i P_{g_i}^2 + d_i^{(e_i P_{g_i})} \right) \tag{11}$$

The limitations listed below apply to the aforementioned aims. The first restriction relates to the capacities of the grid. The entire amount of energy used by the appliances during the course of time interval $t \in T$ should be less than Cg. As a result, the total energy usage is constrained, as indicated:

$$0 \le c_{TL} \le C_g \tag{12}$$

where, c_{TL} denotes the total energy consumed via all sorts of devices in kWh, and C_g represents the grid's maximum power supply capacity.

3. Proposed system model

The MG optimization problem is difficult because neither the generator nor the user load can know the other MG components completely. Despite relying on limited data, MAS is nevertheless capable of accurately achieving the optimization goals for each topic [58–61]. To efficiently combine the MG optimization model with the DR mechanism, this study develops a MAS comprising a DMS, a Microgrid Central

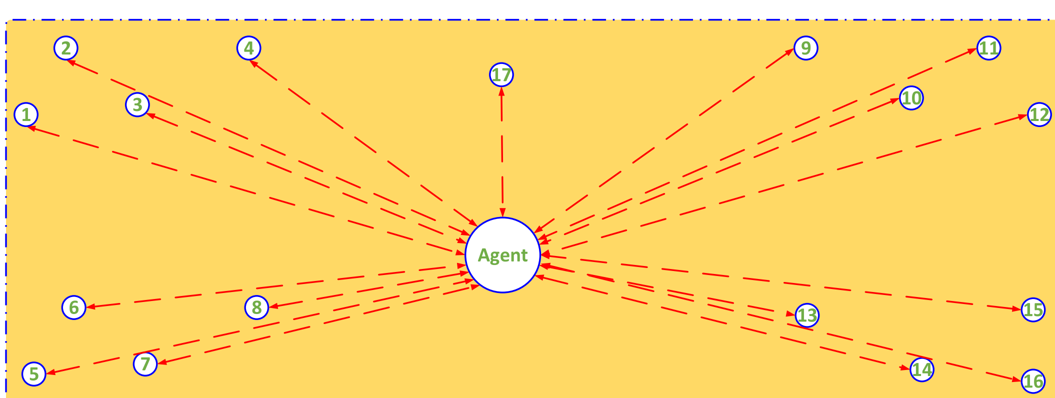

Fig. 4. Exchange information among agents of proposed system.

Controller (MGCC), and an MGCC-controlled agent. In this study, the residential sector is examined, and a microgrid that is connected to the external grid has an installed smart meter that employs the Appliances Scheduler and Energy Management Controller (ASEMC), a proposed hybrid of the GWO and BOA algorithms. The ASEMC gathers all available data, including appliance preferences and power ratings. Fig. 1 depicts the basic system model architecture for scheduling smart buildings appliances and energy management while considering the utility DR program (see Fig. 2).

3.1. Modeling of wind turbine

The radius and local wind speed of a wind turbine has a significant impact on its output power. The remaining variables, like the air density, can be used as constants by being set to a value determined by the control algorithm and the maximum power point method (MPPT) [62, 63]:

$$P_m = \frac{1}{2}\rho A_t C_p(\lambda.\ \beta) V_w^3 \tag{13}$$

A performance factor (C_p) can be defined as;

$$C_p(\lambda.\beta) = 0.5176\left(\frac{116}{\lambda_i} - 0.4\beta - 5\right)e^{-\left(\frac{21}{\lambda_i}\right)} + 0.0068\lambda \tag{14}$$

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1} \tag{15}$$

3.2. Photovoltaic modeling

The greatest power PV panels can produce depends on weather and the maximum installed power. A PV system's output power is influenced by factors such as irradiance, generation efficiency, panel area, and location-specific best orientation. The efficiency of the chosen PV technology is $\eta_{PV} = 15\%$. Here is a breakdown of how much power solar panels produce in a day [64,65]:

$$I = I_{ph;cell} - I_{0;cell}\left[\exp\left(\frac{q(V + IR_{s;cell})}{akT}\right) - 1\right] - \frac{V + IR_{s;cell}}{R_{p;cell}} \tag{16}$$

where, I_{PH}, the cell is photocurrent (A); Id, the cell is current (A) calculated using the PV cell's Shockley diode equation; I_o, the cell is reverse leakage or the PV cell diode's saturation current; T is the temperature of the diode, measured in Kelvin (K), q is the electron charge ($(1.602 \times 10^{-19}\ C)$, k is Boltzmann's constant, and R_s and R_p are the series and parallel resistances of the PV cell, respectively.

3.3. Energy storage system

In this study, BESS is employed to cover the hours of greatest demand shaving and lessen the swings that RESs bring. Li-ion batteries are employed because of their high energy density. The utility pricing signal determines whether to charge or discharge the BESS. The BESS will discharge during the ToU if the energy price exceeds 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, anytime the storage level is lower than the upper charge level, BESS is employed to store the excess generated electricity from the PV and wind systems. As a result, the stored energy in the BESS can be expressed as follows [66]:

$$E_s(t) = E_s(t-1) + T_s\eta_C P_{ch}(t) - \frac{T_s P_{dch}(t)}{\eta_D} \tag{17}$$

where Ts is the time slot duration (hour), $E_s(t)$ is the energy stored in BESS (kWh) at time t, P_{ch}, $P_{dch}(t)$ are the BESS charging and discharging power at time t (kW), and η_C, η_D are the charging and discharging efficiency of the BESS (%).

The amount of stored energy is constrained to the maximum charging border to prevent the battery from being overcharged. To avoid deep discharge, it should not be less than the minimum discharging energy. Therefore, the following restrictions are taken into account.

$$\begin{aligned} &0 \le P_{ch}(t) \le P_{ch}^{max} \\ &0 \le P_{dch}(t) \le P_{dch}^{max} \\ &E_s^{min} \le E_s(t) \le E_s^{max} \end{aligned} \tag{18}$$

where E_s^{min} and E_s^{max} are the minimum and maximum stored energy in the BESS (kWh), and P_{ch}^{max} , P_{dch}^{max} are a maximum BESS charging and discharging power (kW).

3.4. Coordinated EMS with neighborhood power-sharing

This energy management plan incorporates the idea of neighborhood power sharing. To reduce total energy costs and maximize RER energy usage within the neighborhood, the aggregator agent in this model also distributes the aggregated neighborhood power profile to all residential agents. Based on the overall cost minimization goal, the controller chooses the neighborhood power exchange activities and how best to schedule all household appliances. Aggregators and all home agents work together to implement output-optimal processes. The following calculation provides the neighborhood area's total energy cost [67]:

$$\begin{aligned} min\ \mathscr{C}_{\text{total}} = \sum_{n=1}^{N}\sum_{t=1}^{T} P_{fnet}(n,t) * (\gamma_c^t) - P_{sf}(n,t) * \gamma_{FTT} + P_{\text{purchased}}(n,t)((\gamma_c^t) - \gamma_I) - \\ P_{sc}(n,t) * (\gamma_{FrT} + \gamma_I - \gamma_c^t) - P_{\text{sold}}(n,t)((\gamma_{FrT}) + (\gamma_I)) * \tau \end{aligned} \tag{19}$$

where, $P_{fnet}(n,t)$ and $P_{sf}(n,t)$ are the final net power and final surplus power of nth smart building after the neighborhood power exchange process, respectively. $P_{\text{purchased}}(n,t)$ and $P_{\text{sold}}(n,t)$ are the amount of purchased and sold power by n^{th} smart building from the neighborhood area at time instant t.

Aggregator agents gather information on each smart building's net power requirement and the availability of additional RER electricity. The following information is then assessed and distributed to all building agents in preparation for the neighborhood power exchange process [67]. The aggregated neighborhood surplus power ($P_{\text{asurp}}(t)$) and the aggregated neighborhood net power requirement ($P_{\text{anet}}(t)$) details are calculated by:

$$P_{\text{anet}}(t) = \sum_{n=1}^{N} P_{\text{net}}(n,t) \tag{20}$$

$$P_{\text{asurp}}(t) = \sum_{n=1}^{N} P_s(n,t) \tag{21}$$

The values of the n^{th} smart building's purchased/sold power in the neighborhood are calculated using:

$$P_{\text{purchase}}(n,t) = \begin{pmatrix} \left(P_{\text{asurp}}(t) * \left(\frac{P_{\text{net}}(n,t)}{P_{\text{anet}}(t)}\right)\right) & P_{\text{net}}(n,t) > 0; P_{\text{anet}}(t) > P_{\text{asurp}}(t) \\ P_{\text{net}}(n,t) & P_{\text{net}}(n,t) > 0; P_{\text{anet}}(t) < P_{\text{asurp}}(t) \\ 0 & \text{otherwise} \end{pmatrix} \tag{22}$$

$$P_{\text{sold}}(n,t) = \begin{pmatrix} P_s(n,t) & P_s(n,t) > 0; P_{\text{anet}}(t) > P_{\text{asupp}}(t) \\ \left(P_{\text{anet}}(t) * \left(\frac{P_s(n,t)}{P_{\text{asum}}(t)}\right)\right) & P_s(n,t) > 0; P_{\text{anet}}(t) < P_{\text{asump}}(t) \\ 0 & \text{otherwise} \end{pmatrix} \tag{23}$$

The n^{th} smart home's final net power and excess power values are calculated using [67]:

$$P_{\text{fnet}}(n,t) = P_c(n,t) + P_b(n,t) - P_{pv}(n,t) - P_{wt}(t) - P_{\text{purchased}}(n,t) + P_{\text{sold}}(n,t) \tag{24}$$

$$P_{\text{fnet}}(n,t) = \begin{pmatrix} P_{\text{fnet}}(n,t) & P_{\text{fnet}}(n,t) > 0 \\ 0 & P_{\text{fnet}}(n,t) \le 0 \end{pmatrix} \tag{25}$$

$$P_{sf}(n,t) = \begin{pmatrix} 0 & P_{\text{fnet}}(n,t) > 0 \\ P_{\text{fnet}}(n,t)(-1) & P_{\text{fnet}}(n,t) \le 0 \end{pmatrix} \tag{26}$$

3.5. Communication of multi-agent system (MAS)

In order to create an effectively distributed consensus controller for MG energy management, the MG system is viewed as a multi-agent system with information capability transmission between the local device and the neighbors. The distributed consensus controller may consult neighbors to find the optimal solution for the local element while being connected to MG elements like inverters, loads, and DGs. The information flow diagram between these agents can be represented as an undirected graph with nodes and edges. In a consensus algorithm, each agent can be referred to as a node, and the evidence of communication links between agents i and j can be shown as an edge (i, j) with a weighted factor of w_{ij}. Schematic of an information flow $\mathscr{G} = \{\mathscr{N}, \mathscr{E}, \mathscr{A}\}$ can be used to represent a graph, where $\mathscr{N} = \{1, \ldots, \mathscr{K}\}$ denotes the number of agents, E denotes the communication links between two neighboring nodes $\mathscr{A} \in \mathscr{R}^{\mathscr{K} \times \mathscr{K}}$, and $\mathscr{E}(i, j)$, is a weighted matrix. The w_{ij} weighted factors as;

$$w_{ij} = \begin{cases} 1/\left(max\left[l_{ii}, l_{jj}\right] + 1\right) & j \in \mathscr{K}_i \\ 1 - \sum_{j \in \mathscr{K}_i} 1/\left(max\left[l_{ii}, l_{jj}\right] + 1\right) & j = i \\ 0 & otherwise \end{cases} \tag{27}$$

where i and j are the number of units, $\mathscr{K}_i$ is the agent set associated with unit i, and l_{ii} and l_{jj} are the components of the laplacian matrix. The components of the Laplacian matrix are as follows [68,69];

$$\begin{cases} l_{ii} = \sum_{i \ne j} a_{ij} & on - diagonal\ elements \\ l_{ij} = -a_{ij} & off - diagonal\ elements \end{cases} \tag{28}$$

4. Butterfly optimization algorithm

Arora and Singh presented the Butterfly Optimization Algorithm (BOA) in 2019 as a metaheuristic algorithm motivated by butterflies' cooperative foraging behaviors [70]. The ability to smell allows butterflies to locate food and mates even when they are far away. A population is used, which is butterflies. Depending on the strength of the stimulus intensity at the instance/step *t*, the sensory modality (c), and the power exponent (a), each butterfly emits fragrance *f*(*t*). It has to do with butterfly fitness. A butterfly's increased degree of (*t*) release will be noticed and pique the interest of butterflies nearby. The important parameter (*t*) determines how many steps the butterfly will take when updating its location, as seen in the illustration below.

$$f(t) = c \cdot I(t)^a \tag{29}$$

4.1. Butterflies movement

The features of butterflies are idealized as follows to illustrate the aforementioned topics in terms of a search algorithm [71].

1. All butterflies should release some kind of scent that attracts other butterflies.
2. Each butterfly will migrate randomly or toward the butterfly that emits the most smell.
3. The objective function's landscape influences or determines a butterfly's stimulus intensity.

The BOA process is divided into three phases: initialization, iteration, and final. Each time BOA is run, the initialization phase comes first, followed by iterative searching, and in the final phase, the method is stopped when the best solution has been identified. The algorithm at the initialization stage defines the goal function and its solution space. Additionally, the values for the BOA parameters are assigned. After configuring the variables, the algorithm creates a starting population of butterflies for optimization. The total number of butterflies does not vary over the course of the BOA simulation; hence a fixed-size memory is assigned to store the data for the butterflies. Butterfly locations are generated randomly in the search region, and fitness and fragrance values are computed and recorded. The algorithm has now completed the startup phase and is in the iteration phase when the search is conducted utilizing the created artificial butterflies.

The second phase, often known as the iteration phase, is where the procedure goes through a number of iterations. Each iteration results in a new location for each butterfly in the solution space, and their fitness values are then determined. The first step in the process is to locate various points in the solution space where each butterfly's fitness values can be found. Equation (21) can then predict where these butterflies will create a scent. The method's two key phases are the global and local search phases. During the global search period, represented by Equation (22), the butterfly moves toward the fittest butterfly/solution [71].

$$x_i^{t+1} = x_i^t + \left(r^2 \times g^* - x_i^t\right) \times f_i \tag{30}$$

where x_i^t is the solution vector for the *ith* butterfly in iteration number *t*, denoted by the symbol x_i. Here, $g*$ stands for the current top solution discovered in the most recent iteration of the problem. f_i represents the scent of the ith butterfly, while *r* is a random value between [0, 1].

The local search phase can be represented as

$$x_i^{t+1} = x_i^{\,t} + \left(r^2 \times x_j^{\,t} - x_k^{\,t}\right) \times f_i \tag{31}$$

where $x_j^{\,t}$ and $x_k^{\,t}$ are *jth* and *kth* butterflies from solution space. If $x_j^{\,t}$ and $x_k^{\,t}$ belongs to the same swarm, and *r* is a random number in [0, 1].

Both locally and globally, butterflies might search for food and a partner. A butterfly's efforts to find a mate or food source may make up a significant portion of its total activity when considering physical closeness and other factors like rain, wind, etc. BOA employs a switch probability of p to move from a common global search to an intense local search.

Up until the halting requirements are not met, the iteration process is continued. The maximum CPU time used, the total number of iterations finished, the total number of iterations without improvement, the achievement of a particular error rate, or any other appropriate condition can all be used to determine the halting criteria. After the iteration phase, the approach produces the best solution with the highest fitness. The butterfly optimization method is made up of the three steps indicated above, and “”Algorithm 1 explains its pseudo code [71,72].

Algorithm 1
Butterfly optimization algorithm

```
Objective function f(x), x = (x_1, x_2, ..., x_dim), dim = no. of dimensions
Generate initial population of n Butterflies x_i = (
Stimulus Intensity I_i at x_i is determined by f(x_i)
Define sensor modality c, power exponent a and switch probability p
    while stopping criteria not met do
        for each butterfly bf in population do
        end for
        Find the best bf
        for each butterfly bf in population do
        Generate a random number r from [0, 1]
            if r < p then
            move towards best butterfly solution
            else
            move randomly
            end if
        end for
        Update the value of a
    End while
Output the best solution found
```

4.2. Constraint of peak load

Ensures the microgrid load h_j is within a limit specified by local distribution companies (LDCs), $\widehat{P}^{max}_{h_j,t}$.

$$\sum_{i\in\Omega} P_{i,h_j} S_{i,h_j,t} + \sum_{z\in LI} P_{LI_{z,h_j}} L_{z,h_j,t} + \sum_{i\in\{B,ESD\}} P^{LDC}_{i,h_j,t} - \sum_{i\in\{R,ESD\}} P^{H}_{D_{i,h_j,t}} - P^{H}_{PV,h_j,t} \leq \widehat{P}^{max}_{h_j,t}, \forall h_j \in \mathscr{H} \tag{32}$$

In (4), the domestic load is made up of the power used via appliances, the power used to charge the PV panel battery and the energy storage devices (ESD), net of the power used to power some of the household loads with electricity produced by the PV panel.

$$\widehat{P}^{max}_{h_j,t} = P^{max}_{h_j,t} - \alpha_{h_j,t} P^{FLEX}_{j,t}, \forall t \in \mathscr{T}; \forall h_j \in \mathscr{H}; \forall j \in \mathscr{N} \tag{33}$$

The customer’s flexibility index represents a part of the needed flexibility by bus based on the previous maximum permissible demand: $j : \alpha_{h_j,t}$, $\widehat{P}^{max}_{h_j,t}$, to determine the current maximum demand for the house, $P^{max}_{h_j,t}$. Constraint (25) illustrates the two-way communication between the local distribution companies (LDCs) and the HEMS.

4.3. Balance power

As stated below, the household appliances’ combined power needs are satisfied. By balancing the energy produced by the PV system, the energy drawn from the grid, the energy discharged to the house from the ESD and PV panel batteries, and the overall energy demand of the home’s appliances, this is accomplished [73]:

$$\sum_{i\in\mathscr{R}} P_{i,h_j} S_{i,h_j,t} = P^{H}_{LDC,h_j,t} + \sum_{q} P^{H}_{D_{q,h_j,t}} + P^{H}_{PV,h_j,t}, \forall t \in \mathscr{T}; \forall h_j \in \mathscr{H} \tag{34}$$

It is unrealistic to suppose that the ESD charge level was known at each time period. The time frame for charging and draining is shown below:

$$E_{ESD,h_j,t} = E_{ESD,h_j,t-1} + \tau\left[P^{L}_{C^{LDC}_{ESD,h_j,t}}\eta_1 - \left(P^{L}_{D^{LDC}_{ESD,h_j,t}} \frac{+P^{H}_{D_{ESD,h_y,t}}\Big)}{\eta_2}\right], \forall t \in \left\{t^{AR}_{h_j}, t^{DEP}_{h_y}\right\}; \forall h_j \in \mathscr{H} \tag{35}$$

$$E^{min}_{ESD,h_j} \leq E_{ESD,h_j,t} \leq E^{max}_{ESD,h_j}, \&\forall t \in \left\{t^{AR}_{h_j}, t^{DEP}_{h_j}\right\}; \forall h_j \in \mathscr{H} \tag{36}$$

$$P^{LDC}_{C_{EW,h_j,t}} \leq S_{C_{EW,h_j,t}} P^{max}_{C_{ESD,h_j}}, \&\forall t \in \left\{t^{AR}_{h_j}, t^{DEP}_{h_j}\right\}; \forall h_j \in \mathscr{H} \tag{37}$$

$$P^{LDC}_{D_{ESD,h_j,t}} + P^{H}_{D_{ESD,h_j,t}} \leq S_{D_{ESD,h_y,t}} P^{max}_{D_{kD,h_j}}, \forall t \in \left\{t^{AR}_{h_j}, t^{DEP}_{h_j}\right\}; \forall h_j \in \mathscr{H} \tag{38}$$

$$S_{C_{EED,h_j,t}} + S_{D_{EED,h_j,t}} \leq 1, \forall t \in \left\{t^{AR}_{h_j}, t^{DEP}_{h_y}\right\}; \forall h_j \in \mathscr{H} \tag{39}$$

$$E_{ESD,h_j,t} \geq \omega_{h_j} E^{max}_{ESD}, \forall t = t^{DEP}_{h_j}; \forall h_j \in \mathscr{H} \tag{40}$$

$$E_{ESD,h_j,t} = E^{AR}_{ESD}, \forall t = t^{AR}_{h_j}; \forall h_j \in \mathscr{H} \tag{41}$$

4.4. Objective function

Minimizing operational costs during the schedule period is the goal of energy management for microgrids. The objective function is defined as follows [74]:

$$min \sum_{t\in N_T} c^{G}_{1}\left(p^{\mathrm{DG}}_{t}\right)^2 + c^{G}_{2} p^{\mathrm{DG}}_{t} + \lambda_t p^{\mathrm{UG}}_{t} + b\left(p^{\mathrm{UG}}_{t}\right)^2 \tag{42}$$

The three-goal functions’ expenses are as follows: The objective is to reduce the price of buying energy from the external grid in the final term, where λ_t is the energy sport price, b is the price sensitivity coefficient, and p^{DG}_t is the purchased power. c^G_1 and c^G_2 are generation cost parameters, while p^{UG}_t is the DG generation in the first two terms, which aims to lower the energy costs of DGs.

4.5. DG operation constraints

The DG capacity constraint is represented by constraint (43) and consists of maximum and minimum limitations of the DG active power generation, $p^{\mathrm{DG},max}_t$ and $p^{\mathrm{DG},min}_t$, respectively. The DG ramping constraint (44) specifies the up-ramping and down-ramping limitations as $p^{\mathrm{DG,ur}}_t$ and $p^{\mathrm{DG,dr}}_t$ respectively.

$$p^{\mathrm{DG},min}_t \leq p^{\mathrm{DG}}_t \leq p^{\mathrm{DG},max}_t, \forall t \in N_T \tag{43}$$

$$\begin{cases} p^{\mathrm{DG,dr}}_t \leq p^{\mathrm{DG}}_t - p^{\mathrm{DG}}_{t-1} \leq p^{\mathrm{DG,ur}}_t \\ p^{\mathrm{DG,dr}}_{t_1} \leq p^{\mathrm{DG}}_{t_1} - p^{\mathrm{DG}}_0 \leq p^{\mathrm{DG,ur}}_{t_1}, \end{cases} \forall t \in N_T \tag{44}$$

5. Grey Wolf Algorithm

The leadership chain inspired the grey wolves’ new hunting method, GWO [75], a meta-Heuristic algorithm. The technique included four different wolf species and was motivated by the hierarchy of grey wolves: these four leadership levels, namely alpha, beta, delta, and gamma. The hierarchical level is beta and delta, and gamma is the group’s weakest member. Gamma cannot, therefore, be taken into account for leadership. In HEM, alpha is considered the most fitting member to achieve the objective cost minimization function. The initial population is randomly generated. Additionally, there are three key phases of hunting: discovering the target, attacking it, and enclosing it. According to the hierarchy of wolves still, in existence, the alpha is the most fit to practice, followed by the beta, delta, and omega.

The proposed energy management approach consists of input, processing, and output. To create the best scheduling strategy for the

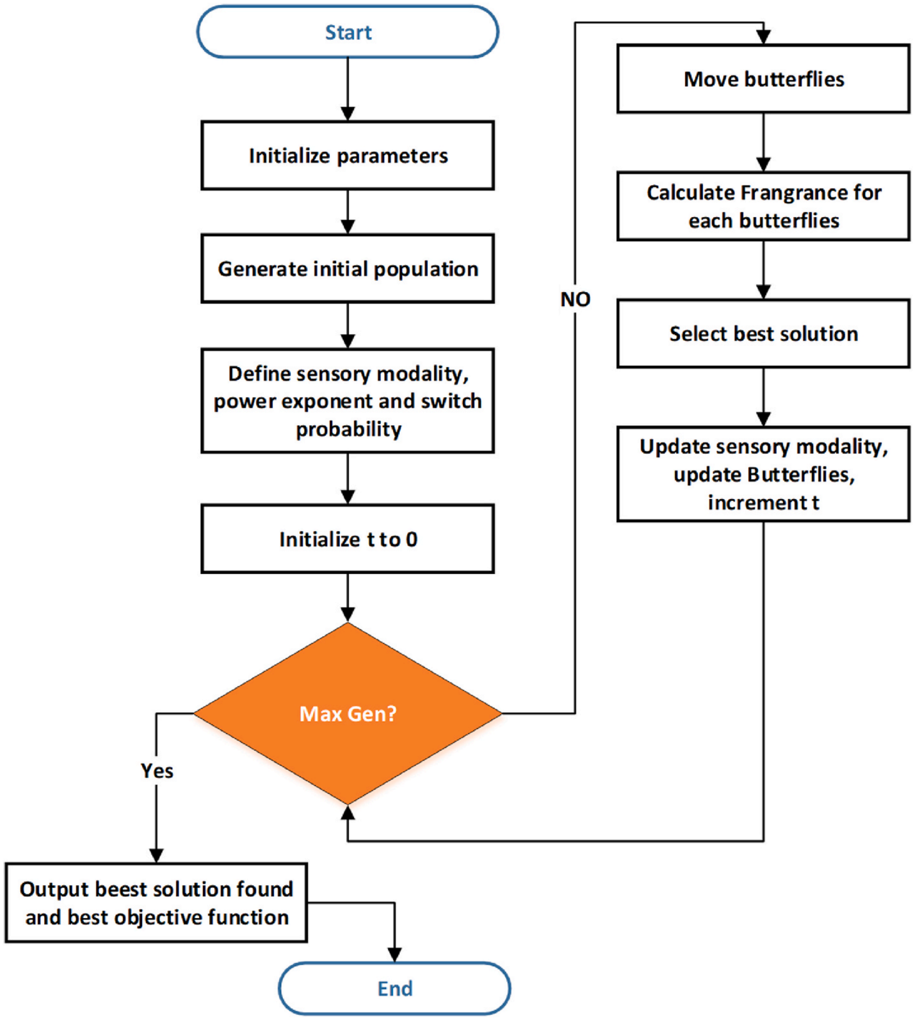

Fig. 5. Flowchart of BOA

devices that produce the maximum degree of pleasure, or the output, the home energy management systems of the demand-side management approach handle the input variables to compute the total satisfied desired day satisfaction values. These systems then deliver all the computed input parameters to the grey wolf satisfaction algorithm. Further discussion of the approach's computation method.

The GWO accretive satisfaction algorithm's objective is to generate the ideal timetable for home appliances while determining the complete degree of satisfaction [76,77].

$$\mathrm{Obj}(\mu_s, C_\beta) = max(\mu_s) \tag{45}$$

Given that $C_{s\_\mathrm{index}}(\$)$ is dependent on both customer satisfaction and overall consumer spending, the cost function of the Grey Wolf accretive satisfaction algorithm is also known as:

$$\mathrm{Obj}(C_{s\_\mathrm{index}}(\$)) = min(C_{s\_\mathrm{index}}(\$)) \tag{46}$$

5.1. Constraints

The Grey Wolf accretive pleasure algorithm's energy usage is constrained in two ways. Total user electricity expenses (TU_{exp}), which are the budget restriction of the Grey Wolf accretive satisfaction algorithm, must be less than the consumer's already established budget limit C, or as follows:

$$TU_{\mathrm{exp}} \leq C_\beta \tag{47}$$

$$TU_{\mathrm{exp}} = TEC \times UT \tag{48}$$

$$TEC = \sum_{n=A}^{Z} (TOT_n \times TPR_n) \tag{49}$$

where TOT_n is a total operational time, TPR_n is a total power rating.

Given that the consumer can eat throughout the day, the energy constraint that shouldn't be exceeded is the maximum amount that is readily available. Thus, energy may be restricted:

$$TEC \leq TAE \tag{50}$$

$$TEA = \frac{C_\beta(\$)}{UT(\$/kWh)} \tag{51}$$

where total energy TEA is available to consumers as much as possible as their energy budget can be determined,

$$X^d(t+1) = \begin{cases} 1, S\left(X_1^d + X_2^d + \dfrac{X_3^d}{3}\right) \geqslant r_8 \\ 0, & \text{otherwise} \end{cases} \tag{52}$$

$$\begin{aligned} X_1 &= |X_\alpha - 2a \cdot r_1 - a \cdot \overline{D}_\alpha| \\ X_2 &= |X_\beta - 2a \cdot r_1 - a \cdot \overline{D}_\beta| \\ X_3 &= |X_\delta - 2a \cdot r_1 - a \cdot \overline{D}_\delta| \end{aligned} \tag{53}$$

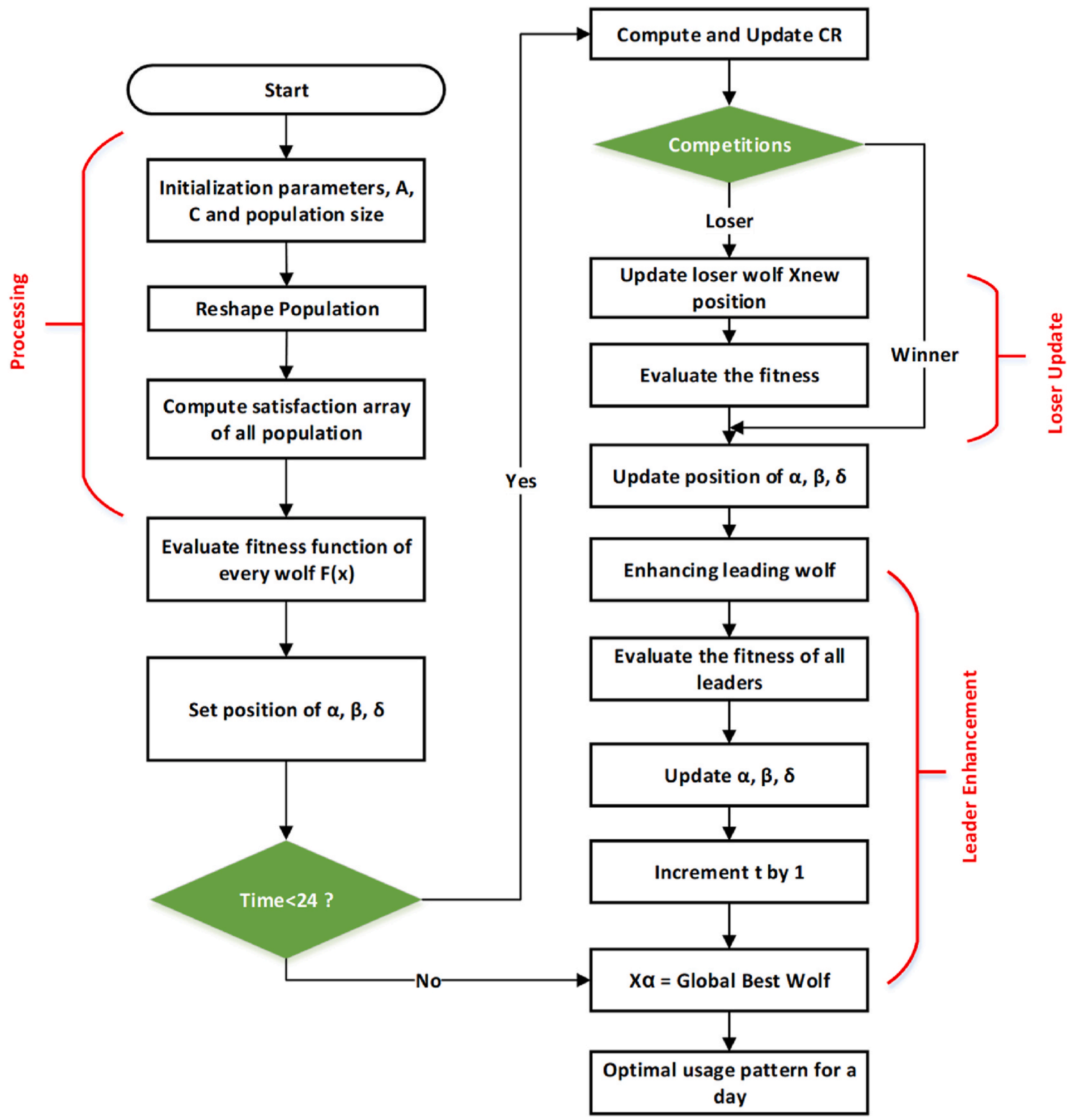

Fig. 6. Grey wolf algorithm.

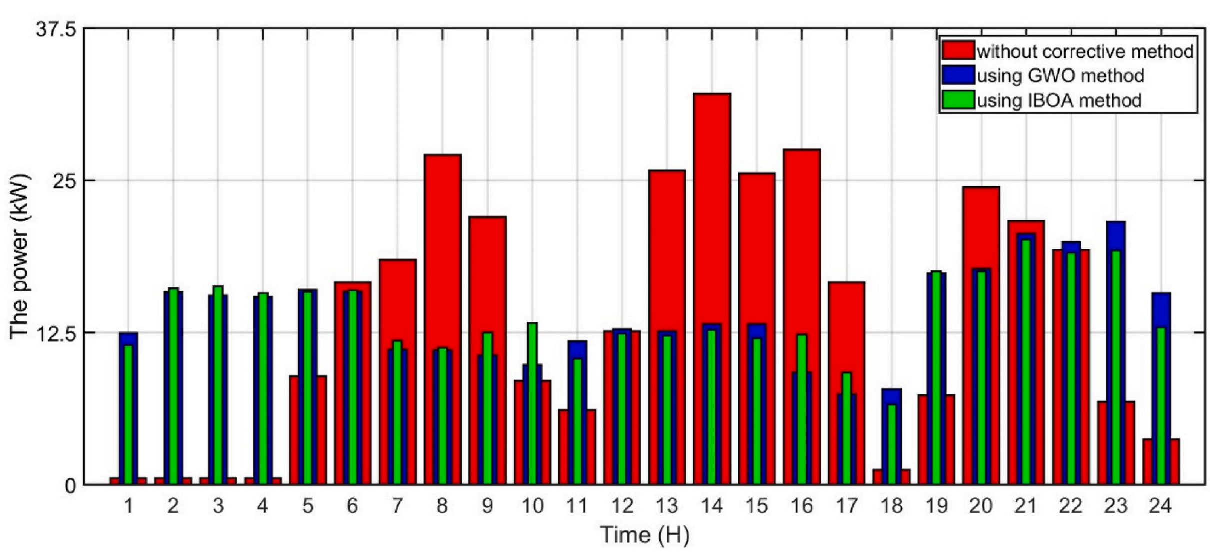

Fig. 7. Hourly energy consumption using ToU tariffs in the case without corrective method, using GWO, and using IBOA.

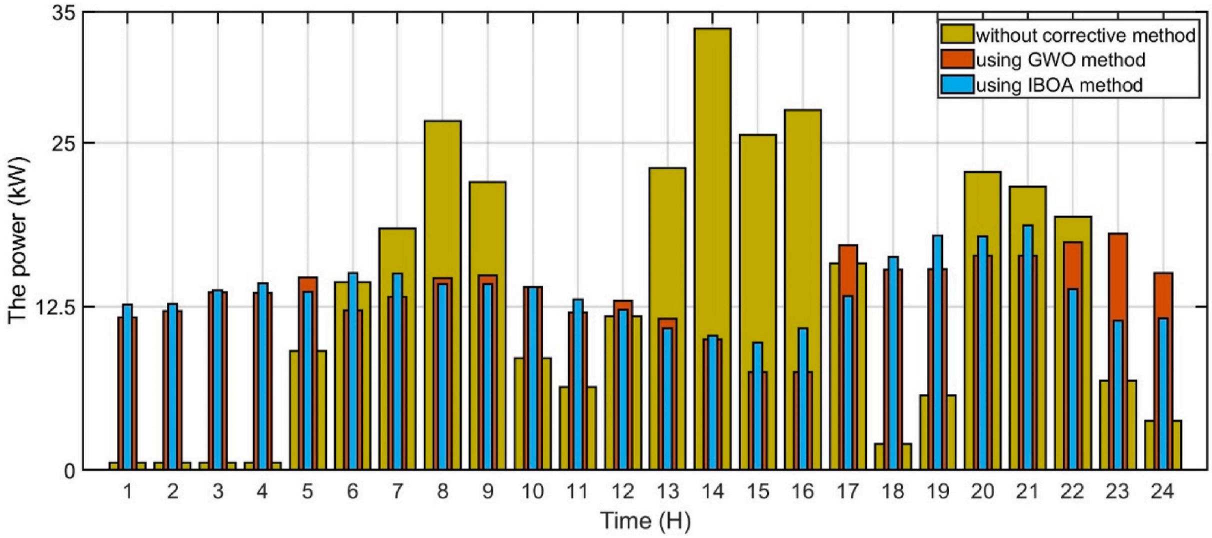

Fig. 8. Hourly energy consumption using CPP tariffs in the case without corrective method, using GWO, and using IBOA.

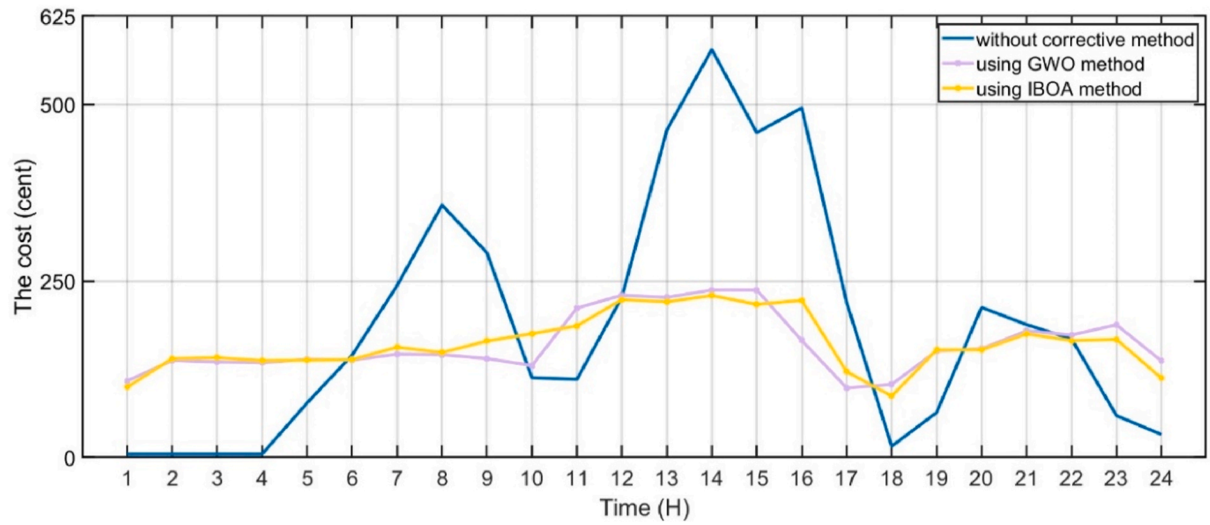

Fig. 9. Cost ToU without corrective method, using GWO, and using IBOA.

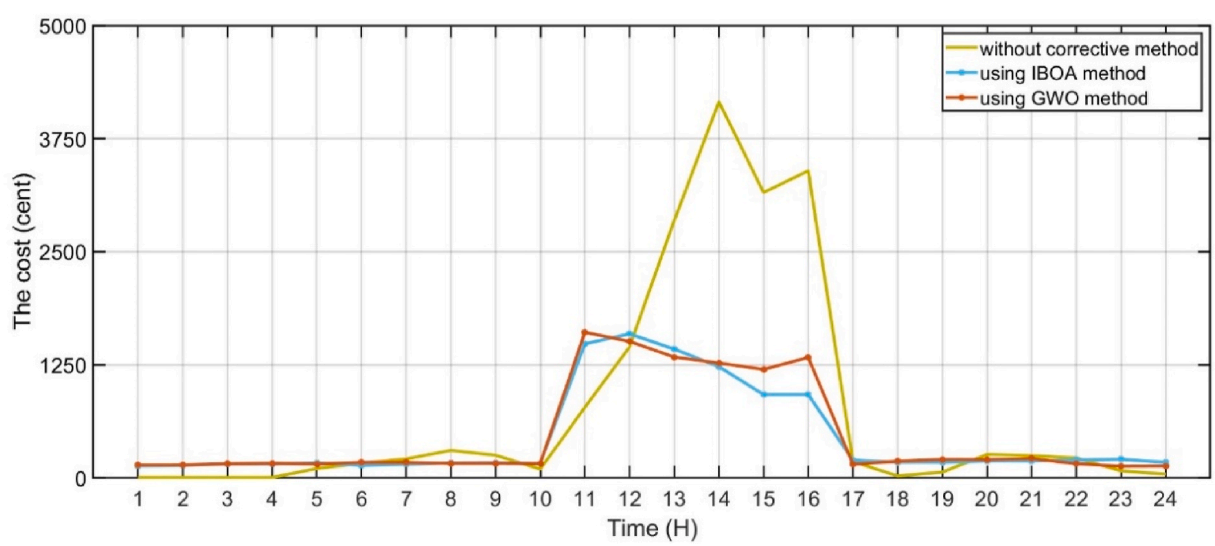

Fig. 10. Cost CPP without corrective method, using GWO, and using IBOA.

Table 1
Hourly energy consumption without corrective method, using GWO, and using IBOA.

Hours	ToU Pricing			CPP Pricing		
	Without correction	With GWO	With IBOA	Without correction	With GWO	With IBOA
1	0.5625	12.4755	11.475	0.5625	11.6365	12.616
2	0.5625	15.7895	16.11	0.5625	12.129	12.6965
3	0.5625	15.5615	16.2465	0.5625	13.5575	13.693
4	0.5625	15.427	15.7725	0.5625	13.534	14.25
5	8.885	15.995	15.8405	9.1025	14.7155	13.5925
6	16.6575	15.86	15.9435	14.34	12.193	15.025
7	18.4375	11.0855	11.9325	18.4375	13.225	14.9775
8	27.0875	11.0335	11.2645	26.6375	14.649	14.187
9	21.9625	10.615	12.499	21.9625	14.8525	14.2205
10	8.5625	9.863	13.288	8.5625	13.977	13.9425
11	6.15	11.758	10.357	6.325	12.013	13.0405
12	12.61	12.7625	12.425	11.735	12.8995	12.2255
13	25.765	12.6	12.25	23.065	11.5375	10.8265
14	32.1025	13.175	12.7425	33.6775	9.9625	10.2855
15	25.5625	13.175	12.047	25.5625	7.4625	9.7235
16	27.5	9.2125	12.3625	27.5	7.4625	10.7875
17	16.6275	7.4625	9.2125	15.7525	17.1725	13.2685
18	1.21	7.8395	6.5895	1.9975	15.3085	16.26
19	7.3275	17.3475	17.531	5.6625	15.3305	17.8925
20	24.4375	17.706	17.5325	22.7725	16.3705	17.8525
21	21.625	20.6185	20.1245	21.625	16.3845	17.6765
22	19.3125	19.946	19.0445	19.3125	17.3795	13.8045
23	6.8125	21.6005	19.2275	6.8125	18.0425	11.3925
24	3.75	15.726	12.917	3.75	15.0475	11.6055

where r_1 belongs to the vector of [0, 1]. X_1^d, X_2^d, X_3^d are updated position at iteration t as defined in Equation (53) (see Fig. 5). The value of $\overline{D}_\alpha$, $\overline{D}_\beta$, $\overline{D}_\delta$ can be obtained from Ref. [77]. Fig. 6 shows the GWO algorithm flowchart:

$$\begin{aligned} A &= 2a \times r_1 - a \\ C &= 2r_2 \\ a &= 2 - 2(t/T) \end{aligned} \tag{54}$$

$$L^a = \begin{cases} \text{rand}(0,1) & \text{if} \quad \text{CR} \le r_9 \\ X_L^d, & \text{otherwise} \end{cases} \tag{55}$$

$$CR = 0.9 - 0.9\left(\frac{t}{T}\right) \tag{56}$$

6. Simulations results

The suggested energy management system simulation results are provided in this section. This work's primary objectives are to lower the price of electricity usage, lower the Peak-to-Average Ratio (PAR), and raise user comfort (UC) by cutting down on waiting times. For 24 h, the ideal scheduling strategy is discovered. A comparison between the three case studies is implemented. The three case studies are without the corrective method, the GWO method, and the IBOA method. Two pricing tariffs are used, CPP and ToU, to evaluate the electricity bill cost.

Fig. 7 shows the system load profile for the 24-h period in the three case studies considering the ToU pricing tariff. The load without the corrective method exhibits peaks of 26.4 kWh, 24.3 kWh, 34.2 kWh, and 23.9 kWh in time slots 8, 9, 14, and 16, respectively. However, the lowest load values are achieved in time slots 1, 2, 3, 4, 18, and 24. After applying the proposed energy management scheme and demand response program, the optimal scheduling of the system load is obtained, as shown in Fig. 7. Using the IBOA improves the system load profile more than the GWO algorithm. The proposed algorithms reduce the maximum load in the unplanned pattern's time slots 8,14, and 16 to 11.25 kWh with a reduction of 48.4%. As shown in Figs. 7 and 8, the peak load using IBOA is 18.5 kWh with ToU pricing and 17.3 kWh in the CPP tariff. However, the maximum load using the GWO algorithm is 20.4 kWh for ToU pricing and 22.2 kWh with CPP tariff, as represented in Figs. 7 and 8. The electricity cost for the three case studies is demonstrated in Figs. 9 and 10 for the ToU and CPP tariffs. By using ToU pricing, the maximum electricity bill for the three case studies is 4539.935 cents, 3873.723 cents, and 3850.61 cents in Without correction, With GWO, and With IBOA time slots, respectively, as introduced in Fig. 9. Also, using CPP pricing, the maximum electricity bill for the three case studies is 18046.87 cents, 11217.57 cents, and 10595.8 cents for the three case studies in Without correction, With GWO, and With IBOA time slots respectively as introduced in Fig. 10. Table 1 introduces the hourly energy consumption for the three case studies including without corrective action, with GWO, and with IBOA for ToU and CPP tariffs. The hourly electricity bill without corrective method, using

Table 2
Hourly electricity bill without corrective method, using GWO, and using IBOA.

Hours	ToU Pricing			CPP Pricing		
	Without correction	With GWO	With IBOA	Without correction	With GWO	With IBOA
1	4.89375	108.5368	99.8325	6.4125	143.8225	132.656
2	4.89375	140.157	140.157	6.4125	144.74	138.2705
3	4.89375	135.385	141.3445	6.4125	156.1003	154.5555
4	4.89375	134.215	137.2208	6.4125	162.45	154.2875
5	77.2995	139.1565	137.8123	103.7685	154.9545	167.7568
6	144.9203	137.982	138.7085	163.476	171.285	139.0003
7	243.375	146.3285	156.189	210.1875	170.7435	150.765
8	357.555	145.6423	148.6915	303.6675	161.7318	166.9985
9	289.905	140.118	164.9868	250.3725	162.1138	169.3185
10	113.025	130.1915	175.4015	97.6125	158.9445	159.3378
11	110.7	211.644	186.426	780.505	1609.198	1482.405
12	226.98	229.725	223.65	1448.1	1508.628	1591.798
13	463.77	226.8	220.5	2846.225	1335.99	1423.728
14	577.845	237.15	229.365	4155.8	1269.23	1229.373
15	460.125	237.15	216.846	3154.4	1199.88	920.8725
16	495	165.825	222.525	3393.5	1331.178	920.8725
17	219.483	98.505	121.605	179.5785	151.261	195.7665
18	15.972	103.4815	86.9815	22.7715	185.3698	174.517
19	63.74925	150.9233	152.5198	64.5525	203.9745	174.7678
20	212.6063	154.0423	152.5328	259.6075	203.5185	186.6238
21	188.1375	179.381	175.0833	246.525	212.912	186.7833
22	168.0188	173.5303	165.6873	220.1625	157.3713	198.1263
23	59.26875	187.9243	167.2793	77.6625	129.8745	205.6845
24	32.625	136.8163	112.378	42.75	132.3028	171.5415

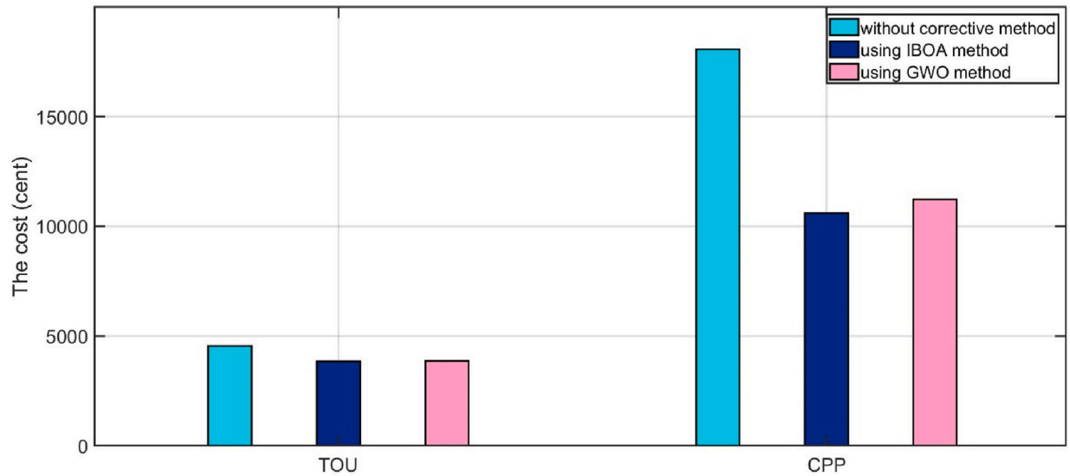

Fig. 11. Total cost per day for both simulation scenarios in case without corrective method, using Grey Wolf Algorithm, and using Improved Butterfly Optimization Algorithm.

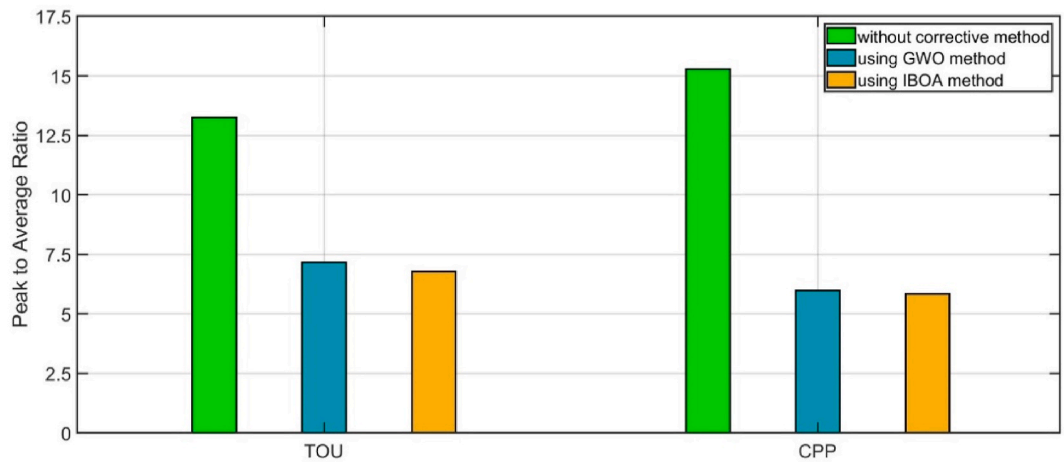

Fig. 12. PAR for both ToU and CPP scenarios in case without corrective method, using GWO, and using IBOA.

Table 3
Comparison between the three cases without corrective method, using GWO, and using IBOA.

	ToU Pricing					CPP Pricing				
	Without correction	With GWO	% Improvement	With IBOA	% Improvement	Without correction	With GWO	% Improvement	With IBOA	% Improvement
Total electricity cost (cents)	4539.935	3873.723	14.67%	3850.61	15.183%	18046.87	11217.57	37.842%	10595.8	41.28%
Peak load (kW)	32.1025	21.6005	32.71%	20.1245	37.31%	33.6775	18.0425	46.42%	17.6765	47.73%
PAR (kW)	13.2525	7.162225	45.95%	6.7922	48.744%	15.2885	5.984825	60.85%	5.83255	62.06%
Waiting time	104 s	34	67.3%	25	75.96%	109	36	66.97%	29	73.39%

GWO, and using IBOA is represented in Table 2 for ToU and CPP tariffs.

Figs. 9 and 10 show that the unplanned pattern forces the customer to pay more for electricity use at different times of the day, notably during peak hours. In each of the simulated scenarios, the best plans make an effort to place the loads outside of peak times so that the consumer pays less during those times. The price of electricity consumed in time slot 14 of the unscheduled pattern in the first and second scenarios, using the ToU and CPP signal as the electricity tariff, is 577.845

Table 4
Comparison between the two optimization algorithms according to the run time and the number of iterations to get the optimal solution.

	Run time				Iteration number			
	ToU	% Improvement	CPP	% Improvement	ToU	% Improvement	CPP	% Improvement
GWO	87 s	13%	98 s	2%	400	60%	450	55%
IBOA	53 s	47%	74 s	26%	190	81%	200	80%

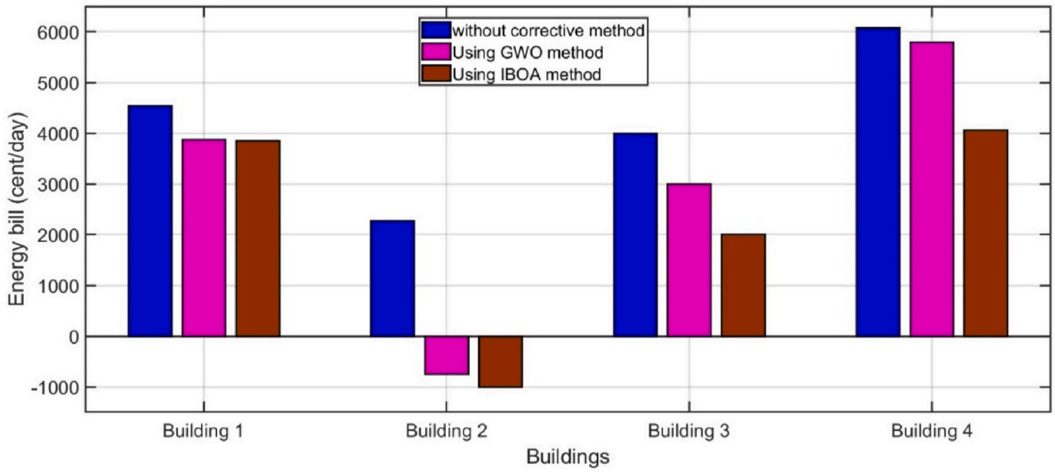

Fig. 13. Comparison of smart buildings' energy bills in the case without corrective method, using Grey Wolf Algorithm, and using Improved Butterfly Optimization Algorithm using ToU tariffs.

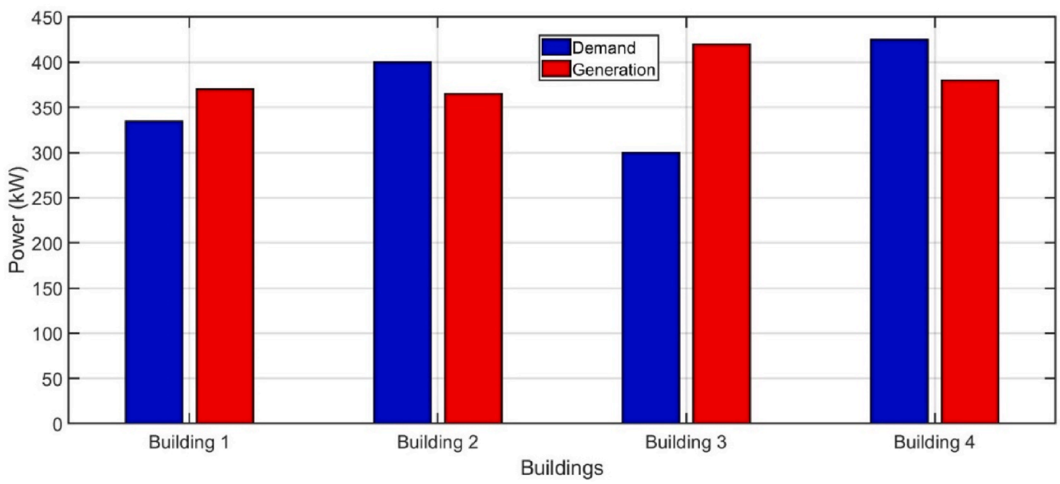

Fig. 14. Generation-demand power mismatch using ToU tariffs.

cents and 4155.8 cents, respectively. For instance, the IBOA plan successfully lowered the overall cost of power consumed during this time, which is the peak hour, by more than 60.3% in the first scenario (ToU). The GWO algorithm can cut the overall cost of electricity used during these two times by 58.95% in the identical situation. The IBOA program successfully reduced the overall cost of power consumed during this

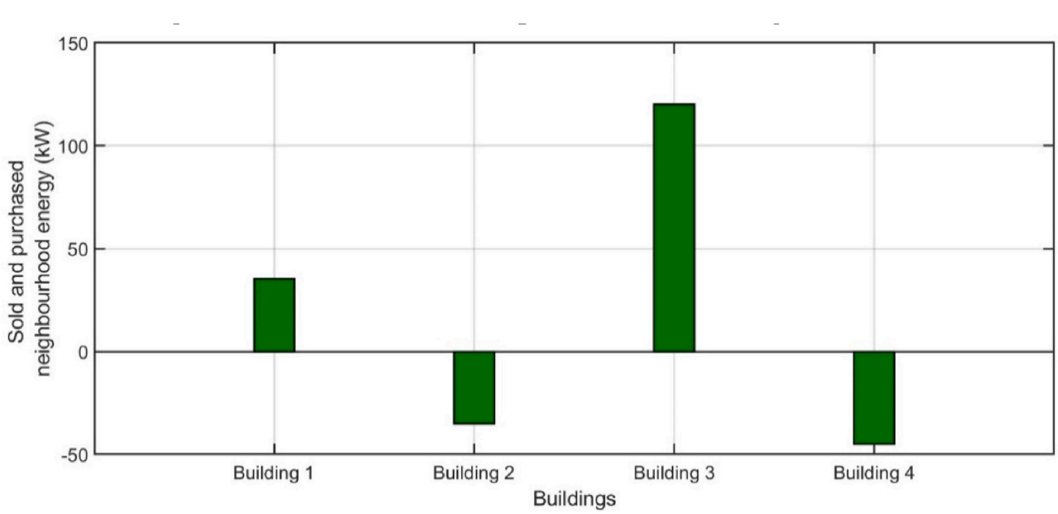

Fig. 15. Smart buildings neighborhood aggregated energy transaction in a day using ToU tariffs.

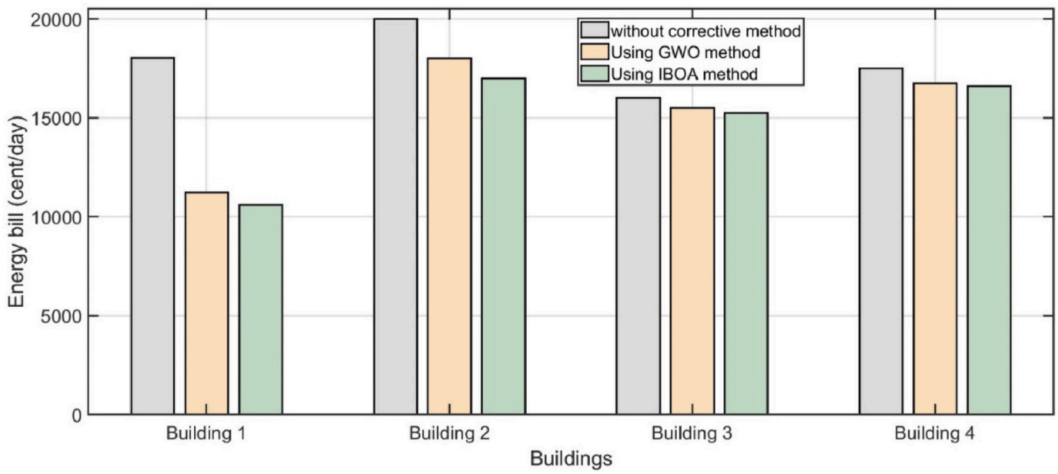

Fig. 16. Comparison of buildings' energy bills in the case without corrective method, using Grey Wolf Algorithm, and using Improved Butterfly Optimization Algorithm using CPP tariffs.

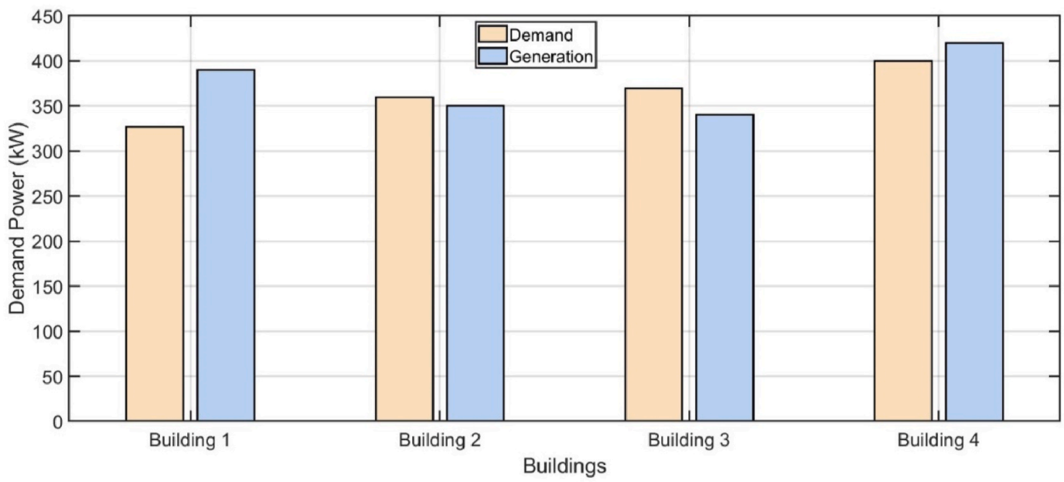

Fig. 17. Generation-demand power mismatch using CPP tariffs.

time, which is the peak hour, by more than 70.41% in the second scenario (CPP). The GWO project cut the total cost of electricity used during these two periods by 69.45% in the identical scenario.

Fig. 11 compares the total daily electricity costs for the two simulated scenarios based on ToU and CPP pricing. As shown in Figs. 11 and 12 compares the PARs produced in each simulation scenario utilizing both the ToU and CPP tariffs. In each of the simulation scenarios, all scheduling plans were successful in effectively lowering the PAR

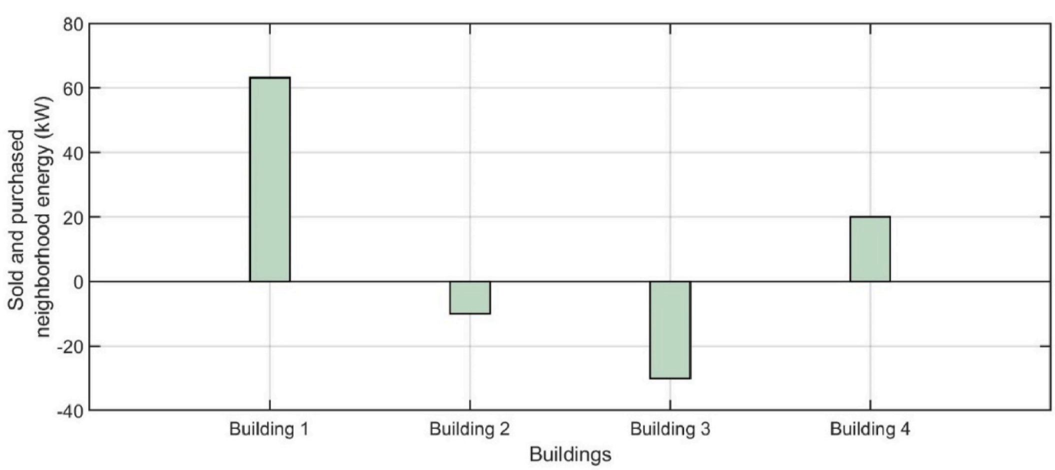

Fig. 18. Smart buildings neighborhood aggregated energy transaction in a day using CPP tariffs.

value.

Even if the PAR values produced by the second scenario (CPP) were not higher than the PAR values in the first scenario, there is still a trade-off between the values of the goal functions in the optimization schedule. Further inspection of the Figures reveals that optimization strategies have attempted to shorten waiting times to improve user comfort, as seen by the fact that waiting times in the second scenario were lower than in the first. Due to the trade-off between user convenience and PAR, the PAR values in the second scenario are not much worse than the PAR values in the first. The trade-off between the values of the objective functions by adjusting the problem's parameters and constraints must be performed.

A comparison between the three cases without the corrective method, using GWO and IBOA, is implemented in Table 3. With applying GWO, the total electricity cost, peak load, PAR, and waiting time are improved with 3873.723 cents, 21.6005 (kW), 7.162225 (kW), and 87 s respectively for ToU pricing and 11217.57 (cents), 18.0425 (kW), 5.984825 (kW), and 98 s respectively for CPP tariff. However, using the IBOA Improves the total electricity cost, peak load, PAR, and waiting time by 3850.61 (cents), 20.1245(kW), 6.7922 (kW), and 53 s respectively, for ToU and 10595.8 (cents), 17.6765 (kW), 5.83255 (kW), and 74 s for CPP tariff.

Also, a comparison between the two optimization algorithms based on the run time and the total number of iterations required to obtain the optimal solution in Table 4. It is noted that the run time is improved using GWO and IBOA by 13% and 47%, respectively, for ToU and 2% and 26% for CPP. However, the number of iterations required to obtain the optimal solution is reduced using the GWO and IBOA by 60% and 81% for ToU and 55% and 80% for CPP tariffs.

The simulations show that the proposed algorithm for the microgrid energy management system does a good job of locating the solution that establishes the best trade-off between the objective functions. As seen by the statistics above, a significant reduction in electricity costs was achieved in the scenarios by utilizing meta-heuristic algorithms to identify the best consumption pattern for building equipment.

In this work, a neighborhood community area of four smart buildings is used to evaluate the performance of the suggested paradigm. The installation of various distributed energy resources, including solar PV units, WT units, and BESS, in smart homes is a given. Fig. 13 compares smart buildings' energy bills in cases without corrective methods, using GWO and IBOA using ToU tariffs. Fig. 14 shows the generation-demand power mismatch using ToU tariffs. Fig. 15 shows smart buildings' neighborhood aggregated energy transactions in a day using ToU tariffs. Fig. 16 compares smart buildings' energy bills in the case without corrective method, using GWO and IBOA for CPP tariffs. Fig. 17 shows a generation-demand power mismatch using CPP tariffs. Fig. 18 shows smart buildings' neighborhood aggregated energy transactions in a day using CPP tariffs.

7. Conclusion

Determining a fair pricing strategy for multi-energy MAS between prosumers is a complicated problem. This study proposes a novel economic dispatch in the stand-alone system using improved butterfly optimization algorithm. A coordinated neighborhood power-sharing strategy is suggested in this study for the energy management of neighborhood smart buildings. According to on-site RER power generation availability, smart building consumers in the surrounding area can serve as either consumers or producers in this proposed paradigm. The primary goals of the suggested neighborhood power-sharing model are to increase the use of local RER energy, minimize the electricity costs of all smart buildings, and decrease the amount of energy that must be imported from the main grid. This paper proposes a DSM to minimize electricity cost, PAR, and user discomfort simultaneously. The proposed framework is evaluated by comparing it with GWO and W/O scheduling cases. With applying GWO, the total electricity cost, peak load, PAR, and waiting time are improved with 3873.723 cents, 21.6005 (kW), 7.162225 (kW), and 87 s respectively for ToU pricing and 11217.57 (cents), 18.0425 (kW), 5.984825 (kW), and 98 s respectively for CPP tariff. However, using the IBOA Improves the total electricity cost, peak load, PAR, and waiting time by 3850.61 (cents), 20.1245 (kW), 6.7922 (kW), and 53 s respectively, for ToU and 10595.8 (cents), 17.6765 (kW), 5.83255 (kW), and 74 s for CPP tariff. Also, It is noted that the run time is improved using GWO and IBOA by 13% and 47%, respectively, for ToU and 2% and 26% for CPP. However, the number of iterations required to obtain the optimal solution is reduced using the GWO and IBOA by 60% and 81% for ToU and 55% and 80% for CPP tariffs. The outcomes demonstrate that the created BOA algorithm outperforms GWO and W/O scheduling cases regarding the targeted objectives and is advantageous to utilities and customers.

In the future, other innovative algorithms can be used along with a combination of fuzzy techniques to increase the efficiency of load management in smart buildings. We'll also concentrate on concerns like smart network security and privacy protection. (see Figs. 3 and 4)

Credit authors statement

Bilal Naji Alhasnawi: Resources, Writing - Original Draft, Funding acquisition, Investigation, Basil H. Jasim: Formal analysis, Resources, Writing - Original Draft, Supervision, Vladimír Bureš: Writing - Review & Editing, Funding acquisition, Bishoy E. Sedhom: Formal analysis, Investigation, Arshad Naji Alhasnawi: Resources, Review & Editing, Data Curation, Rabeh Abbassi: Formal analysis, Review & Editing, Majid Razaq Mohamed Alsemawai: Review & Editing, Pierluigi Siano: Resources, Writing - Review & Editing, Supervision, Josep M. Guerrero: Resources, Writing - Review & Editing, Supervision.

Declaration of competing interest

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

Data availability

The authors do not have permission to share data.

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