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RESEARCH ARTICLE

Exploring LBWO and BWO Algorithms for Demand Side Optimization and Cost Efficiency: Innovative Approaches to Smart Home Energy Management

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ABSTRACT Demand side management (DSM) involves technologies and strategies that allow customers to actively participate in the optimization of their energy usage patterns, ultimately contributing to a more sustainable and efficient energy system. In this paper, leader beluga whale optimization improvement (LBWO) and original beluga whale optimization (BWO) are used to implement a DSM scheme that enables lower peak-to-average ratio (PAR) and decreasing the expenses associated with electricity consumption. In the context of this research, electricity consumers decide to store, buy, or sell the electricity to maximize profits while minimizing its costs and PAR. Electricity consumers make their decisions based on the amount of electricity generated from their mini-grid, electricity prices and demand from the public network. The mini-grid is a combination of a photovoltaic (PV) panel and a wind turbine connected to an energy storage system (ESS). An ESS is used for maintaining power system stability because the power generated from renewable energy source (RES) has intermittent characteristics depending on environmental conditions. The proposed scheme is tested on three different cases from a study, the first case is the traditional house, the second case is the smart house with DSM, and the last case is the smart house with its mini-grid and DSM. Simulation results indicate that in case 2, LBWO and BWO achieved a remarkable reduction in electricity cost by 61% and 51% respectively. In case 3, the reduction was even more significant, with LBWO and BWO lowering the cost by 76% and 64% respectively. Moreover, LBWO generated a revenue of 154 (cents), while BWO generated a revenue of 118 (cents). The results confirm the effectiveness and robustness of the suggested scheme in reducing electricity costs and the PAR (Peak to Average Ratio), while simultaneously increasing profits for electricity consumers.

INDEX TERMS Beluga whale optimization, demand side management, leader beluga whale improvement, mini-grid, renewable energy source, storage system.

I. INTRODUCTION

Energy is a necessary component of everyday life. Currently, social growth is dependent on the use of an adequate energy supply [1], [2]. Energy usage rises in tandem with global population expansion, technological and industrial advancement. The majority of the world's energy consumption is based on fossil fuel resources such as coal, natural gas, and oil [3], [4]. As a result of the scarcity of fossil fuels, meeting future energy demand will be difficult. Furthermore, fossil

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fuels are to blame for rising carbon emissions and global warming. According to the International Energy Agency, the combustion of gas (21%), particularly coal (42%) and fossil fuels (70%) produces nearly of the world's total energy [5]. Ensuring a satisfactory power provision is currently regarded as one of the most difficult jobs for assuring sustained industrial and economic development. Energy production and consumption are linked to environmental sustainability and energy safety. Unproductive use of natural resources wastes a considerable amount of energy resources. For the purpose of the increasing need for electricity and the impact of power plants to climate change, the scientific community has begun to investigate alternate energy choices for power generation [6].

The performance of the electric network is determined by the balance of electricity generation and the ability to fulfill the growing demand of users. Furthermore, the amount of energy consumed has an impact on the energy distribution system. This phenomenon renders grid operation risky and unpredictable. As a result, unpredictability in renewable energy supply must be considered in order to meet increasing electricity needs and ensure the sustainability of the system. The smart grid (SG) is an electric network that incorporates control systems, communication technologies, advanced sensing technologies, and smart meters to represent the energy system of the future [7]. The foundation of the smart grid's theory has developed to ensure efficient distribution and supply of electricity, along with effective load control. The bidirectional flow of energy and data between the client and the energy supplier is one of the major aspects of SG [8]. As a result, the SG introduces new possibilities for efficiently and dynamically delivering electricity to consumers.

DSM can help to address reliability challenges and grid sustainability. The DSM is a collection of load management actions that involve the monitoring, implementation, and design of pre-defined activities that affect the energy use patterns of consumers [9]. The DSM can systematically transport and distribute available energy, reducing carbon emissions and peak loads while also allowing customers to select their preferred energy type [10]. The DSM was developed for the first time in 1970 [11]. The electrical business developed the DSM model to manage both timing and quantity of electricity consumption, in addition to analyze electricity load patterns among consumers. Through the coordination of diverse smart appliances and the production of renewable energy, the integration of a DMS program with RES, distributed micro-generators and energy storage devices, can create an optimal management framework [12]. The price of electricity has a substantial impact on consumer energy consumption [13], [14]. However, the DSM implementation in Singapore can readily handle the power market's demand patterns as well as assess and reshape load profiles. This approach lowers customer peak load demand, enhancing grid stability, sustainability, and security; it also lowers carbon emissions, grid operation expenses, and power bills. Furthermore, by regulating and supervising decentralized energy resources, which encompass manageable end-use devices, successful DSM activities can simply eliminate the unneeded development of electrical infrastructure. These actions can help to control the electrical market by taking power distribution, transmission, and generation into account.

RESs have arisen as a pivotal solution to address the challenges posed by fossil fuels, such as environmental degradation, energy security concerns, and the global pursuit of sustainable development. These sources, including solar, wind, hydroelectric, and geothermal energy, offer several compelling advantages. Firstly, they are inherently abundant and widely distributed, reducing the dependence on finite fossil fuel reserves and minimizing geopolitical tensions associated with resource scarcity. Secondly, renewable energy production emits significantly fewer greenhouse gases and pollutants compared to conventional fossil fuel-based methods, thus mitigating the adverse effects of climate change. Additionally, harnessing renewable resources fosters local economic growth by creating jobs, enhancing energy resilience, and promoting energy independence. Moreover, the development of advanced technologies in this sector continues to drive down costs, making renewable energy increasingly competitive and accessible. As nations transition towards cleaner and more sustainable energy systems, the integration of renewable energy sources stands as a cornerstone in shaping a greener and more environmentally conscious future.

This study introduces a smart home concept designed to generate and store its own power through a mini-grid. This enables prudent consumers to not only draw energy from the main grid but also produce and reserve it. Additionally, the paper aims to optimize the benefits derived from energy exchange between electricity consumers and the commercial grid.

The strategic decisions made by electricity consumers are influenced by electricity tariffs, with the goal of minimizing the PAR per hour and overall electricity costs, while simultaneously maximizing revenue. In the context of the smart home, consumers strategically purchase electricity during low-cost time slots, which assists in lowering the PAR. Conversely, surplus electricity generated in the smart home is sold back to the commercial grid during high-cost time periods, helping to reduce overall load demand.

To establish electricity costs for both selling and purchasing, the study employs two Real-Time Pricing (RTP) schemes. In the final phase, an extensive comparative analysis is conducted, focusing on the efficiency of two distinct optimization algorithms: the LBWO and BWO This analysis aims to provide a clear understanding of the strengths and limitations of these algorithms when addressing intricate optimization challenges. Performance metrics are evaluated across various scenarios.

This work presents several noteworthy contributions that significantly advance the field. These contributions can be summarized as follows:

- The study introduces two novel algorithms, LBWO and BWO, which are designed to efficiently manage and schedule electrical appliances for energy consumption optimization.
- The smart home system is equipped to make informed decisions about participating in electricity exchange with the commercial grid or conserving excess energy for future use, ensuring a cost-effective and sustainable energy strategy.
- The research highlights how intelligent consumers can derive economic benefits by engaging in energy trading with the commercial grid. This approach empowers consumers to make efficient choices regarding energy consumption and cost savings.
- The study conducts a thorough evaluation to assess the suitability and independent decision-making capabilities of both LBWO and BWO algorithms. The primary focus of this analysis is their proficiency in optimizing the scheduling of power trading for appliances connected to the electrical grid.

The paper's structure is organized into distinct sections. In Section II, a comprehensive review of prior studies and relevant literature related to the research topic is presented, setting the stage for this study. Section III focuses on articulating the problem statement under consideration. Following that, in Section IV, we delve into the BWO algorithm, outlining its key principles. Section V is dedicated to an in-depth discussion of the LBWO algorithm. In Section VI, the paper shifts its focus to practical case studies and the corresponding simulation results. Finally, in Section VII, we draw our study to a close, offering concluding remarks and a concise summary of our findings.

II. LITERATURE REVIEW

In this section, we will explore some of the research works addressed the problems facing the smart home and the electrical network, such as reducing the cost of electricity and reducing PAR while maximizing user comfort and balancing the load between supply and demand.

Liu et al. [15] have presented the home energy management system (HEMS) idea. They outlined the fundamental elements of HEMS and compared various technological approaches. They also highlighted some of the worries and difficulties. Beaudin et al. [16] have conducted a comparative review of the HEMS literature, focusing on modeling methodologies and their impact on HEMS operations and outcomes. They examined forecast uncertainty, modeling device heterogeneity, multi-objective scheduling, computing constraints, timing considerations, and modeling customer well-being. Zhou et al. [17] have presented a brief introduction of smart HEMS architecture and functional modules. The modern HEMS infrastructures and smart house home equipment are then thoroughly researched and reviewed. The use of various building renewable energy resources in HEMS, such as solar, wind, biomass, and geothermal energy, was investigated. Finally, several home appliance scheduling solutions were examined in order to lower domestic electricity costs and increase energy efficiency from power generation utilities. Ahmad et al. [18] have presented optimal HEMS that not only allow for the integration of RES and ESS, but also integrate the domestic sector into DSM operations. The planned HEMS reduced the electricity invoice by coordination domestic devices and ESS in response to the electricity market's dynamic pricing. The constrained optimization problem is first mathematically formulated using multiple knapsack problems, then solved using heuristic algorithms such as genetic algorithm(GA), bacterial foraging optimization (BFO), binary particle swarm optimization (BPSO), the wind driven optimization (WDO), hybrid GA-PSO (HGPO). Mahapatra et al. [19] have provided a thorough study of the many technical and conceptual components of effective power management at home. They concentrate on the principles, technological background, architecture, and infrastructure, as well as numerous plans and aims, in addition to diverse concerns and obstacles associated with HEMSs. They suggest a revolutionary way for improving house system structure by combining the implementation of green building principles to reduce energy consumption for homeowners. Waseem et al. [20] have used crows and gray wolf search optimization algorithms for scheduling of household devices. In the existence of RTP tariff, the cost of minimizing electricity, optimizing consumer convenience, and decreasing the PAR of household appliances was investigated. Due to the high load ratio of the air conditioners, an optimization technique was also employed to schedule the ACs to enhance the comfort of the end users in their usage. Deep reinforcement learning was given in [21] hierarchical layers for the distributed energy resources such as an electric vehicle, an ESS and optimization of energy usage of smart house devices. This study presents an approach that employs a two-tier deep reinforcement learning structure. In the initial tier, scheduling of household devices is based on user preferences and comfort levels. In the subsequent tier, the charging and discharging schedules of electric vehicles and ESS are determined, taking into account the optimal solution from the first tier and user-specific environmental factors. Lissa et al. [22] proposed creating a deep reinforcement learning algorithm for indoor and domestic hot water temperature regulation, with the goal of reducing energy consumption by optimizing PV energy output. They developed a methodology for a new definition of dynamic internal temperature, which allows for better flexibility and cost reductions. El Sayed et al. [23] have used genetic algorithm, particle swarm optimization, sine cosine algorithm, and whale optimization algorithm for scheduling devices of multiple and single houses using combined inclining block rate and the time of use.

In SG, the algorithms can tackle optimization challenges. These optimization concerns include minimizing electricity prices, total energy usage, and PAR, maximizing customer convenience and integrating RESs efficiently [24]. Previous research, for example, presented various GA based

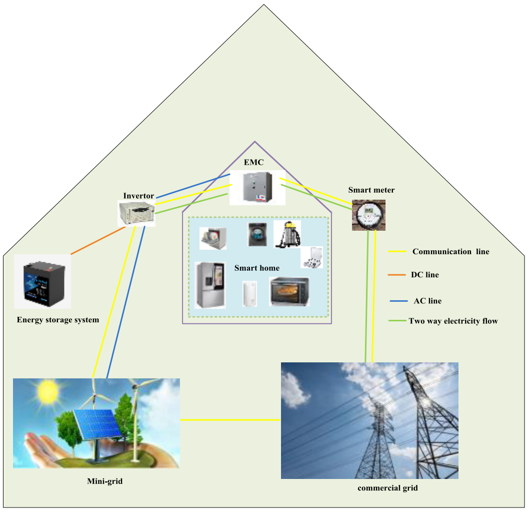


FIGURE 1. Proposed system model.

optimization methods for lowering electricity expenses [25], [26], [27]. Furthermore, ant colony optimization (ACO), BPSO and GA, were utilized to manage the energy usage. In [28], elite evolutionary strategy artificial ecosystem-based optimization is used to schedule household device for reducing PAR, electricity cost, improve the grid electrical, and maximize user comfort. In [29], improved bald eagle search is applied for developing HEMS to control load demand, minimize PAR, reduce electricity bills, and enhance customer comfort. In [30], sine cosine algorithm is presented to create ideal HEMS, which use DSM load shifting technique to improve a smart house's energy consumption patterns.

III. PROBLEM STATEMENT

This paper proposes a SG model whose goal is to minimize the total maximum load through the operation of the public electrical grid, reduce electricity costs for users in a smart home, and create the electric grid stability. The smart home contains different smart devices and is also equipped with a mini-grid. This mini-grid is capable of producing, distributing and storing electricity. The electric grid has the characteristics of two-way communication, effective control and monitoring, etc. like the SG and linked with the commercial utility company. This last, makes electricity available to many users. The mini-grid is a represented as a PV panel and a wind turbine connected to an ESS. An ESS is used for maintaining power system stability because the power generated from RES has intermittent characteristics depending on environmental conditions. The proposed system model is illustrated in Fig. 1.

A. TYPES OF SMART HOUSE APPLIANCES

The smart home is outfitted with a variety of smart appliances ($\boldsymbol{A}$), each having distinct operational time durations and power ratings [31]. In this section, home appliances are

TABLE 1. The classifications of the devices.

Device category	Device	Power rating (kw)	Times (h) of Varying operational	Time(h) of Earliest starting	Time(h) of Least finishing
Interruptible appliances	Electrical car	3.5	3	18	8
	Vacuum cleaner	1.2	1	9	17
	Desktop	0.3	3	18	24
	Laptop	0.1	2	18	24
	Microwave	1.7	1	6	10
	Cooker oven	5	1	15	20
	Cooker hub	3	1	6	10
Uninterruptible appliances	Spin dryer	2.5	1	13	18
	Washing machine	1.5	2	7	15
	Dish washer	1.5	2	9	17
Essential appliances	Refrigerator	0.3	24	1	24
	Interior lighting	0.84	6	16	24

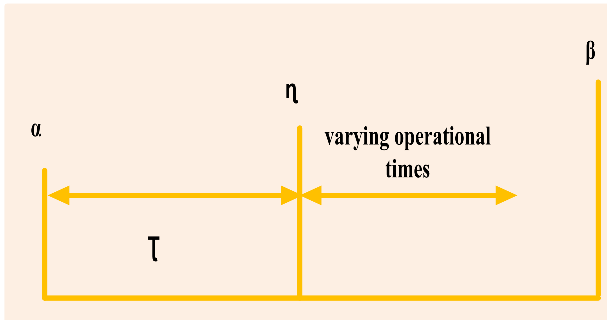


FIGURE 2. The execution pattern status of the appliances.

divided into three main groups namely interruptible, uninterruptible, and essential appliances. Each of these groups of devices has different characteristics and limitations that are described in the next section. In this study, the proposed scheme will be implemented within one day that divided into 24 time periods, each time period is 1 hour. Moreover, each device is connected to the internet and has the capacity to communicate with the energy management controller (EMC). Furthermore, the proposed scheme will be implemented within one day that divided into 24 time periods, each time period is 1 hour. In the proposed system, the runtime must be completed for each smart device. The execution pattern of the device is represented in Fig. 2. Table 1 shows the classifications of the devices.

1) ESSENTIAL APPLIANCES

Essential appliances are the mainstay of every home. These devices are alternatively known as non-interruptible and non-switchable devices. Primary load devices remain unaffected and uninterrupted during their operational tasks. The essential appliances will be denoted as ($\boldsymbol{EA}$) in this study, and their energy usage as ($\boldsymbol{E_{EA}}$). Because each appliance has a power rating ($\lambda_{\boldsymbol{EA}}$), the total energy spent in each time slot is computed using the following equation:

$$E_{EA} = \sum_{t=1}^{T} \left(\sum_{EA \in A} \left(\lambda_{EA} \times \alpha_{EA}(t) \right) \right) \tag{1}$$

Equation (2) and (3) are employed to compute the cost of electricity consumed per hour and per day,

$$\sigma_{\mathrm{EA}}^{t} = \sum_{\mathrm{EA} \in \mathrm{A}} \left(\lambda_{EA} \times \rho\,(t) \times \alpha_{EA}\,(t) \right) \tag{2}$$

$$\sigma_{\mathrm{EA}}^{\mathrm{Total}} = \sum_{t=1}^{T} \left(\sum_{\mathrm{EA} \in \mathrm{A}} \left(\lambda_{EA} \times \rho\,(t) \times \alpha_{EA}\,(t) \right) \right) \tag{3}$$

where $\boldsymbol{\sigma_{EA}^{t}}$ represents the hourly cost of essential appliances, $\boldsymbol{\sigma_{EA}^{\mathrm{Total}}}$ is the total daily electricity cost for essential appliances and $\boldsymbol{\alpha_{EA}}$ indicates the status of essential appliances. Describes the representation of the ON/OFF status of essential appliances as follows:

$$\alpha_{EA}(t) = \begin{cases} 1, & \text{If EA is } ON \\ 0, & \text{If EA is } OFF \end{cases} \tag{4}$$

2) INTERRUPTIBLE APPLIANCES

In this section, the definition of interruptible appliances is explained. Because these appliances have flexibility in their operational duration, they can be paused or postponed during operation. In this study, interruptible appliances are denoted by (IA), and their energy consumption is denoted by $\boldsymbol{E_{IA}}$:

$$E_{\mathrm{IA}} = \sum_{t=1}^{T} \left(\sum_{\mathrm{IA} \in \mathrm{A}} \lambda_{\mathrm{IA}} \times \alpha_{\mathrm{IA}}(t) \right) \tag{5}$$

Each appliance has a power rating ($\boldsymbol{\lambda_{IA}}$). The hourly cost of electricity for all interrupted devices paid to the commercial grid can be calculated as follows:

$$\sigma_{\mathrm{IA}}^{t} = \sum_{\mathrm{IA} \in \mathrm{A}} \left(\lambda_{IA} \times \rho(t) \times \alpha_{\mathrm{IA}}(t) \right) \tag{6}$$

The total cost of electricity for all interrupted devices paid to the commercial grid can be calculated as follows:

$$\delta_{\mathrm{IA}}^{\mathrm{Total}} = \sum_{t=1}^{T} \left(\sum_{\mathrm{IA} \in \mathrm{A}} \left(\lambda_{IA} \times \rho(t) \times \alpha_{\mathrm{IA}}(t) \right) \right) \tag{7}$$

where $\boldsymbol{\sigma_{IA}^{t}}$ represents the hourly cost of interrupted appliances, δ_{IA}^{Total} is the total daily electricity cost for interrupted appliances and $\boldsymbol{\alpha_{IA}(t)}$ indicates the ON/OFF status of interrupted appliances.

3) UNINTERRUPTIBLE APPLIANCES

The third-class study, uninterruptible appliances are denoted by ($\boldsymbol{UN}$), while energy usage is denoted by ($\boldsymbol{E_{UN}}$). Each appliance has a power rating by $\boldsymbol{\lambda_{UN}}$. The energy consumption can be calculated as follows:

$$E_{UN} = \sum_{t=1}^{T} \left(\sum_{\mathrm{UN} \in \mathrm{A}} \left(\lambda_{UN} \times \alpha_{UN}(t) \right) \right) \tag{8}$$

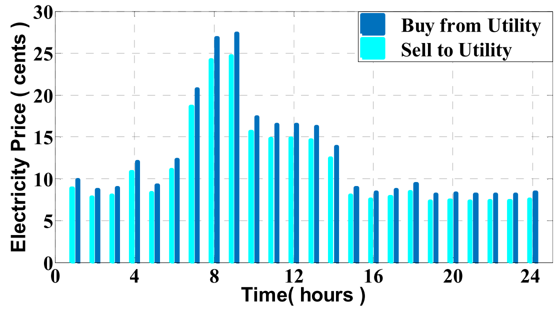


FIGURE 3. Electricity prices.

The hourly cost of electricity for all uninterrupted devices paid to the commercial grid can be calculated as follows:

$$\sigma_{\mathrm{UN}}^{\mathrm{t}} = \sum_{\mathrm{UN} \in \mathrm{A}} \left(\lambda_{\mathrm{UN}} \times \rho(\mathrm{t}) \times \alpha_{\mathrm{UN}}(\mathrm{t}) \right) \tag{9}$$

The total cost of electricity for all interrupted devices paid to the commercial grid can be calculated as follows:

$$\delta_{\mathrm{UN}}^{\mathrm{Total}} = \sum_{\mathrm{t}=1}^{\mathrm{T}} \left(\sum_{\mathrm{UN} \in \mathrm{A}} \left(\lambda_{\mathrm{UN}} \times \rho(\mathrm{t}) \times \alpha_{\mathrm{UN}}(\mathrm{t}) \right) \right) \tag{10}$$

where $\boldsymbol{\sigma_{UN}^{t}}$ represents the hourly cost of uninterrupted appliances, $\boldsymbol{\delta_{UN}^{\mathrm{Total}}}$ is the total daily electricity cost for uninterrupted appliances and $\boldsymbol{\alpha_{UN}(t)}$ indicates the ON/OFF status of uninterrupted appliances.

B. PRICE TARIFF

The utility company offers various electricity tariffs to encourage users to manage their load requirements. The performance of the suggested system is evaluated by RTP tariff. This tariff is discussed in the following subsection. At every hour, there is a price for buying electricity and another price for selling excess electricity to the commercial network, as shown in Fig. 3. The electricity selling can be calculated as follows [31]:

$$tariff^{sell} = 0.90 * tariff^{buy} \tag{11}$$

where $\mathrm{tariff}^{\mathrm{sell}}$ represents the rate at which electricity is sold to the commercial grid, and $\mathrm{tariff}^{\mathrm{buy}}$ refers to the purchasing rate for each hour. The electricity selling rate is 90% of the purchasing rate for each hour [31]. Users are responsible for remitting the entire costs to utilities in exchange for the electricity they consume. The electricity cost for a one hour without mini-grid integration can be calculated as follows:

$$\sigma^{t} = \sum_{A} \lambda_{A} \times \rho\,(t) \times \alpha\,(t) \tag{12}$$

The electricity cost for a one hour with mini-grid integration can be calculated as follows:

$$\varsigma^{t} = \left(\left(\sum_{A} \lambda_{A} \times \alpha(t) \right) \right) - E(t)) * tariff^{buy}(t) \tag{13}$$

The electricity cost for a one day without mini-grid integration can be calculated as follows:

$$\delta^{total} = \sum_{t=1}^{24} (\sum_{dn} \lambda_{dn} \times \rho\,(t) \times \alpha\,(t)) \tag{14}$$

The electricity cost for a one day without mini-grid integration can be calculated as follows:

$$\varsigma^{total} = \sum_{t=1}^{24} ((\sum_{A} \lambda_{A} \times \alpha(t)) - E(t)) * tariff^{buy}(t) \tag{15}$$

The smart home, at the start of each hour, takes the decision whether to buy, sell or store electricity. The smart home stores the electricity generated from its mini-grid in the ESS for future trading and purchasing electricity for load demand in the event that the electricity price is low, but if the electricity price is high, it uses its mini-grid or ESS to meet its loads. The surplus electricity is quantified and subsequently traded back to the commercial grid. The calculation is performed in the following manner:

$$\eta^{sell}\,(t) = (\sum_{A} \lambda_{A} \times \alpha(t)) - [E\,(t) + ESS] \tag{16}$$

$$\eta^{sell}\,(t) = \begin{cases} \eta^{sell}\,(t)\,, & If\, \eta^{sell}\,(t) < 0, \\ 0, & otherwise \end{cases} \tag{17}$$

where η^{sell} is hourly sold electricity and η^{t} is total sold electricity, The cumulative electricity sent back to the commercial grid can be calculated as follows:

$$\eta^{\mathrm{t}} = \sum_{\mathrm{t=1}}^{\mathrm{T}} [\eta^{\mathrm{sell}}\,(\mathrm{t})] \tag{18}$$

The earnings from a local grid for a one hour can be calculated as follows:

$$\text{ȩ}^{\mathrm{earn}}\,(\mathrm{t}) = \eta^{\mathrm{sell}}\,(\mathrm{t}) * \mathrm{tariff}^{\mathrm{sell}}(\mathrm{t}) \tag{19}$$

The earnings from a local grid for a one day can be calculated as follows:

$$\text{ȩ}^{\mathrm{t}} = \sum_{\mathrm{t=1}}^{\mathrm{T}} [\eta^{\mathrm{sell}}\,(\mathrm{t}) * \mathrm{BC}^{\mathrm{sell}}(\mathrm{t})] \tag{20}$$

C. MINI-GRID

A mini-grid is a localized and decentralized energy system that operates independently or in coordination with the main electrical grid. It typically encompasses a combination of distributed energy resources (DERs) like solar panels, wind turbines, and ESSs. In this study, the micro-grid consists of m number of RES. The total electricity produced by the mini-grid in one hour is mathematically calculated as follows:

$$E(T) = \sum_{m \in M} \varepsilon_m(t) \tag{21}$$

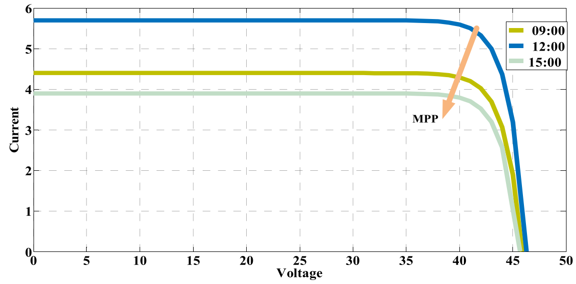


FIGURE 4. The curve of voltage-current of PV panel.

The total electricity produced by the mini-grid in one day is mathematically calculated as follows:

$$E = \sum_{t}^{T} \sum_{m \in M} \varepsilon_m(t) \tag{22}$$

where t refers to individual time intervals and T refers to the maximum number of time intervals. An important point to consider is that renewable energy sources exhibit an intermittent nature. An ESS is used for maintaining power system stability because the power generated from RES has intermittent characteristics depending on environmental conditions [32].

1) SOLAR PANEL

Solar panels, also known as PV panels, have emerged as a key player in the quest for sustainable energy solutions. These panels harness the abundant energy from the sun's rays and convert it into electricity through a process known as the PV effect. Solar panels consist of multiple solar cells, usually made from silicon, which absorb sunlight and generate DC electricity. An inverter then converts this DC electricity into AC, suitable for powering homes. In the hours of high electricity price from the public grid, the smart home tries to meet its requests from the mini-grid to reduce the cost to a minimum and increase the convenience of the user. Integration of PV cell performance models allows the extraction of a current-voltage (I-V) curve and maximum power point (MPP), aiding in the optimization of PV cells. Fig. 4 illustrates the current-voltage curve. The energy produced using solar panels can be calculated mathematically as follows:

$$p = V_{PV} I_{PV} \tag{23}$$

where p is the energy produced using solar panels, V_{PV} is the voltage of PV cells and I_{PV} is the current of PV cells. The mathematical calculation of PV cells' performance is as outlined below:

$$\begin{aligned} i_L - i_S \exp\left[\alpha\left(v_{pv} + R_S i - pv\right)\right] \\ - 1 v_{pv} + R_S i_{pv} / R_{Sh} - i_{pv} = 0 \end{aligned} \tag{24}$$

where the current of light is denoted by i_L, the current of diode saturation denoted by i_S, resistance of shunt is denoted by R_{Sh}, resistance of series is denoted by R_S and the ideality factor is denoted by α and can be calculated mathematically as follows:

$$\alpha = q/nskT \tag{25}$$

where temperature is denoted by T = 298 K, solar cells number is denoted n_s, $q = 1.60 \times 10 - 19$ and $k = 1.38 \times 1023$ j/K. In this study, a solar panel with a capacity of 230 watts and a total of 5 solar panels was used.

2) WIND TURBINE

Wind turbines are innovative devices that harness the kinetic energy of wind to generate clean and renewable electricity. Functioning like modern windmills, wind turbines consist of rotor blades connected to a hub that is mounted atop a tower. As the wind blows, the kinetic energy is transferred to the rotor blades, causing them to rotate. This rotational movement activates the turbine's generator, converting the mechanical energy into electrical power. The mathematical calculation for determining the electric power generated by the wind turbine is presented as follows:

$$P_t^{wt} = 1/2 \cdot C_p \cdot (\lambda) \cdot \rho \cdot A \cdot \left(V_t^{wt}\right)^3 \tag{26}$$

where P_t^{wt} is the electric power produced by the wind turbine, V_t^{wt} is wind speed, ρ is the air density, A is the area of the rotor and C_p is the coefficient of performance. The wind turbine produces electrical power within the wind speed range defined as the cut-out and cut-in wind speeds. The cut-out speed refers to the maximum wind speed at which the wind turbine produces the highest amount of energy. If the wind speed is greater than the cutting speed, the operation of wind turbines is exposed to risks. Wind turbines must be turned off for safety reasons. If the wind speed is less than the cut-in speed, the power generation will be zero [33]. The constraints of wind turbines can be represented mathematically as follows:

$$V^{cut-in} \leq V_t^{\mathrm{wt}} \leq V^{cut-out}, \quad \forall t \tag{27}$$

$$V_t^{\mathrm{wt}} \geq V^{\mathrm{cut-out}}, \quad \forall t, 0 \tag{28}$$

$$V_t^{wt} \leq V^{\mathrm{cut-in}}, \quad \forall t, 0 \tag{29}$$

where $V^{\mathrm{cut-in}}$ and $V^{\mathrm{cut-out}}$ refer to the minimum and maximum wind speeds at which the wind turbine produces electricity.

3) ENERGY STORAGE SYSTEM

An ESS plays a pivotal role in modern energy management by bridging the gap between consumption and energy generation. ESS technologies provide the capability to store surplus energy during periods of low demand and release it when demand is high, thus ensuring a stable and reliable energy supply. These systems are crucial for integrating RES, such as wind power and solar, into the commercial grid, as they can store excess energy during peak generation times for use during periods of low generation. In this study, the capacity of the ESS is 5 kWh. The ESS is switchable and the energy storage levels are 10% for minimum storage and 90% for maximum storage. In the event that electricity prices rise or the small network is unable to meet the demand for electricity, the ESS is discharged. If the ESS is at full capacity, any extra electricity is returned to the commercial grid for sale [34]. Mathematically, it can be expressed as:

$$SE(t) = SE(t-1) + k \cdot \eta^{ESS} \cdot ES^{ch}(t) - k \cdot ES^{dis}(t)/\eta^{ESS} \tag{30}$$

where, stored electricity is denoted by E, time slot is denoted by t, efficiency of ESS is denoted by η^{ESS}, the charging electricity of ESS is denoted by $\mathrm{ES}^{\mathrm{ch}}$ and the discharging electricity of ESS is denoted by $\mathrm{ES}^{\mathrm{dis}}$. The constraints of ESS can be represented mathematically as follows:

$$ES_t^{ch} <= ES(\max) \tag{31}$$

$$ESS_t^{ch} < ESS(\mathrm{upl}) \tag{32}$$

$$ES_t^{dis} >= ES(\min) \tag{33}$$

IV. BELUGA WHALE OPTIMIZATION

In 2022, Zhong et al. introduced the BWO algorithm, designed to address optimization problems by drawing inspiration from the behaviors of beluga whale herds [35]. The BWO algorithm incorporates three phases: exploration, exploitation, and whale fall, which mirror the behaviors of pair swimming, prey hunting, and whale falling observed in beluga whales. Two critical components in BWO are the self-adapting balancing factor and the likelihood of whale falls, which regulate the balance between exploration and exploitation. To enhance global convergence during the exploitation phase, the algorithm also introduces Levy flights.

Beluga whales, found in marine environments, are distinctive aquatic mammals known for their all-white coloration in adulthood. They are often referred to as the "canaries of the sea" due to their diverse vocalizations. Medium-sized beluga whales have a robust and rounded body shape. Their excellent hearing and vision abilities enable them to navigate and locate prey using sound. As shown in Fig. 5, belugas in aquariums exhibit friendly behavior and graceful movements. While our understanding of beluga whale social behavior remains incomplete, some evident social and sexual activities have been observed in beluga whales living under human care [36].

A. MATHEMATICAL FORMULATION OF BELUGA WHALE OPTIMIZATION

The BWO algorithm imitates beluga whale activities like swimming, hunting, and whale falls. BWO, similar to other metaheuristics, comprises both an exploitation phase and exploration phase. Through random selection of beluga whales, the exploitation phase focuses on conducting local searches within that space, while the exploration phase ensures global exploration of the design space. The beluga whales are viewed as search agents that can move in search space by changing their location vectors in order to simulate the behaviors. Furthermore, BWO takes into account the possibility of a whale falling, which alters the beluga whales' positions.

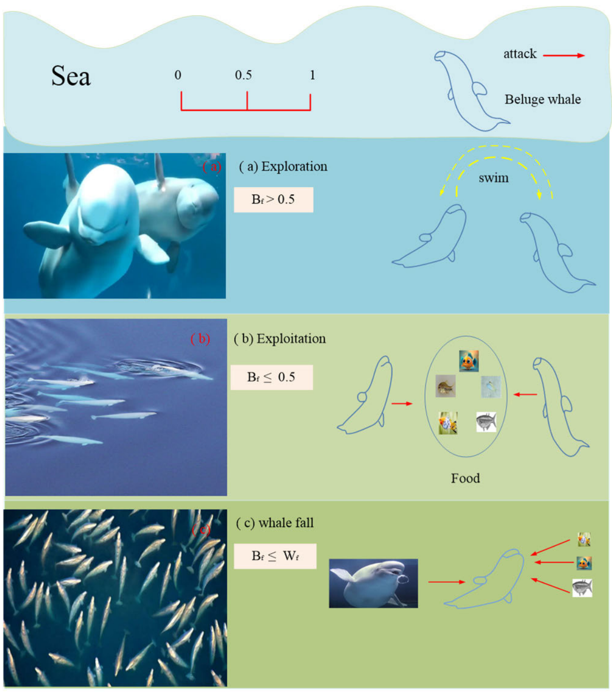


FIGURE 5. **Beluga whale behaviors: (a) the phase of exploration (b) the phase of exploitation (c) the phase of fall.**

Each beluga whale serves as a search agent within the population-driven framework of BWO, with each whale embodying a potential solution that undergoes iterative optimization. The representation of the matrix of search agent positions is as follows:

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,d} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,d} \end{bmatrix} \tag{34}$$

where d stands for the number of design variables and n is the beluga whale population size. The respective values of fitness for every beluga whale are kept as follows:

$$F_X = \begin{bmatrix} f\left(x_{1,1}, x_{1,2}, \ldots, x_{1,d}\right) \\ f\left(x_{2,1}, x_{2,2}, \ldots, x_{2,d}\right) \\ \vdots \\ f\left(x_{n,1}, x_{n,2}, \ldots, x_{n,d}\right) \end{bmatrix} \tag{35}$$

The transition from exploration to exploitation in the BWO algorithm is determined by the balance factor B_f, defined as:

$$B_f = B_0\left(1 - T/2T_{\max}\right) \tag{36}$$

where T represents the current iteration, T_{max} the maximum number of iterations, and B_0 fluctuates at random between (0, 1) during each iteration.

When the balance factor B_f is greater than 0.5, the exploration phase begins, and when B_f is less than 0.5, the exploitation phase begins. The fluctuation range of B_f decreases from (0, 1) to (0, 0.5) as iteration T rises, showing the considerable change in probabilities for the exploitation and exploration phases while the probability of the exploitation phase rises as iteration T rises

1) EXPLORATION PHASE

The swimming behavior of beluga whales is incorporated into the establishment of the exploring phase in the BWO algorithm. Beluga whales can engage in various social-sexual behaviors, often demonstrated in different postures, as shown in Fig. 5. This includes paired swimming of two beluga whales in close proximity, moving synchronously or mirroring each other [35]. Observing this behavior has been documented in beluga whales that are kept under human care. The beluga whale pair swims serve as a guide for search agents' positions, and the updating of beluga whale positions is performed in the following manner:

$$\begin{cases} X_{i,j}^{T+1} = X_{i,p_j}^{T} + \left(X_{r,p_1}^{T} - X_{i,p_j}^{T}\right)(1 + r_1), \\ X_{i,j}^{T+1} = X_{i,p_j}^{T} + \left(X_{r,p_1}^{T} - X_{i,p_j}^{T}\right)(1 + r_1) \end{cases} \tag{37}$$

where $X_{i,j}^{T+1}$ is the ith beluga whale's new position on the jth dimension, $p_j(j = 1, 2, \ldots, d)$ is a random number chosen from the d-dimension, X_{i,p_j}^{T} is the ith beluga whale's position on the p_j dimension, and X_{r,p_1}^{T} and X_{i,p_j}^{T} are the current iterations the ith and rth beluga whales on the p_j dimension. r is a randomly chosen beluga whale. r_1 and r_2 are random numbers between (0, 1), and $\cos(2\pi r_2)$ and $\sin(2\pi r_2)$ indicate that the mirrored beluga whales' fins are pointing upward. The revised positions reflect the synchronized or mirrored behaviors of beluga whales during swimming or diving, based on the dimensions determined by even and odd numbers. To improve the random operators in the exploration phase, two random numbers, r_1 and r_2, are used.

2) EXPLOITATION PHASE

The exploitation stage of BWO is modeled after beluga whales' hunting techniques. Beluga whales can travel and forage together depending on the proximity of other beluga whales. Therefore, beluga whales hunt by exchanging information about job openings among themselves and selecting the best applicant among them. In order to improve convergence, the Levy flight technique is added during the exploitative stage of BWO [36]. We assumed that they could use the Levy flight method to capture their prey, and the mathematical model is represented as follows:

$$X_i^{T+1} = r_3 X_{\text{best}}^{T} - r_4 X_i^{T} + C_1 \cdot L_F \cdot \left(X_r^{T} - X_i^{T}\right) \tag{38}$$

where X_r^T and X_i^T represent the ith beluga whales and a random beluga whale's current position, X_{best}^T denotes the best position among beluga whales, r_3 and r_4 denote random numbers between (0, 1), and $C_1 = $ 2r4(1-T /T_{MAX}) denotes the random jump strength used to measure the Levy flight's intensity. Levy flight function (LF) is determined as follows:

$$L_F = 0.05 \times \frac{u \times \sigma}{|v|^{1/\beta}} \tag{39}$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\pi\beta/2)}{\Gamma((1+\beta)/2) \times \beta \times 2^{(\beta-1)/2}} \right)^{1/\beta} \tag{40}$$

In this equation, β represents the predefined constant of 1.5, while u and v stand for randomly generated values following a normal distribution.

3) WHALE FALL

Killer whales, polar bears, and people pose threats to beluga whales throughout their migration and foraging. Most beluga whales are intelligent and have the ability to evade threats by communicating with each other. A few beluga whales, though, have perished and are buried in the deep sea. The occurrence called "whale fall" offers nourishment for a considerable array of creatures. The dead whale's exposed bones and bodies draw a large group of hair crustaceans, as well as a significant population of invertebrates and sharks, to dine on them. Finally, the skeleton either decomposes or is inhabited for decades by bacteria and corals. In each iteration, minor changes within the groups are simulated by selecting the probability of whale fall from the population of individuals, mimicking the behavior of whale fall. It is speculated that these beluga whales were either transported or shot and subsequently descended into the ocean's depths. The positions of beluga whales and the magnitude of steps taken by whale falls are utilized to calculate the new position, ensuring the population size remains unchanged. The mathematical formulation of the model is:

$$X_i^{T+1} = r_5 X_i^T - r_6 X_r^T + r_7 X_{\text{step}} \tag{41}$$

If X_{step} is the whale fall's step size and r_5, r_6, and r_7 are random values between (0, 1).

$$X_{\text{step}} = (u_b - l_b) \exp(-C_2 T / T_{\max}) \tag{42}$$

where u_b and l_b are the variables' upper and lower bounds and C_2 is the step factor that correlates with the likelihood of whale falls and population size ($C_2 = 2W_F$ n). It is evident that the step size is influenced by the maximum iterative number, iteration, and design variable bounds.

$$W_f = 0.1 - 0.05T/T_{\max} \tag{43}$$

The probability of a whale fall occurring decreases from 0.1 in the initial iteration to 0.05 in the final iteration, signifying that the potential threat posed by beluga whales diminishes as they approach their food source throughout the optimization process.

B. THE BWO TECHNIQUE

The prior hypothesis said that BWO had three primary stages: the exploration phase, which simulates swimming activity; the exploitation phase, mimicking predatory behavior, and the whale fall phase, which takes its cue from the fall of beluga whales. When the exploitation phase and the exploration phase of every iteration of the optimization process are complete, the whale fall phase is put into action. This section outlines the basic steps of BWO. The BWO algorithm's flowchart is depicted in Fig. 6.

Step 1: Initialization.

The population size n and the maximum number of iterations (T_{max}) of the method are chosen. Random initial positions are assigned to all beluga whales within the search space, followed by the assessment of fitness values using the objective function.

Step 2: An update on the phase of exploitation and exploration.

Based on the balancing factor B_f, every beluga whale is assigned to either the the exploitation phase or exploration phase. A beluga whale's updating mechanism enters the exploration phase if $B_f > 0.5$, and Eq. (37) updates the position of the beluga whale. If $B_f < 0.5$, the exploitation phase regulates the updating, and Eq. (38) is used to update a beluga whale's position. The best outcome for the current iteration is then determined by calculating and sorting the fitness values of the new places.

Step 3: A report on the phase of the whale fall.

In every iteration, the potential occurrence of beluga whale mortality and their descent into the deep ocean is considered. This leads to the adjustment of a beluga whale's position as outlined in Equation (41).

Step 4: Ending condition assessment.

The BWO algorithm terminates if the number of iterations remaining exceeds the maximum number. If not, proceed to Step 2 again.

C. COMPLEXITY OF COMPUTATION

The computational complexity of BWO, a critical parameter for assessing its effectiveness, is encompassed by three processes: initialization, fitness evaluation, and beluga whale updating. Keep in mind that the initialization method for beluga whales has a computational complexity of $O(n)$. The exploration and exploitation phases incur a computational cost estimated at $O(n \times T_{max})$, where n represents a parameter and T_{max} denotes the maximum number of iterations. With an estimated complexity of approximately $O(0.1 \times n \times T_{max})$ the whale fall probability (W_f) and balance factor (B_f) operate within the computational framework, Affect the computational complexity in the whale fall phase. Consequently, it is estimated that BWO's computational complexity is roughly $O(n(1 + 1.1 \times \times T_{max}))$.

V. THE PROPOSED LEADER BWO ALGORITHM

The proposed technique, named Leader BWO optimization algorithm, is based on the BWO algorithm as well as the incorporation of Leader-based mutation-selection [37]. The proposed LBWO technique develops the low convergence speed and the weak local optimum of the original BWO algorithm thus improving the performance of the

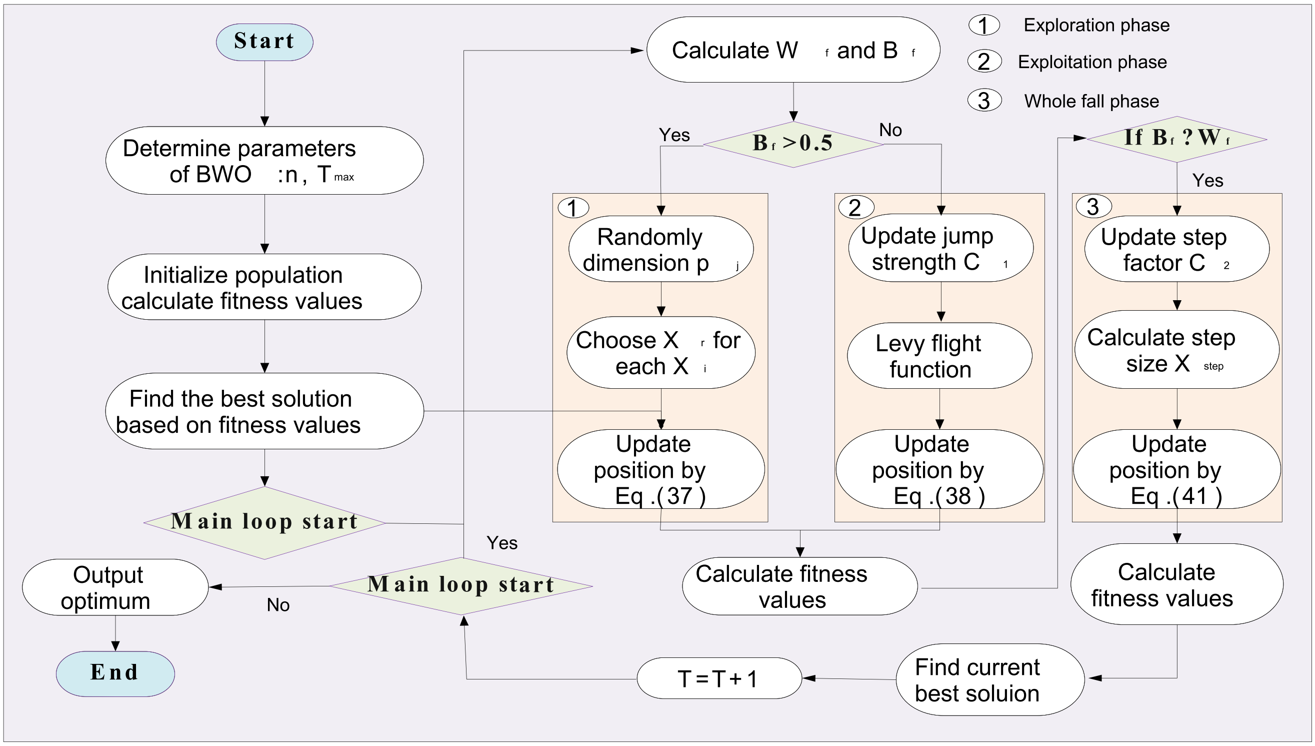


FIGURE 6. The flowchart of BWO algorithm.

suggested technique to attain the optimal value for the fitness function. This adjustment utilizes the optimal location vectors x_{best}^t, x_{best-1}^t and x_{best-2}^t based on the objective function value of the new position vector x_i (new), accounting for the population count. This approach proves to be a particularly effective method for addressing these challenges and reinforcing the performance and resilience of the original BWO algorithm.

Then the new mutation location vector x_i (mut) is given by [38]:

$$\begin{aligned} x_i\,(\text{mut}) = x_i\,(\text{new}) + 2\times\left(1-\frac{t}{\text{Max\_it}}\right)\times(2\times\text{rand}-1) \\ \times\left(2\times x_{best}^t-\left(x_{best-1}^t+x_{best-2}^t\right)\right)+(2\times\text{rand}-1) \\ \times\left(x_{best}^t-x_i\,(\text{new})\right) \end{aligned} \tag{44}$$

Then, the next position is updated using the following equation:

$$x_i\,(t+1)=\begin{cases} x_i\,(\text{mut})\; f\,(x_i\,(\text{mut})) < f\,(x_i\,(\text{new})) \\ x_i\,(\text{new})\; f\,(x_i\,(\text{mut})) \geq f\,(x_i\,(\text{new})) \end{cases} \tag{45}$$

In conclusion, the optimal solution is revised as follows:

$$x_{best}=\begin{cases} x_i\,(\text{mut})\; f\,(x_i\,(\text{mut})) < f\,(x_{best}) \\ x_i\,(\text{new})\; f\,(x_i\,(\text{new})) < f\,(x_{best}) \end{cases} \tag{46}$$

The flowchart of the proposed LBWO technique is displayed in Fig. 7. The place of Leader-based mutation-selection in the proposed algorithm is presented in this figure. This modification leads to enhance the exploration of the proposed LBWO algorithm based on the simultaneous crossover and mutation using the three best leaders. This adjustment results in an improvement in the exploration aspect of the proposed LBWO algorithm.

VI. SIMULATION RESULTS AND DISCUSSION

The experiments for the 23 benchmark functions were conducted using MATLAB (R2016a) on a computer equipped with an Intel(R) Core i5-4210U CPU running at 2.40 GHz and 8GB of RAM. MATLAB simulations were employed to evaluate the performance of the proposed system, and the results are presented below. The simulation outcomes are utilized to establish optimal scheduling and energy exchange strategies for residential use. These evaluations encompass three distinct scenarios under a single RTP pricing tariff using LBWO, viewed from both the perspectives of the intelligent user and the electric grid. Furthermore, a comparative analysis is conducted between the outcomes derived from our suggested approach and those obtained from BWO. The analysis is carried out on a singular household featuring a total of 12 appliances denoted as ‘A’, categorized as previously mentioned. It is worth noting that appliances categorized as essential loads may not partake in PAR reduction or electricity cost minimization, as they remain non-adjustable and must operate in accordance with user preferences.

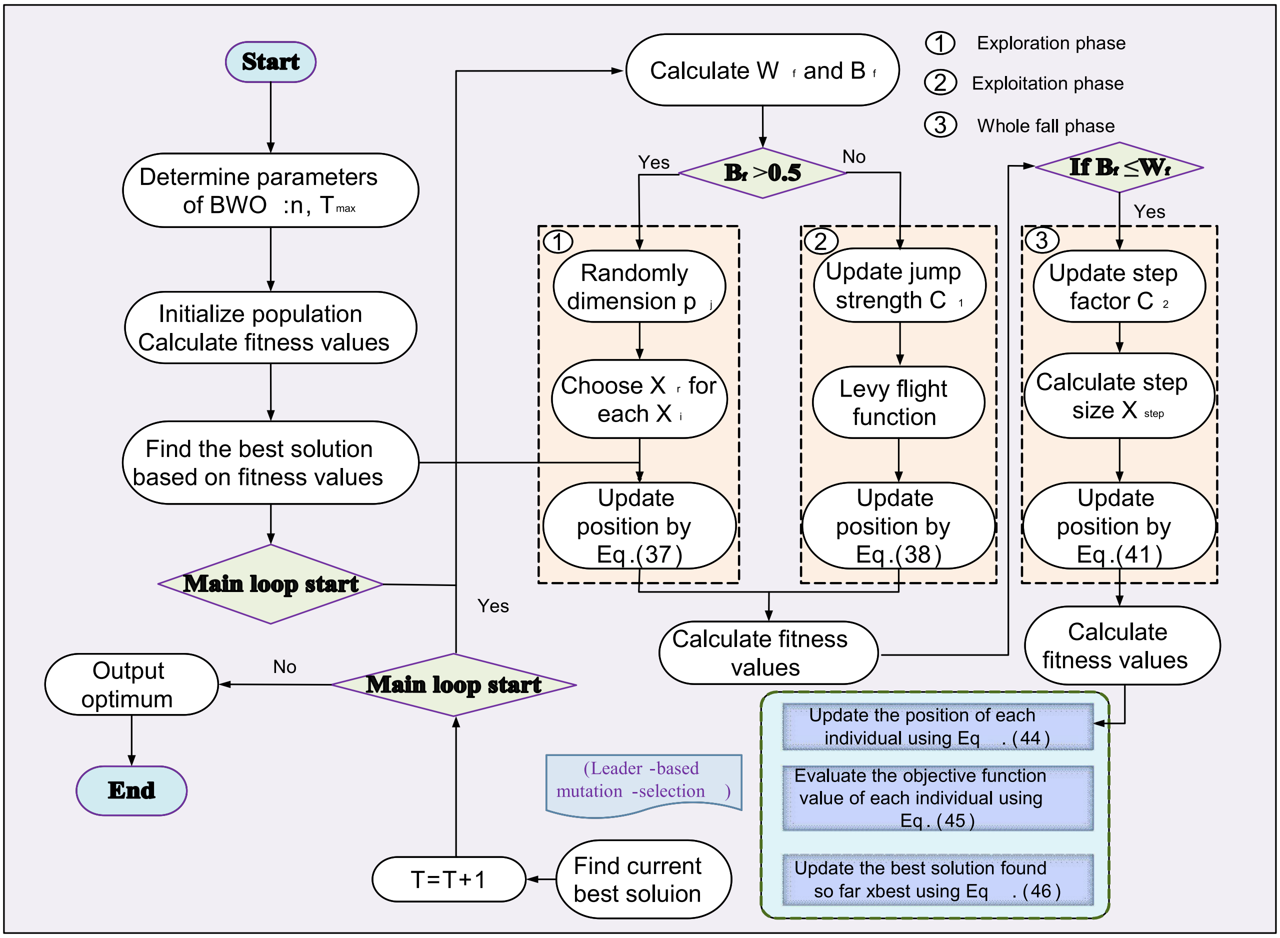


FIGURE 7. Flowchart of proposed LBWO algorithm.

The initial case study involves a conventional and uncomplicated household behavior where electricity consumption occurs without consideration of peak hours or electricity prices. The subsequent case study revolves around a savvy consumer who enjoys certain benefits, including the utilization of a personal microgrid for electricity generation. This case facilitates a comparative assessment from both the consumer's standpoint and the overall electrical network's perspective. The intelligent consumer is empowered to make autonomous decisions while interacting with the power grid. In the third and concluding case study, the smart consumer retains the advantages observed in the second case, while also incorporating an ESS. This allows the consumer not only to manage load transfers, but also to engage in electricity trading, storage, purchase, and sale. The proposed system strives to achieve a comprehensive performance equilibrium. The pertinent factors for our specific case scenario are outlined in Table 2 [31].

TABLE 2. Factors for case studies.

Factors	$V^{cut-off}$	V^{cut-in}	$wind^{cap}$	$solar^{cap}$	SOC	ESS^{CA}	η^{ESS}
Values	25	5	2 kW	1 kW	90%	5 kW	95 %

A. BENCHMARK FUNCTIONS

Within this subsection, the effectiveness of the suggested LBWO algorithm is showcased through evaluations across 23 benchmark functions [39]. This paper employs 23 widely recognized benchmark test functions to evaluate the performance of the LBWO algorithm. This paper sets the maximum iteration limit for all utilized metaheuristic techniques at 200, with a population count of 50. Within this section, a comparison is drawn between the proposed LBWO technique and several recent algorithms. These include five recently introduced algorithms, among which is BWO, artificial rabbits optimization (ARO) [40], supply demand based optimization (SDO) [41], wild horse optimizer (WHO) [42], and INFO [43]. Within this investigation, the solution's quality is assessed through the utilization of both standard deviation and mean value. A technique exhibiting lower standard deviation and mean value can be deemed as possessing robust global optimization capabilities and greater stability. Table 3 presents the statistical outcomes obtained

TABLE 3. Analyzing the statistical outcomes of benchmark functions involves assessing the performance of both the proposed lbwo algorithm and other recently introduced algorithms.

Function		LBWO	BWO	ARO	SDO	WHO	INFO
F1	Best	7.4E-179	1.5E-111	1.59E-26	1.39E-55	5.08E-21	4.44E-49
	Mean	5.3E-172	3.8E-106	1.07E-21	1.37E-51	2.85E-18	1.84E-43
	Median	3E-174	6.8E-108	4.68E-23	3.74E-54	1.14E-18	9.67E-46
	Worst	6.7E-171	2.5E-105	7.08E-21	8.43E-51	1.11E-17	2.45E-42
	std	0	6.8E-106	2.18E-21	2.74E-51	3.57E-18	5.79E-43
	Rank	1	2	5	3	6	4
F2	Best	1.23E-90	1.95E-57	1.34E-14	1.83E-29	4.13E-13	1.08E-24
	Mean	2.48E-87	2.56E-54	1.15E-12	3.76E-25	1.3E-10	1.83E-22
	Median	7.45E-88	1.15E-54	1.22E-13	1.13E-26	5.29E-11	1.11E-23
	Worst	2.87E-86	1.18E-53	1.78E-11	3.98E-24	6.34E-10	3.2E-21
	std	6.36E-87	3.58E-54	3.94E-12	9.1E-25	1.77E-10	7.11E-22
	Rank	1	2	5	3	6	4
F3	Best	1.1E-171	6.4E-104	4.28E-21	6.27E-46	5.13E-13	1.16E-39
	Mean	1.1E-163	5.5E-100	5.08E-15	6.91E-34	1.2E-08	1.27E-32
	Median	1.9E-166	1.2E-101	6.99E-17	1.4E-39	6.29E-11	4.71E-35
	Worst	2.1E-162	7.3E-99	6.41E-14	1.38E-32	2.3E-07	1.65E-31
	std	0	1.6E-99	1.51E-14	3.09E-33	5.14E-08	3.71E-32
	Rank	1	2	5	3	6	4
F4	Best	1.34E-89	9.97E-55	8.35E-13	1.11E-26	5.11E-09	1.21E-22
	Mean	2.41E-85	2.03E-52	2.6E-09	4.52E-23	3.5E-07	8.95E-19
	Median	4.75E-87	5.03E-53	7.79E-10	1.14E-23	1E-07	1.88E-20
	Worst	4.56E-84	1.38E-51	2.28E-08	1.94E-22	2.14E-06	1.5E-17
	std	1.02E-84	4.03E-52	5.09E-09	6.34E-23	6.09E-07	3.34E-18
	Rank	1	2	5	3	6	4
F5	Best	0	0.000406	0.048127	27.90967	26.68451	23.12486
	Mean	1.67E-22	0.010977	2.57084	28.65096	37.10656	24.43097
	Median	0	0.006422	1.069097	28.74726	27.67985	24.41788
	Worst	2.88E-21	0.05599	16.26736	28.98699	208.5133	25.78378
	std	6.46E-22	0.015734	3.783419	0.295026	40.37046	0.620893
	Rank	1	2	3	5	6	4
F6	Best	0	2.47E-08	0.009568	0.039957	0.013248	1.16E-06
	Mean	0	5.36E-07	0.044563	2.568541	0.064784	1.47E-05
	Median	0	3.77E-07	0.039666	2.038779	0.058665	8.52E-06
	Worst	0	1.4E-06	0.098375	7.250251	0.16971	3.81E-05
	std	0	4.28E-07	0.026373	1.852701	0.043941	1.31E-05
	Rank	1	2	4	6	5	3
F7	Best	1.12E-05	2.65E-06	3.22E-05	8.66E-05	0.000605	0.000201
	Mean	0.00018	0.000257	0.001407	0.002356	0.001779	0.00178
	Median	0.000126	0.000225	0.00115	0.001136	0.001387	0.00135
	Worst	0.000516	0.000674	0.003564	0.013813	0.004938	0.005593
	std	0.000156	0.000205	0.001071	0.003331	0.001255	0.001428
	Rank	1	2	3	6	4	5
F8	Best	-12569.5	-12569.5	-9902.5	-1655	-1807.46	-10946.2
	Mean	-12569.5	-12569.4	-9268.23	-1312.83	-1721.44	-9296.21
	Median	-12569.5	-12569.5	-9276.94	-1385.86	-1729.69	-9130.51
	Worst	-12569.5	-12568.9	-7798.04	-598.802	-1630.81	-7925.88
	std	1.87E-12	0.133263	494.4779	294.008	54.13894	668.4098
	Rank	1	2	4	6	5	3
F9	Best	0	0	0	4.33E-30	0	0
	Mean	0	0	0	1.75E-22	1.11E-05	0
	Median	0	0	0	4.17E-25	1E-09	0
	Worst	0	0	0	3.02E-21	0.000177	0
	std	0	0	0	6.75E-22	3.96E-05	0
	Rank	1	1	1	5	6	1
F10	Best	8.88E-16	8.88E-16	3.29E-14	8.88E-16	8.88E-16	8.88E-16
	Mean	8.88E-16	8.88E-16	5.19E-12	8.88E-16	1.003597	8.88E-16
	Median	8.88E-16	8.88E-16	1.26E-12	8.88E-16	7.99E-06	8.88E-16
	Worst	8.88E-16	8.88E-16	5.25E-11	8.88E-16	20.01369	8.88E-16
	std	0	0	1.17E-11	0	4.474524	0
	Rank	1	1	5	1	6	1
F11	Best	0	0	0	0	0	0

TABLE 3. *(Continued.)* **Analyzing the statistical outcomes of benchmark functions involves assessing the performance of both the proposed lbwo algorithm and other recently introduced algorithms.**

	Mean	0	0	0	0	1.83E-16	0
	Median	0	0	0	0	0	0
	Worst	0	0	0	0	3.66E-15	0
	std	0	0	0	0	8.19E-16	0
	Rank	1	1	1	1	6	1
F12	Best	1.57E-32	1.98E-09	0.000211	0.001152	4.64E-05	1.2E-07
	Mean	1.57E-32	9.39E-08	0.002555	0.23467	0.026544	0.005185
	Median	1.57E-32	5.17E-08	0.002594	0.067805	0.000309	1.34E-06
	Worst	1.57E-32	3.94E-07	0.004551	1.492821	0.207386	0.103675
	std	2.81E-48	1.04E-07	0.001218	0.352063	0.056802	0.023182
	Rank	1	2	3	6	5	4
F13	Best	1.35E-32	2.39E-09	0.005253	0.046216	0.011802	1.79E-05
	Mean	1.35E-32	5.23E-07	0.038605	1.867552	0.173897	0.098529
	Median	1.35E-32	2.89E-07	0.020631	1.934246	0.136817	0.097379
	Worst	1.35E-32	2.7E-06	0.218513	2.999924	0.700833	0.529646
	std	2.81E-48	6.67E-07	0.051532	0.961284	0.157716	0.119127
	Rank	1	2	3	6	5	4
F14	Best	0.998004	0.998004	0.998004	0.998004	0.998004	0.998004
	Mean	1.146516	1.246841	0.998004	3.494696	1.097209	1.047705
	Median	0.998004	0.998005	0.998004	1.495017	0.998004	0.998004
	Worst	3.96825	1.992033	0.998004	12.67051	2.982105	1.992031
	std	0.664167	0.441415	2.97E-16	3.953203	0.443659	0.222271
	Rank	4	5	1	6	3	2
F15	Best	0.000308	0.00031	0.000308	0.000307	0.000307	0.000307
	Mean	0.00065	0.000393	0.000441	0.00067	0.000602	0.002556
	Median	0.00044	0.000388	0.000404	0.000527	0.000593	0.000307
	Worst	0.001266	0.000627	0.000694	0.002121	0.001223	0.020363
	std	0.000395	7.9E-05	0.000131	0.000473	0.000286	0.006103
	Rank	4	1	2	5	3	6
F16	Best	-1.03163	-1.03162	-1.03163	-1.03163	-1.03163	-1.03163
	Mean	-1.03163	-1.03136	-1.03163	-1.03005	-1.03163	-1.03163
	Median	-1.03163	-1.03136	-1.03163	-1.03163	-1.03163	-1.03163
	Worst	-1.03163	-1.03076	-1.03163	-1.00046	-1.03163	-1.03163
	std	2.22E-16	0.000251	2.5E-12	0.006966	5.09E-17	2.04E-16
	Rank	1	5	4	6	1	1
F17	Best	0.397887	0.398229	0.397887	0.397887	0.397887	0.397887
	Mean	0.397887	0.40143	0.397887	0.397987	0.397887	0.397887
	Median	0.397887	0.400402	0.397887	0.397887	0.397887	0.397887
	Worst	0.397887	0.405685	0.397887	0.399795	0.397887	0.397887
	std	1.09E-10	0.002409	1.28E-10	0.000426	0	0
	Rank	3	6	4	5	1	1
F18	Best	3	3.007563	3	3	3	3
	Mean	3	3.711781	3	4.371758	3	3
	Median	3	3.290779	3	3	3	3
	Worst	3	6.445678	3	30.41145	3	3
	std	9.23E-16	0.936975	1.16E-15	6.129111	1.13E-15	1.51E-15
	Rank	1	5	4	6	1	1
F19	Best	-3.86278	-3.86145	-3.86278	-0.30048	-0.30048	-3.86278
	Mean	-3.86273	-3.85575	-3.86278	-0.2893	-0.30048	-3.86278
	Median	-3.86278	-3.85678	-3.86278	-0.30038	-0.30048	-3.86278
	Worst	-3.86183	-3.84711	-3.86278	-0.19165	-0.30048	-3.86278
	std	0.000213	0.004055	3.73E-15	0.026531	1.14E-16	2.19E-15
	Rank	3	4	2	6	5	1
F20	Best	-3.32094	-3.31363	-3.322	-3.322	-3.322	-3.322
	Mean	-3.2661	-3.24498	-3.31597	-3.09697	-3.21756	-3.28038
	Median	-3.30217	-3.25436	-3.322	-3.2031	-3.322	-3.322
	Worst	-3.20008	-3.14068	-3.2031	-0.89904	-2.43178	-3.2031
	std	0.054509	0.054354	0.026567	0.550986	0.239908	0.058182
	Rank	3	4	1	6	5	2
F21	Best	-10.1532	-10.1227	-10.1532	-10.1532	-10.1532	-10.1532
	Mean	-10.1532	-9.74473	-10.1187	-8.703	-9.77706	-9.26726
	Median	-10.1532	-9.79808	-10.1532	-10.1532	-10.1532	-10.1532
	Worst	-10.1532	-8.72237	-9.81141	-4.99677	-2.63047	-2.63047
	std	1.95E-15	0.386374	0.090338	2.23952	1.682133	2.210894
	Rank	1	4	2	6	3	5
F22	Best	-10.4029	-10.3758	-10.4029	-10.4029	-10.4029	-10.4029
	Mean	-10.4029	-9.42752	-10.1364	-8.45822	-9.75463	-9.15563
	Median	-10.4029	-9.95721	-10.4029	-10.4029	-10.4029	-10.4029

TABLE 3. *(Continued.)* **Analyzing the statistical outcomes of benchmark functions involves assessing the performance of both the proposed lbwo algorithm and other recently introduced algorithms.**

	Worst	-10.4029	-5.08737	-5.07631	-1.0677	-2.75193	-2.7659
	std	4.14E-08	1.306109	1.191013	3.128689	2.031123	2.598756
	Rank	1	4	2	6	3	5
F23	Best	-10.5364	-10.5033	-10.5364	-10.5364	-10.5364	-10.5364
	Mean	-10.5364	-9.65071	-10.1522	-7.90449	-10.5364	-7.51581
	Median	-10.5364	-9.992	-10.5364	-10.5357	-10.5364	-10.5364
	Worst	-10.5364	-6.91712	-3.83543	-3.79083	-10.5364	-2.42173
	std	1.67E-07	1.015355	1.502943	3.015319	1.58E-15	3.843362
	Rank	2	4	3	5	1	6
Average Rank		1.565217	2.826087	3.130435	4.826087	4.26087	3.130435
Final ranking		1	2	3	6	5	3

from the proposed LBWO algorithm and five contemporary algorithms, applied to address 23 benchmark functions. The results are portrayed in terms of standard deviation and mean value, with optimal outcomes emphasized in bold. Referring to the provided table, the LBWO algorithm demonstrates superiority over the compared algorithms across the majority of benchmark functions, considering average values. The above discussion highlights that the LBWO algorithm is capable of obtaining superior solutions when compared to numerous recently introduced techniques, particularly in the context of solving various benchmark functions. Additionally, the superiority of the LBWO algorithm over BWO, ARO, SDO, WHO, and INFO techniques in solving benchmark functions is evident. This discussion solidly illustrates the high effectiveness of the proposed LBWO algorithm.

Also from this table, the evident ranking order reveals that the proposed LBWO algorithm surpasses all the compared techniques across the spectrum of 23 benchmark optimization problems. The BWO and ARO algorithms demonstrate commendable robustness, securing the second and third positions in terms of effectiveness. This leads to the conclusion that the proposed LBWO technique establishes itself as a potent algorithm for addressing these particular problem types.

Additionally, the convergence curves using these techniques for each 23 benchmark functions are shown in Fig. 8. Every benchmark function undergoes 20 separate runs. Additionally, Fig. 8 illustrates that the proposed LBWO algorithm exhibits significantly improved convergence behavior when contrasted with the original BWO, ARO, SDO, WHO, and INFO algorithms. The LBWO algorithm's rapid convergence capability positions it as a proficient and promising solution for addressing real-world optimization challenges. In order to analyze the obtained results, a boxplot depicting the performance across 23 benchmark functions is presented in Fig. 9. Boxplots are exceptional graphical representations for showcasing data distribution, making them an excellent choice for emphasizing the alignment within the dataset. These plots showcase boxes representing the 1st, 2nd, and 3rd quartiles of values, along with vertical lines extending from the boxes known as whisker lines. These whisker lines offer insights into the range of data distribution. Fig. 9 further reveals that the boxplots associated with the proposed LBWO algorithm exhibit narrower shapes and predominantly occupy lower value ranges across a significant portion of the functions.

B. CASE 1: TRADITIONAL HOUSEHOLD

In the absence of energy management and a limited grid capacity, a typical household is unable to generate surplus electricity for resale. This conventional residence struggles to effectively control its electricity usage. Furthermore, the resident unknowingly and without any awareness of electricity costs or other considerations, lacks the capacity to make informed choices regarding electricity consumption. In this scenario, electricity is purchased and utilized without mindful consideration.

Referencing Fig. 10, there is a depiction of pricing signals alongside the electricity consumption of traditional households from the grid. This visual representation clearly demonstrates that the electricity usage by the consumer is haphazard and uninformed, as they disregard electricity prices. Notably, during periods of elevated electricity prices (as shown in the 9-10 timeframe), the consumer continues to purchase and consume electricity, thereby creating consumption peaks that impact the grid's stability.

As highlighted in Fig. 11, the cost of electricity is displayed on an hourly basis. Fig. 12 goes on to exhibit the cumulative electricity expenses. However, it should be noted that the outcomes derived from this scenario serve as a foundational reference for our forthcoming comparisons.

C. CASE 2: HOUSEHOLD HAS AN ENERGY MANAGEMENT SYSTEM BUT LACKS MICROGRID

Home energy management is taken into account, and the intelligent consumer has the ability to control their electricity consumption. Devices with adaptable functionality can change when they operate, moving from times of high demand to times of lower demand. In this situation, an energy management controller is set up, and it adjusts the usage pattern based on pricing and load information. Fig. 13 depicts the hourly electricity consumption under two scenarios: one without any load scheduling, and the other with load scheduling using LBWO and BWO methods.

In Fig. 10, it's evident that the employment of LBWO results in lower electricity consumption compared to the

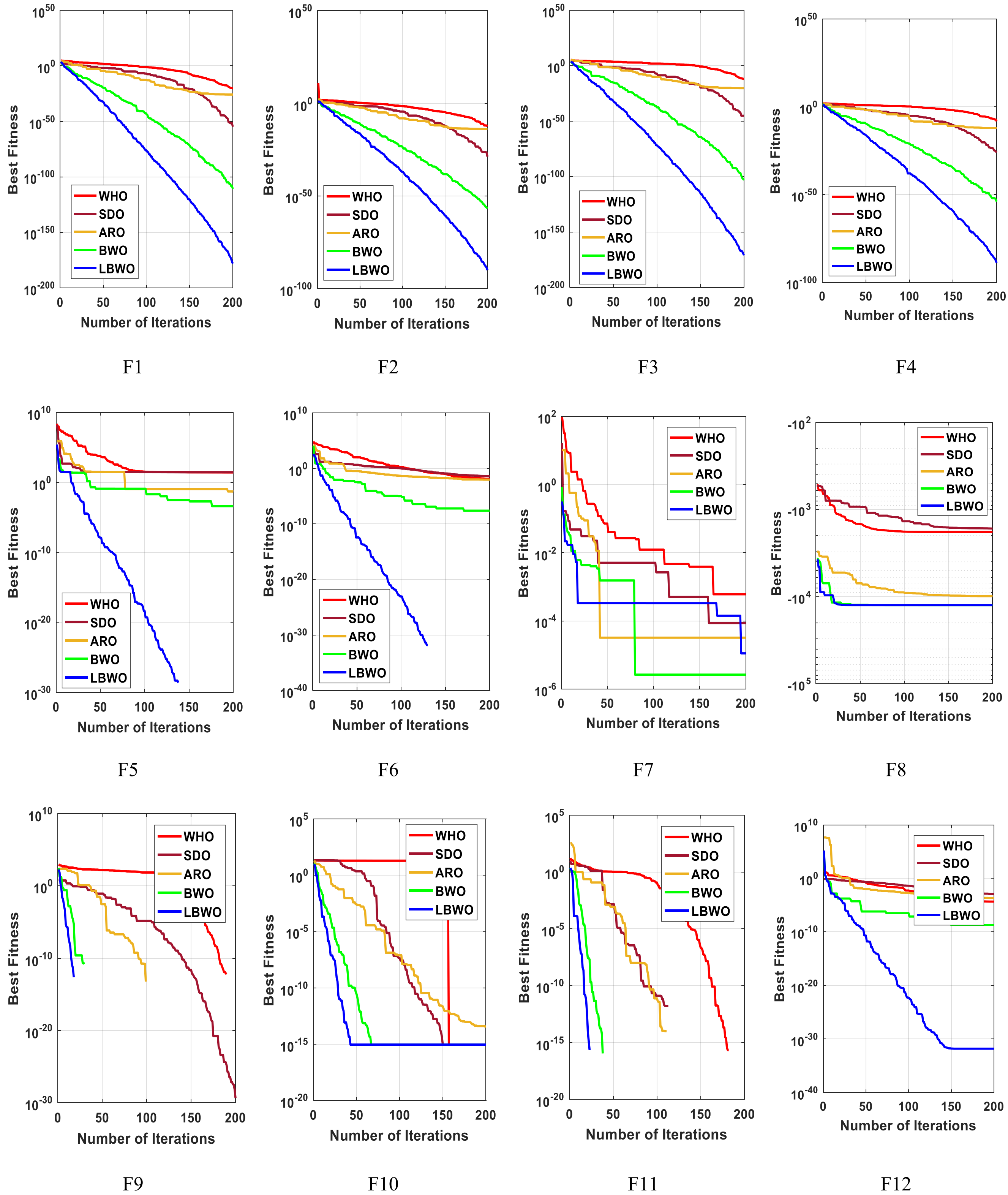
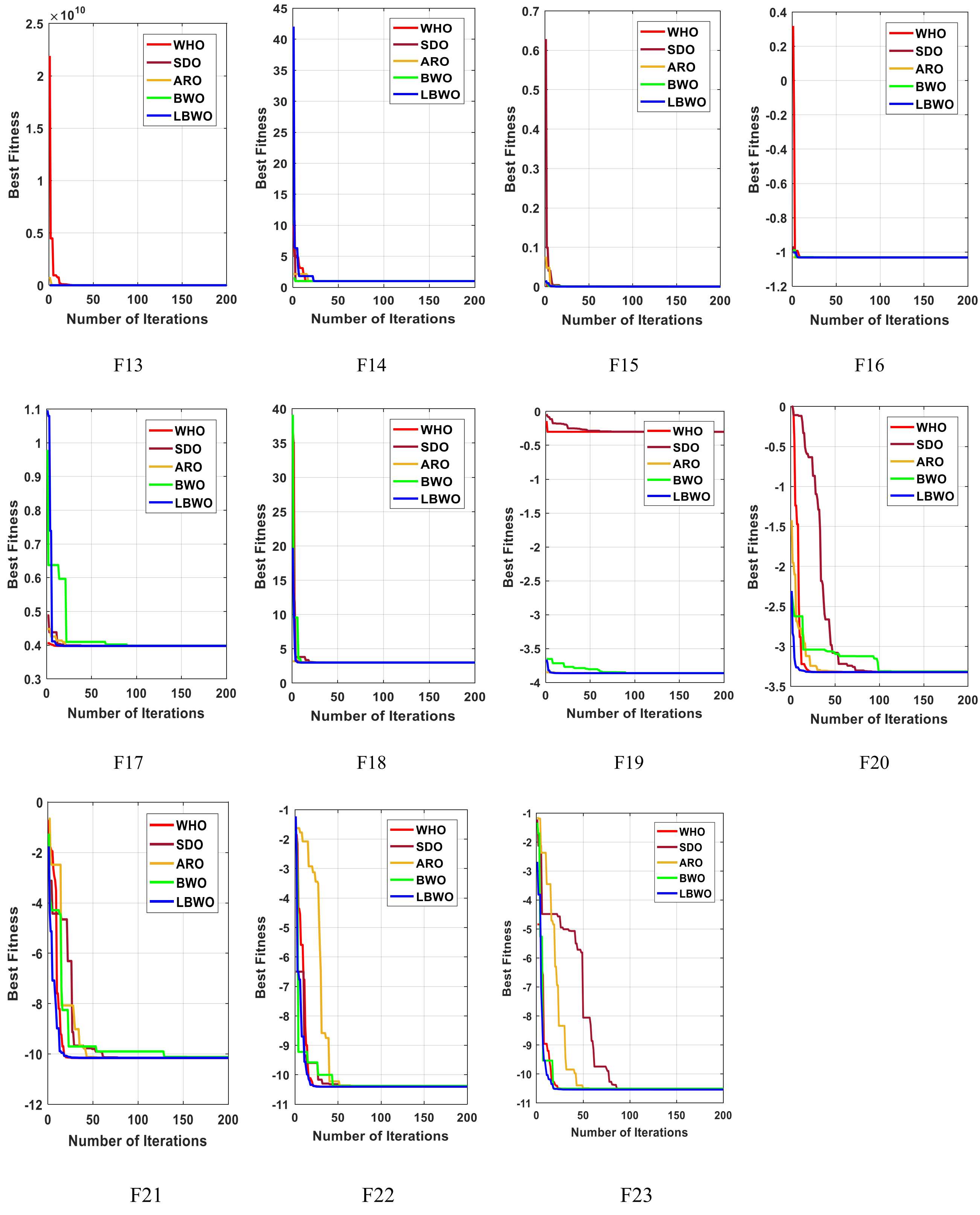


FIGURE 8. Convergence characteristics of applied algorithms for 23 benchmark functions.

utilization of BWO, which leads to a lower consumption than unscheduled electricity usage. Moving on to Fig. 14, it demonstrates the effective reduction of PAR through load shifting. LBWO exhibits notably better performance in



F13 F14 F15 F16

F17 F18 F19 F20

F21 F22 F23

FIGURE 8. *(Continued.)* **Convergence characteristics of applied algorithms for 23 benchmark functions.**

PAR reduction, outperforming both the BWO scenario and the unscheduled condition. Specifically, the application of LBWO and BWO brings about a reduction in PAR by 26% and 15%, respectively.

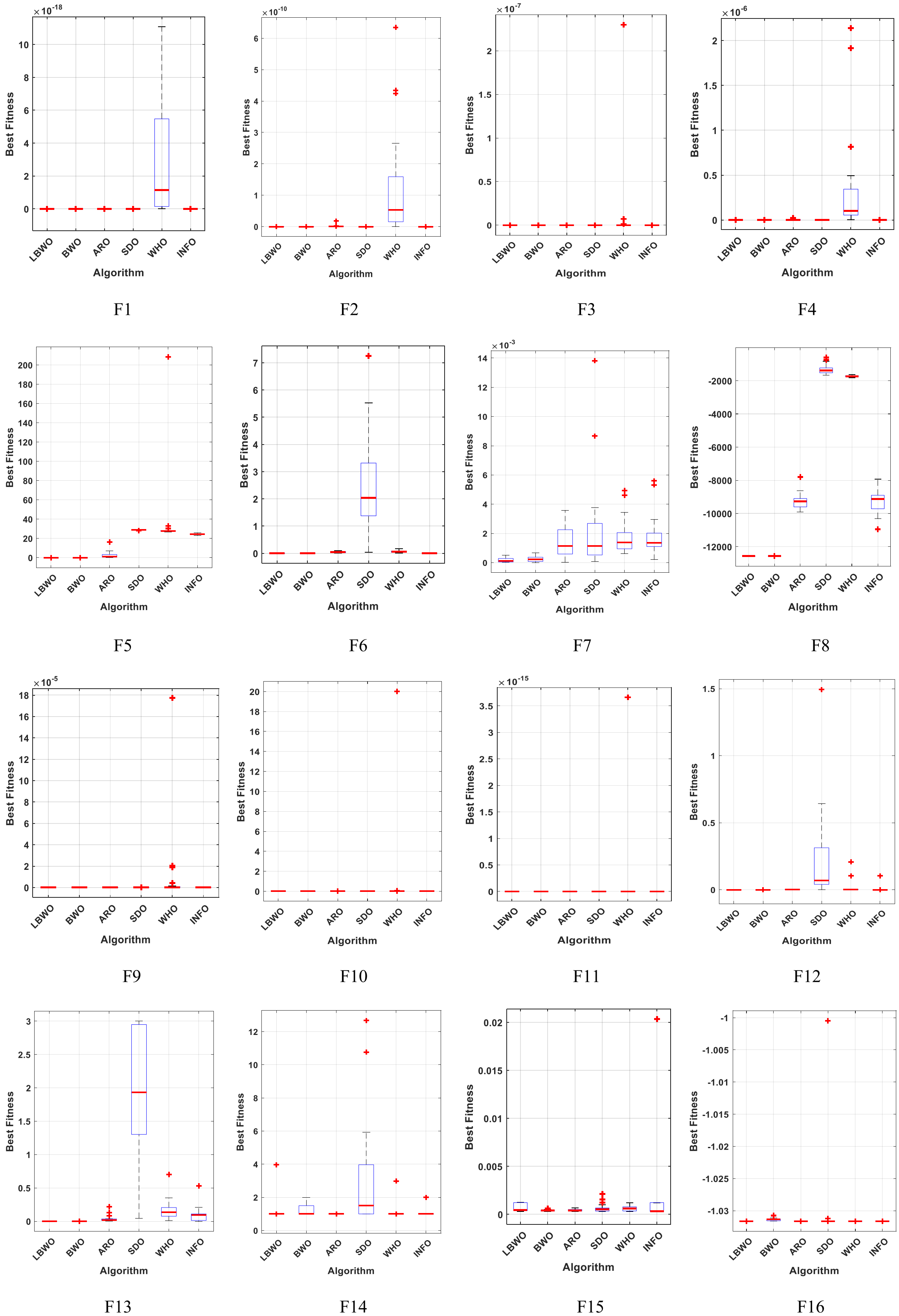


FIGURE 9. Boxplots of applied algorithms for 23 benchmarks functions.

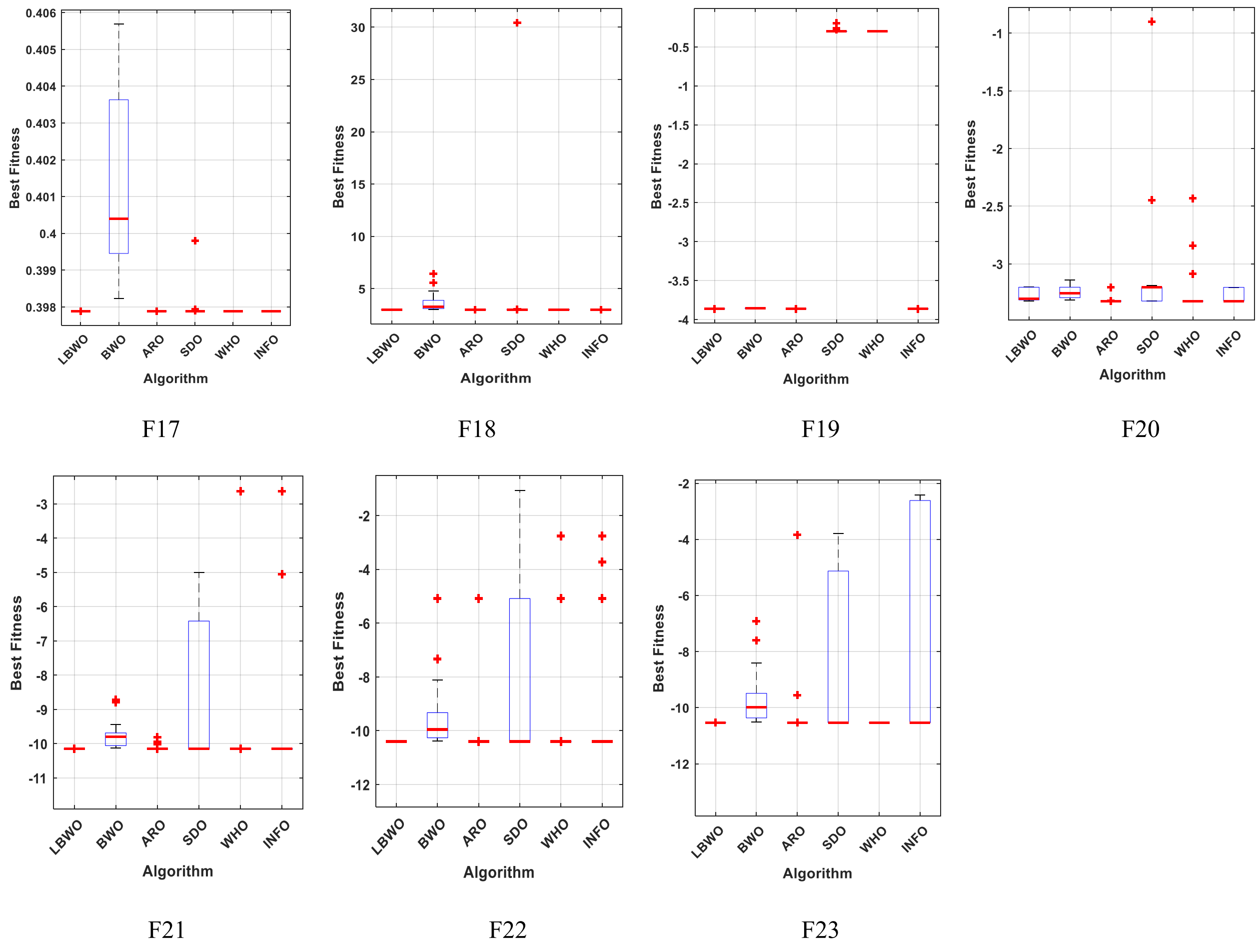


FIGURE 9. *(Continued.)* Boxplots of applied algorithms for 23 benchmarks functions.

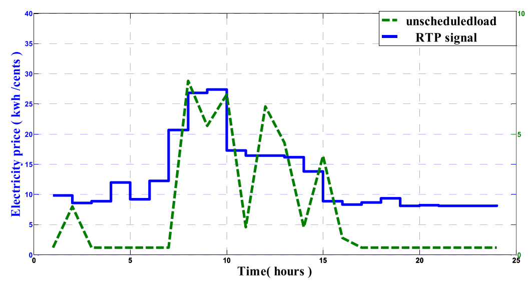


FIGURE 10. Electricity consumption and RTP signal.

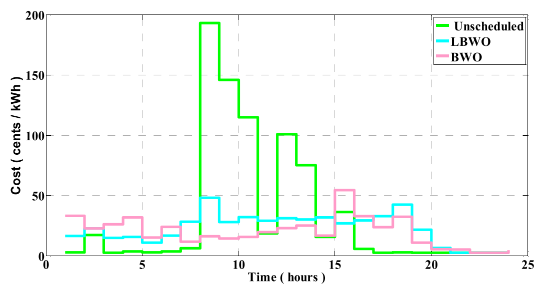


FIGURE 11. Hourly cost of electricity consumption.

Through the implementation of energy management, we effectively reduce the hourly electricity expenses, which consequently leads to the eventual reduction of the overall daily electricity costs. This is clearly demonstrated in Fig. 11, where the application of LBWO and BWO during peak hours results in minimized electricity costs, outperforming unscheduled energy consumption patterns. Fig. 12 offers a graphical representation of the total daily electricity cost. Both figures distinctly show that electricity costs are minimized with the use of LBWO, surpassing the benefits of BWO and unscheduled energy consumption.

Moreover, when employing BWO, the electricity costs are lower compared to unscheduled consumption. In the second scenario, a combined reduction in electricity costs of 61% and 51% is achieved through the utilization of LBWO and BWO, respectively.

D. CASE 3: HOUSEHOLD HAS MICROGRID AND AN ENERGY MANAGEMENT SYSTEM

In this context, the focus shifts towards a microgrid that integrates an ESS, mirroring the intelligent home scenario

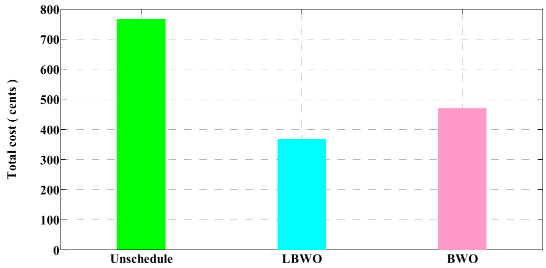


FIGURE 12. The total cost of electricity consumption.

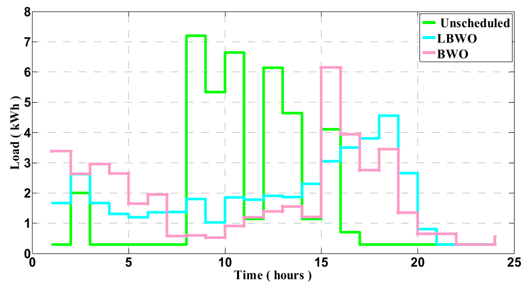


FIGURE 13. Electricity consumption per hour without and with load scheduling.

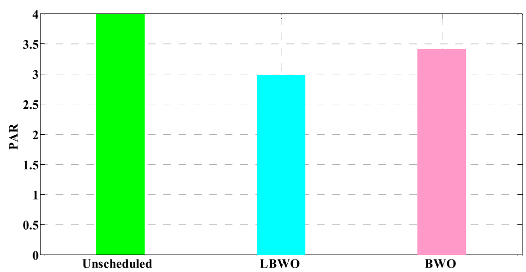


FIGURE 14. PAR.

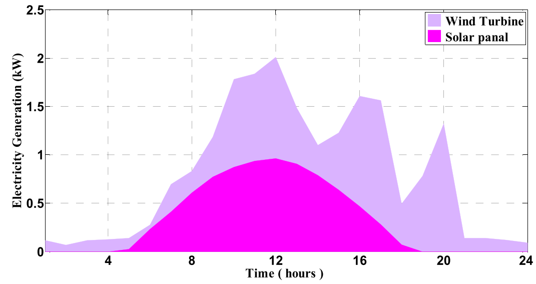


FIGURE 15. Electricity generation from solar panels and wind turbines.

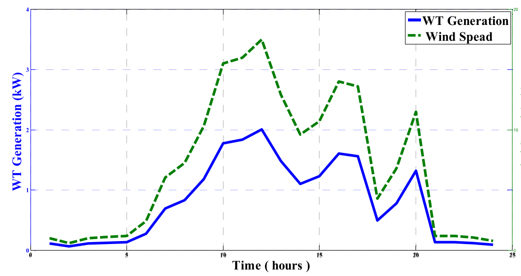


FIGURE 16. The effect of wind speed on electricity generation from wind turbines.

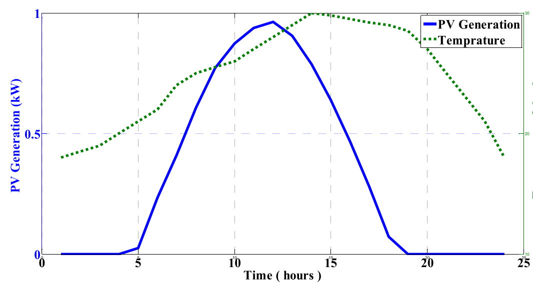


FIGURE 17. The effect of temperature on electricity generation from solar panels.

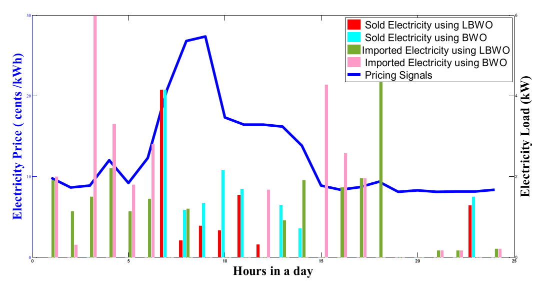


FIGURE 18. Tariff price with electricity selling and importing.

mentioned earlier. The informed consumer possesses the ability to make timely decisions on an hourly basis, adjusting energy usage, purchasing or vending electricity, and storing power. In this situation, surplus electricity is sold back to the grid when prices are high. The microgrid caters to energy demands during peak periods and imports power from the public grid when prices are low. This strategy maximizes the smart home's financial gains. Fig. 15 portrays wind turbines and solar panels for generating electricity. Power generation from the microgrid dwindles in the morning and evening due to decreased sunlight and lower wind velocities. In contrast, the highest output occurs during peak operating hours, coinciding with the peak wind speed and solar radiation in the daytime.

The effectiveness of wind turbine electricity generation hinges on wind speed. Greater wind speeds result in more substantial electricity production. Conversely, low wind speeds lead to diminished output, while high wind speeds escalate electricity generation. Hence, there exists a direct correlation between wind speed and the electricity yielded by wind turbines, as depicted in Fig. 16. Solar panel electricity generation efficiency, on the other hand, hinges on temperature. Generally, higher temperatures enhance the conversion of solar radiation into electricity. This indicates an inverse connection between temperature and solar panel efficiency in power generation, as shown in Fig. 17.

Fig. 18 showcases the collective import and export of electricity facilitated by both the LBWO and BWO algorithms. Proficient execution of these actions enables the

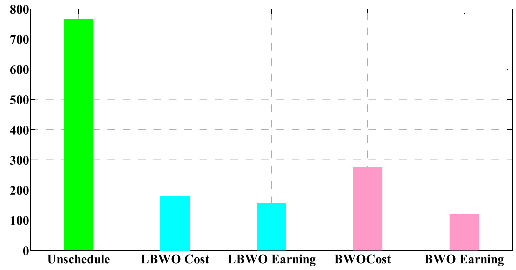


FIGURE 19. Earning and cost for electricity selling and importing.

TABLE 4. Comparison between studied cases.

Parameters	Case 1	Case 2		Case 3	
Technique		LBWO	BWO	LBWO	BWO
PAR	3.99	2.94	3.41	2.11	2.87
Cost (cents)	766	376	470	179	274
Cost savings	0	61%	51%	76%	64%
Earnings (cents)	0	0	0	154	118

consumer to achieve optimal gains through electricity trading. Furthermore, the suggested LBWO algorithm surpasses the performance of BWO, particularly in terms of energy trading during high-cost periods and load distribution. Total profit resulting from electricity sales and overall electricity expenses are depicted in Fig. 19. The proposed LBWO algorithm distinctly excels over BWO in terms of enhancing returns and minimizing electricity costs.

E. DISCUSSION

This section offers an elucidation of the three preceding studied cases, accompanied by a comparative analysis involving the proposed diagrams utilizing LBWO and BWO algorithms. In Fig. 19, there is a notable reduction in electricity costs, highlighting the increased efficiency of Case 3 in comparison to Case 2. Displayed in Fig. 18 is the amalgamated electricity intake from the external grid, and upon juxtaposing the three cases, it becomes evident that Case 3 exhibits the lowest electricity import volume when compared to Cases 2 and 1.

In terms of the PAR, Case 2 surpasses Case 1 in terms of diminishing the PAR value, as evidenced by Fig. 14. The integration of ESSs is imperative to ensure a dependable and stable grid. This integration is exemplified in Case 3, where energy is adeptly managed to enhance profitability, as illustrated in Fig.19. Table 4 encapsulates the comparative analysis among the three cases utilizing LBWO and BWO algorithms.

VII. CONCLUSION

In this study, we successfully implemented DMS in conjunction with a RTP tariff to develop an effective electricity load management strategy utilizing LBWO and BWO techniques. Our primary objective was to optimize electricity consumption for a smart household equipped with a microgrid connected to the main grid, addressing both load optimization and energy trading challenges. The integration of ESSs proved to be essential in ensuring a resilient and consistent power grid operation. This approach empowers smart consumers to efficiently distribute, purchase, sell, or store electricity.

To validate the effectiveness of our proposed scheme, we conducted a comprehensive comparative analysis across various cases and scenarios. The simulation results unequivocally demonstrate the superiority of our approach in terms of profit maximization, PAR reduction, and overall electricity cost savings. In specific instances, such as Case 2, we observed a notable reduction in electricity costs by 61% and 51% through the utilization of LBWO and BWO methods, respectively. In a more challenging setting, for Case 3, the electricity costs demonstrated a remarkable decrease of 76% and 64% with the employment of LBWO and BWO, reaffirming the robustness of our proposed scheme.

Furthermore, our proposed strategy exhibited promising profitability, achieving profits of 154 and 118 cents through LBWO and BWO, respectively. Notably, across all evaluated scenarios, LBWO consistently outperformed BWO in terms of profit maximization, PAR reduction, and cost minimization.

As a direction for future work, our research opens avenues for exploring the integration of advanced machine learning algorithms to enhance load forecasting accuracy and adaptive decision-making. Additionally, investigating the scalability of the proposed scheme to larger and more complex energy systems could provide insights into its applicability in real-world scenarios. Moreover, incorporating real-world data and considering dynamic factors such as changing energy prices and consumer behaviors would contribute to a more comprehensive evaluation of the scheme's performance.

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