Power Management using a modified WOA with Three Chaotic Maps

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Abstract

Electrical devices have become an important part of modern daily life. They are widely used in household activities such as cleaning, laundry, refrigeration, cooling systems, and water pumping. The use of these devices increases electricity consumption. A heavy load on the electrical grid is placed during peak hours because of working many electrical devices simultaneously, which results in higher electricity costs due to time-varying energy prices. To solve this problem, scheduling of household electrical devices has become one of the major research topics in energy management systems. Correct scheduling can prevent multiple devices from operating at the same time, which leads to reducing both peak demand and electricity costs by improving overall energy efficiency. This article proposed an enhanced Whale Optimization Algorithm (WOA) to determine the best scheduling for running the household appliances. The proposed approach aims to minimize electricity cost and power consumption while maintaining efficient device operation. In order to improve the exploration capability of the conventional WOA, three chaotic maps are incorporated into the algorithm with a mutation in some places to determine the search positions instead of using random numbers. This modification helps the algorithm converge faster and achieve better optimization performance. The results show that the proposed method provides effective device scheduling and achieves significant reductions in electricity cost and energy consumption compared with the standard WOA approach.

Keywords- COWA, Chaotic optimization algorithm, REFIT, Personalized Retrofit, standard deviation.

I. INTRODUCTION

Reducing the total electricity cost and maintaining the stability of hourly power consumption using power management is one of the major interesting matters nowadays. In [1], a hybrid optimization method consisting of (DHO – LAO) is used in a renewable system to produce an electrical system with the previous characteristic.

Optimization algorithms are widely used in the field of power management to reduce energy consumption and improve system efficiency. In [2], enhancement L´evy algorithm is used to manage the power in renewable energy sources, which produced better energy cost than other original optimization algorithms.

In another study, a hybridization of the Whale Optimization Algorithm (WOA) and the Genetic Algorithm (GA) was proposed to optimize the utilization of renewable energy resources and reduce reliance on fossil fuels by integrating them into a hybrid microgrid system. The results demonstrated that the proposed method reduced electricity cost by 13%–17% compared with conventional WOA and Grey Wolf Optimization (GWO) methods. Furthermore, the system achieved up to 100% renewable energy utilization while significantly improving the overall efficiency of the microgrid system [3].

Also, (Ga) is used alone to manage a microgrid system for a clean and renewable system. The MG consists of a photovoltaic generator and battery storage system. The objective of this system is to achieve load power requirements with minimum cost and protect the battery from depletion. This work reduces the overall cost of the system by 17.66% when compared with the state space heuristic optimization approach [4].

The Whale Optimization Algorithm (WOA) is considered one of the classical metaheuristic optimization algorithms. It is characterized by its simplicity and the use of a small number of control parameters, which makes it easy to implement in various optimization problems. However, the original WOA suffers from the drawback of being trapped in local optima, which may reduce its exploration capability and affect the quality of the obtained solutions.

To solve this limitation, several researchers have proposed different modification methods by integrating WOA with other optimization techniques or mathematical strategies.

In [5], a nonlinear time-varying self-adaptive perturbation strategy together with an Archimedean spiral structure was incorporated into the original WOA framework. The proposed modification improves the exploration ability of the algorithm and population diversity, leading to better global search performance compared with the standard WOA.
Another method was used to improve the efficiency of WOA. One of these methods chaotic map, which is a mathematic functions(sin, tent, sinusoidal, logistic, etc.) generate a random number used to assign a value for WOA parameters. The random value enlarges the global search space for the WOA and prevent remain in a local optimum, and helps in finding the target faster than the original one [6]. This article aims to use (3) chaotic maps with WOA to manage the power in a smart town and compare the result with the system working on the original WOA. Using a chaotic map leads to producing random numbers for WOA variables improve the exploration and exploration with avoiding fail in the local optimum. The WOA take it behaviors from the hunting method of the humpback whales, with the way of surrounding their prey. The current position of whales is considered the best position for reaching prey or the nearest one to get the prey, as shown in equations (1,2) :

$$\overrightarrow{D} = \left|\vec{C}.\overrightarrow{X_p}(t) - \vec{X}(t)\right| \qquad (1)$$
$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A}.\vec{D} \qquad (2)$$

Where t represents the current iteration, $\vec{A}$, $\overrightarrow{D}$ refers to the coefficient, the position vector of the prey is represented by $\overrightarrow{X_p}$, and $\vec{X}$ denotes the position vector of a whale. The vectors $\vec{A}$ and $\vec{C}$ are calculated from the equation. (3,4):

$$\vec{A} = \overrightarrow{2a}.\overrightarrow{r_1} - \vec{a} \qquad (3)$$
$$\vec{C} = 2.\overrightarrow{r_2} \qquad (4)$$

Where components of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iterations, and r1, r2 are random vectors in [0,1] [5]. The core behavior of WOA is presented in the exploitation phase, which is performed in two ways: in the first method, the distance gradually decreases to the best solution. The whales move in a spiral path toward the prey in the second method, which can be represented in equations (5,6):

$$\vec{X}(\boldsymbol{t}+\boldsymbol{1}) = \overrightarrow{D^1}\, e^{bt} cos(2\pi t) + \overrightarrow{X^*}(t) \qquad (5)$$
$$\text{Where } \overrightarrow{D^1} = \left|\overrightarrow{X^*} - \vec{X}(t)\right| \qquad (6)$$

The encircling and spiral behaviors are indicated by random number p so [7]:

If $p < 0.5$ (encircling behaviors)
If $P \geq 0.5$ (spiral behaviors)
Using a chaotic map with the WOA effect on $\vec{A}$ and $\vec{D}$ parameters which can be represented as shown in (7,8) [6]:

$$\vec{A} = \overrightarrow{2a}.\overrightarrow{U_n} - \vec{a} \qquad (7)$$
$$\vec{C} = 2.\overrightarrow{U_n} \qquad (8)$$

Where $\overrightarrow{U_n}$ calculated from the following equation:

$$\overrightarrow{U_{n=1}} \begin{cases} 2U_{n} & U_k < 0.5 \\ 2(1-U_k) & U_k \geq 0.5 \end{cases} \qquad (9)$$

The above equation is used when (tent) is a chaotic map function [8].

II. RESEARCH ELABORATIONS

In this study, the REFIT Electrical Load Measurements Dataset was used, which is a widely used benchmark dataset for residential energy consumption analysis[9]. The dataset was collected from multiple households in the United Kingdom and contains detailed measurements of power consumption for electrical devices over an extended period. It provides high-resolution energy usage data, enabling accurate modeling and evaluation of power management and scheduling algorithms. Each household dataset includes time-series records of electrical consumption for various devices, such as washing machines, refrigerators, microwaves, and other devices In this work, a subset of the dataset was utilized, where the device-level consumption data were aggregated into hourly values for multiple days. Specifically, data from selected houses were extracted and processed to construct a scheduling problem with a 24-hour horizon per day. Furthermore, the use of the REFIT dataset allows for a realistic evaluation of the proposed algorithm under practical residential energy scenarios, making the obtained results reliable and comparable with existing studies in the literature.
The proposed algorithm is an Advanced - CWOA, which integrates chaotic maps, Lévy flight, mutation, and opposition-based learning with the standard WOA to enhance exploration and exploitation balance, avoiding premature convergence and improving

solution quality. Figure 1 shows the flowchart of the proposed algorithm. To enhance diversity, three chaotic maps are used, which are:

- Logistic map: $x_{n+1} = r.x_n.(1 - x_n)$ (10)
- Tent map: $x_{n+1} = \begin{cases} \frac{x_n}{\mu}, & x_n < \mu \\ \frac{1-x_n}{1-\mu}, & x_n \geq \mu \end{cases}$ (11)
- Sine map $x_{n+1} = \sin(\pi.x_{n)}$ (12)

These maps generate dynamic random value to enhance the diversity of the solutions, improve the randomness of the search, and prevent local optimum. Lévy Flight (Exploration Enhancement) with mutation, to get the new next position, is also used to escape from the local region by producing a random long-distance step with random mutation applied to some dimensions. Finally, opposition–based (OBL), which generates the opposite solution for each solution. When the fitness is better,it replaces the current one.OBL is a technique often used in optimization algorithms to enhance exploration of the search space which can be demonstrated in the following main steps:

- **Define search space**: Identify the lower bound lb and upper bound ub for each dimension of the problem.
- **Generate candidate solution**: Create a random or algorithm-driven solution X = (x1,x2,..., xd).
- **Compute the opposite solution**: For each dimension j, calculate the opposite value:

$$x_{jopposite} = lb_j + ub_{j-}x_j \quad (13)$$

- **Evaluate fitness**: Compute the objective function for both X and its opposite, X-opposite.
- **Select a better solution**: Compare fitness values and keep the one with better performance.
- **Iterate process**: Repeat the steps during initialization or within iterations of the optimization algorithm to enhance convergence and exploration.

This method helps algorithms avoid local optima and increases the chance of finding better solutions by considering both a point and its opposite in the search space.

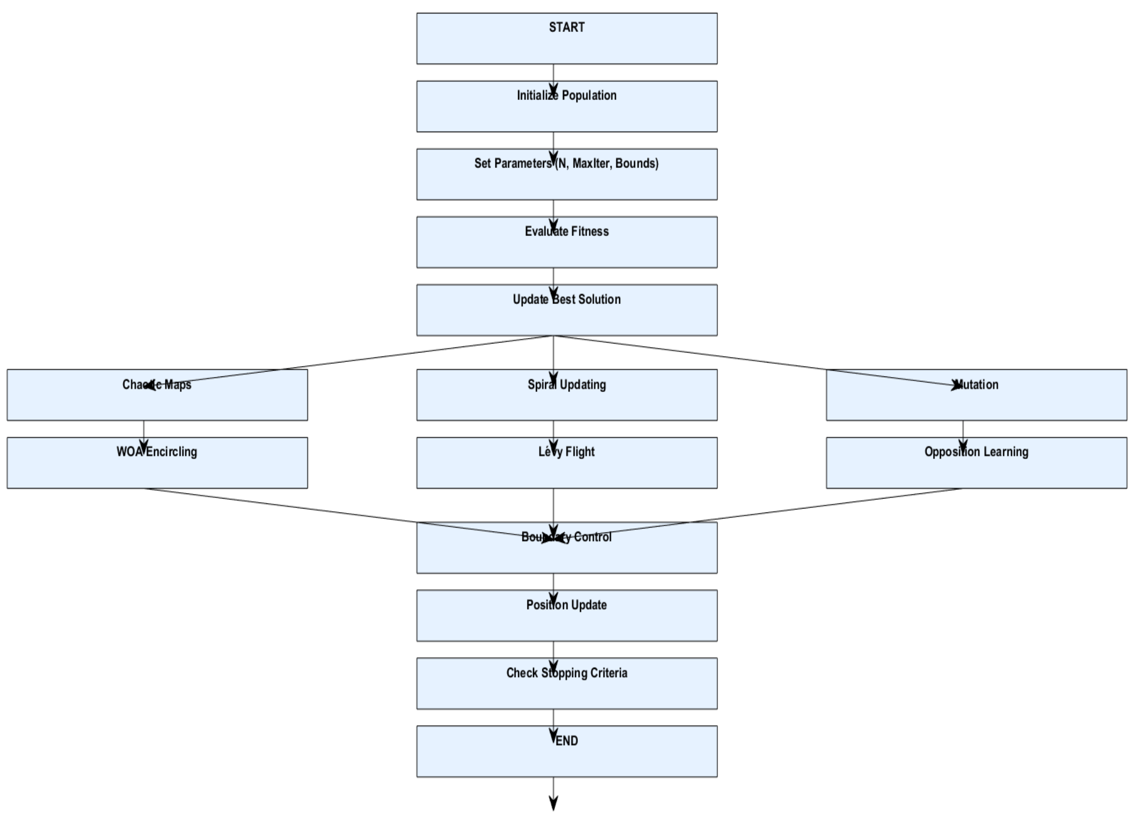

Figure 1: Flow chart of the Proposed Algorithm

III. RESULTS OR FINDINGS

The proposed CWOA_Advanced algorithm was evaluated on three different residential datasets to assess its effectiveness and robustness by taking the information of three houses from the dataset. The cost and the standard deviation which used to measure the performance and stability of the system when using the proposed algorithm in addition to another three optimization algorithms (GA, CWO, GWO) are declared in table 1 and table 2. which show that the proposed algorithm overcome the other algorithms in terms of cost and stability at lower iteration which make it a good choice to use for real time micro grid home energy management system when rabid decision are required. Its behavior came from the fast exploration, which helps to reach the appropriate Google as early as possible. At iteration greater than 20, the GWO overcomes the proposed one in terms of cost, but it is still unstable, which gives the possibility of changing the result at any time. The fast exploration property for the modified CWOA came from adding the chaotic map, Lévy Flight, and OBL. Chotic maps enhance the distribution of agents across the search space to prevent the early convergence, Lévy Flight gives a long-distance move for the agent to prevent local optimum, and finally OBL increases the probability of locating promising search areas by simultaneously considering candidate solutions and their opposite positions.

TABLE I. THE COST AND STANDARD DEVIATION USING 15 ITERATIONS.

House	Algorithm	Mean Cost	Std Dev
House 1	WOA	479658.585833	665.495197
House 1	CWOA	476323.735463	2263.531968
House 1	GWO	493381.314630	5419.568067
House 1	GA	570632.161991	5143.152052
House 2	WOA	698839.505694	448.876030
House 2	CWOA	696577.742870	1629.389454
House 2	GWO	717876.887454	6705.099511
House 2	GA	805313.785000	4745.318345
House 3	WOA	893741.768750	765.884200
House 3	CWOA	889588.401667	2155.441042
House 3	GWO	901335.474907	5041.286425
House 3	GA	978637.099028	5612.976616

Figure 2: Mean cost for the selected algorithms at 15 Iterations for House1

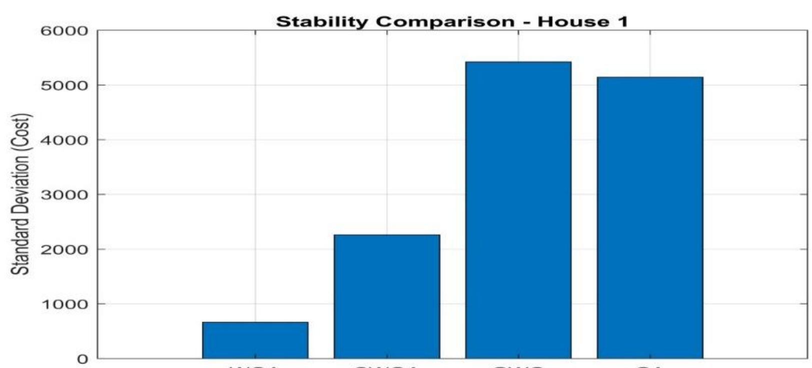

Figure 3: Stability for the selected algorithms at 15 iterations for House1

Figure 4: Mean cost for the selected algorithms at 15 Iterations for House 2

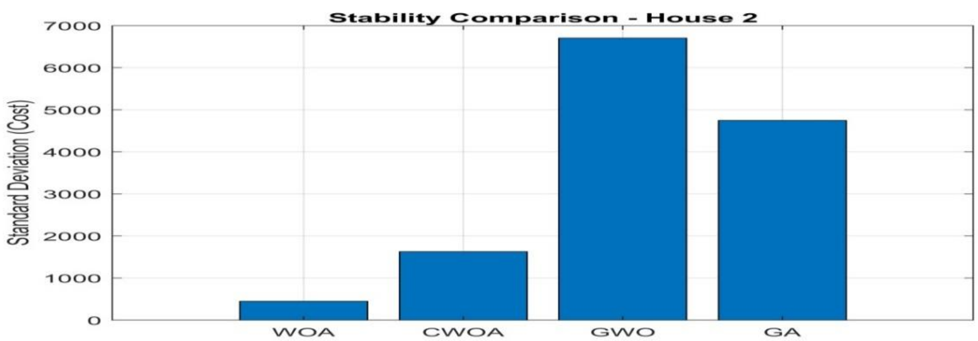

Figure 5: Stability for the selected algorithms at 15 iterations for House 2

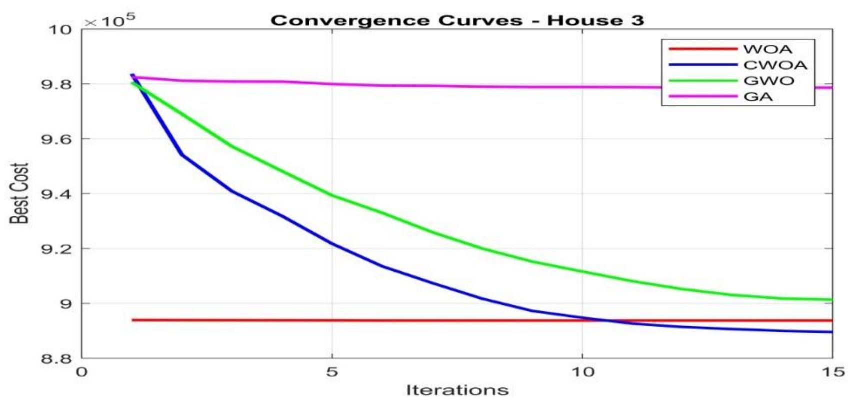

Figure 6: Mean cost for the selected slgorithms at 15 Iterations for House 3

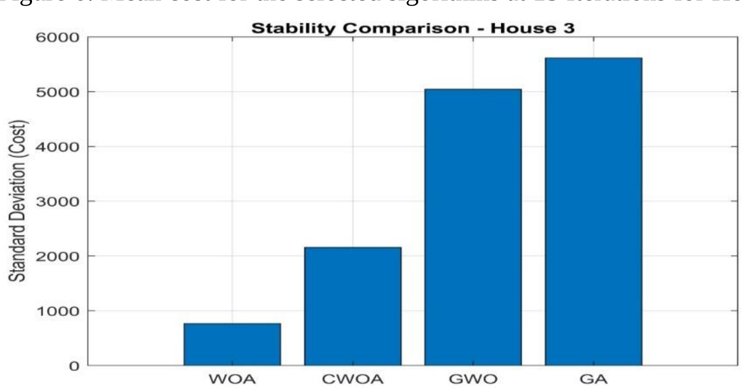

Figure 7: Stability for the selected algorithms at 15 iterations for House 3

TABLE II. THE COST AND STANDARD DEVIATION USING 30 ITERATIONS.

House	Algorithm	Mean Cost	Std Dev
House 1	WOA	479774.912870	602.564461
House 1	CWOA	473364.793750	2671.791010
House 1	GWO	468836.326620	3850.213408
House 1	GA	571607.711528	5481.373080
House 2	WOA	698783.456806	457.165648
House 2	CWOA	694263.987593	1835.365654
House 2	GWO	694594.975556	3427.222015
House 2	GA	804769.112454	5791.556565
House 3	WOA	893583.973194	785.443197
House 3	CWOA	886211.286157	2616.209180
House 3	GWO	879535.903426	4149.070352
House 3	GA	978707.351620	4660.062532

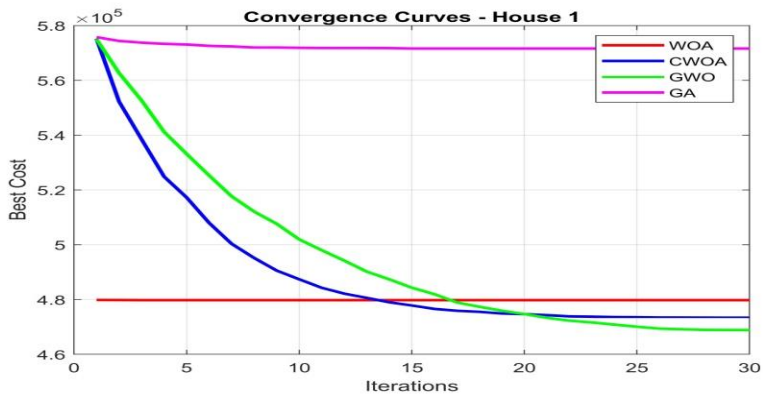

Figure 8: Mean cost for the selected algorithms at 30 Iterations for House 1

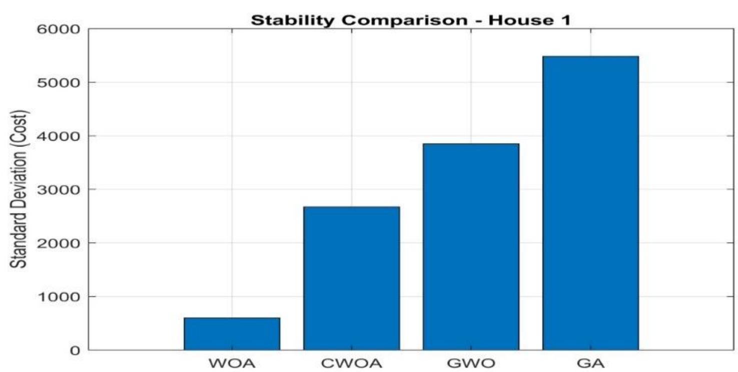

Figure 9: Stability for the selected Algorithms at 30 iterations for House 1

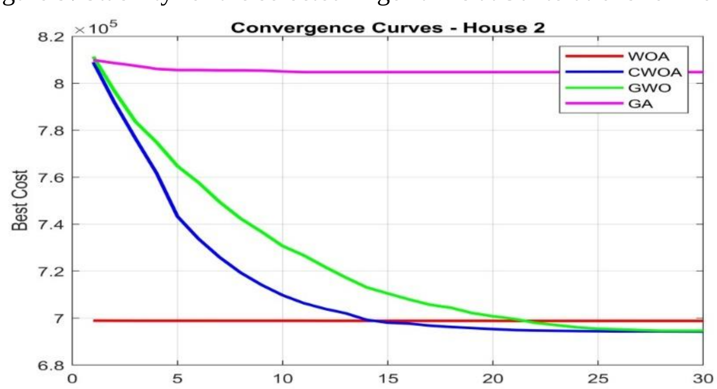

Figure 10: Mean cost for the selected algorithms at 30 Iterations for House 2

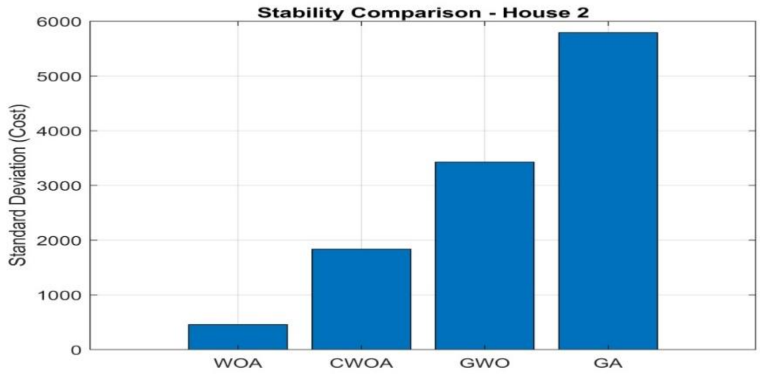

Figure 11: Stability for the Selected algorithms at 30 iterations for House 2

Figure 12: Mean cost for the selected algorithms at 30 Iterations for House 2

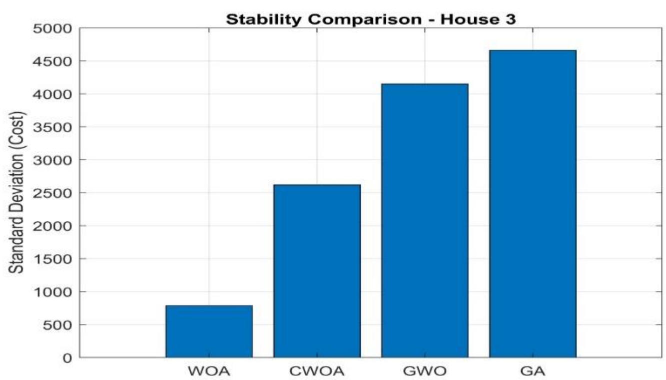

Figure 13: Stability for the selected algorithms at 30 iterations for House 3

IV. CONCLUSION

This paper developed an improved version of the Whale Optimization Algorithm (CWOA) for habitation building energy optimization. The proposed algorithm was compared with several well-known optimization algorithms, such as GA, WOA, and GWO using multiple performance indicators, including solution quality and stability. The results demonstrated that the proposed CWOA achieved superior performance in the early stages of the optimization process, providing lower objective function values and better stability compared with the standard WOA and other competing algorithms at lower iteration numbers. This indicates the effectiveness of the proposed modifications in enhancing the exploration capability and accelerating convergence toward promising solutions. Although GWO achieved slightly better results at higher iteration numbers, the proposed CWOA maintained competitive performance and demonstrated a favorable balance between solution quality and robustness. The statistical analysis further confirmed the reliability of the results obtained, especially at lower iterations. The proposed CWOA can be considered an efficient optimization tool for residential energy management problems, particularly when fast convergence and stable performance are required. Future work may focus on further enhancing the exploitation phase and testing the algorithm on larger-scale and more complex datasets.

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