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Profit Maximization for Generating Companies Using Chaotic Whale Optimization with Inertia Weight

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Abstract: Optimization of power generation scheduling is critical for generating companies (GENCOs) operating in deregulated electricity markets, where maximizing profit under operational constraints is challenging. Traditional metaheuristic algorithms often suffer from premature convergence and poor exploration-exploitation balance. Here we propose an improved Whale Optimization Algorithm incorporating chaotic mapping and inertia weight (CWOA-IW) to enhance population diversity and convergence behaviour. The algorithm is applied to the profit maximization problem of GENCOs, considering market prices and system constraints. Validation on 23 benchmark functions and three power system test cases (3-unit 10-bus, IEEE 39-bus, IEEE 118-bus) demonstrates superior accuracy, stability, and faster convergence compared to standard WOA, Grey Wolf Optimizer, and Particle Swarm Optimization. The results indicate that CWOA-IW provides a robust and scalable optimization framework, offering practical benefits for GENCOs in competitive electricity markets.

Keywords Chaotic Whale Optimization Algorithm, Electricity Market Optimization, Inertia Weight, Metaheuristic Algorithms, Profit Maximization

1. Introduction

The transition from a regulated, vertically integrated structure to a deregulated market structure has created a profound change in the electric power system. The unbundling of the generation, transmission and distribution sectors has introduced market competition, allowing several generating companies (GENCOs) to participate in electricity generation and trading. The goal of these generating companies has now switched from minimizing costs of operating power plants, to maximizing profit by optimizing the scheduling and operation of power plants while adhering to operational and regulatory constraints (Abdi, 2021).

Traditional optimization models such as Mixed Integer Linear Programming (Gilvaei et al., 2021), Lagrangian Relaxation (Sudhakar et al., 2017) and Dynamic Programming (Putz et al., 2021) have been utilized to tackle the profit maximization problem and although these approaches are quick and easy to implement, they suffer from solution-quality problems (Shukla et al., 2015). They are ineffective for large-scale and highly dynamic power systems, and the uncertainty and non-linearities of deregulated markets are not properly handled by these approaches. Therefore, interest in alternative optimization methods has increased, chief among them being metaheuristic algorithms.

Metaheuristic optimization algorithms are a class of optimization algorithms used to solve complex optimization challenges across multiple domains (Abdel-Basset et al., 2018). They play a crucial role in optimization due to their inherent adaptability and efficacy in addressing complex optimization problems where traditional or exact algorithms may fail due to their computational intensity, especially in high-dimensional, nonlinear, or multi-modal search space (Benaissa et al., 2024) s. In optimization problems, the best possible solution is found using mathematical theorems, which is better as opposed to evaluating every possible solution (Tomar et al., 2023). Some of these metaheuristic algorithms include the Particle Swarm Optimization (PSO) (Kennedy et al., 1995) Grey Wolf Optimizer (GWO) (Mirjalili et al., 2014), African Vultures Optimization Algorithm (AVOA) (Abdollahzadeh et al., 2021), War Strategy Optimization (WSO) (Ayyarao et al., 2022) and Dung Beetle Optimizer (DBO) (Xue & Shen, 2023).

Researchers have employed metaheuristic algorithms in addressing the profit maximization problem of generating companies. Ravichandran and Subramanian (2020) addressed the profit maximization problem in a deregulated market using the Elephant Herding Optimization (EHO) algorithm to achieve maximum profits while considering various constraints and tested the algorithm against a 3-unit and 10-unit system. The algorithm obtained higher profits as compared to other metaheuristic algorithms but suffers from local optima entrapment. Kumar et al. (2023) utilized the Monarch Butterfly Optimization (MBO) algorithm to tackle the profit maximization problem and tested the algorithm on 10-unit and 100-unit systems over a 24-hour schedule. It showed improvements in profit as compared to two other algorithms, however, the algorithm had poor convergence capabilities. Dhaliwal and Dillon (2019) proposed a Memetic Binary Differential Evolution algorithm for profit maximization for generating companies in a deregulated energy system. The algorithm combined Binary Differential Evolution for global search with Binary Hill Climbing for local search. The algorithm showed significant improvement compared to other algorithms, however, had a long computational time and did not account for dynamic market price fluctuations.

Durga and Gayathri (2024) tackled the profit maximization problem using the Chaotic Sea-Horse Optimizer to maximize GENCO profits. The paper applied chaotic mapping techniques to the standard Sea-Horse Optimizer (SHO) to enhance its performance. Tested on IEEE-39 bus system, the algorithm realized higher profits compared to the Genetic Algorithm and the Muller Method. Sahoo and Hota (2019) proposed the Moth Flame Optimization algorithm for maximizing profit of generating companies while minimizing societal costs. The algorithm was tested on the IEEE-30 bus system and the algorithm obtained higher profits compared to the Particle Swarm Optimizer and the Genetic Algorithm. Senthilvadivu et al. (2018) proposed an Exchange Market Algorithm to address the profit maximization problem for GENCOs in a deregulated electricity market and was tested on the IEEE-39 bus system with 10 units. It was seen to achieve higher profits as well compared to SFLA and MPPD-ABC. However, in all 3 papers, the algorithms lacked scalability analysis for larger systems and gave the impression of overfitting as it was tested on only one power system.

Ghadi et al. (2016) proposed an Imperialist Competitive Algorithm (ICA) with a cascaded ICA-PSO constraint-handling method to solve the profit maximization problem for GENCOs. The algorithm was tested on 10, 40 and 100-unit systems over 24 hours and outperformed the Particle Swarm Optimizer in terms of the profit obtained. Comparison of the algorithm's performance however was done against only one other optimization algorithm and does not demonstrate how the approach performs relative to a broader set of established algorithms. Krishna and Sao (2016) presented an Improved Teaching-Learning-Based Optimization (I-TLBO) to solve the profit maximization problem in a deregulated environment. An adaptive teaching component, multiple teachers, tutorial-based learning and self-motivated learning were introduced to enhance the standard TLBO. Tested on the IEEE-39 bus system over 10 hours, I-TLBO achieved a profit of $91,120. The method however, lacked comparison with other algorithms, making it difficult to assess its relative effectiveness or contribution.

There is therefore the need to select an algorithm that demonstrates good convergence capabilities, strong exploratory capabilities and a fast execution time. The selected algorithm should be tested on systems of varying size amidst various limitations, and its results should be compared with well-established metaheuristic algorithms previously utilized for profit maximization problems to effectively evaluate its performance and validity.

Numerous metaheuristic algorithms have emerged over time, encompassing human-inspired, physics-based, evolution-based and swarm intelligence-based algorithms. Majority of the algorithms are population-based, meaning they operate on a set of possible solutions that are iteratively refined to arrive at the optimal solution (Tomar et al., 2023). Despite their differing inspirations, population-based metaheuristic algorithms generally follow a similar framework consisting of two stages: exploration and exploitation (Lin & Gen, 2009). During exploration, the algorithm performs a global search of the solution space, where movements are highly randomized to ensure diversity. The most promising regions in the search space identified earlier are then investigated (Mirjalili & Lewis, 2016). Although these algorithms have many advantages, they still suffer from limitations such as slow convergence rates and a poor balance between exploration and exploitation leading to convergence to suboptimal solutions (Benaissa et al., 2024; Shehab et al., 2024).

The whale optimization algorithm is a novel swarm intelligence-based metaheuristic algorithm that has been employed extensively to solve complex optimization problems because of its simplicity and ease of implementation. The algorithm mimics the hunting behaviour of humpback whales and mathematically models three key stunts which are encircling prey, bubble-net attacking method (exploitation phase), and search for prey (exploration phase)(Mirjalili & Lewis, 2016). The whale optimization algorithm has been seen to handle optimization problems in industry and engineering effectively (Gharehchopogh & Gholizadeh, 2019), and has been utilized in many studies such as resource allocation in wireless networks (Pham et al., 2020), clustering (Nasiri & Khiyabani, 2018) and engineering design problems such as welded beam design (Zhou & Hao, 2025). The algorithm, however, has deficiencies consistent with metaheuristic algorithms. There is an imbalance in exploitation and exploration, and the algorithm suffers from premature convergence to suboptimal solutions and slow convergence rates (Wei et al., 2025).

In light of this, many researchers have incorporated various strategies into the standard WOA to address these issues and improve its performance. Deepa and Venkataraman (2021) proposed an enhanced Whale Optimization Algorithm based on Levy Flight mechanism (Levy WOA). The integrated Levy flight mechanism improves the algorithm's ability to break out of local optima and diversifies the population. However, this method introduces uncontrolled large jumps which may take the solution out of a search space in smaller search spaces. Di Cao et al. (2023) presented an Enhanced WOA (EWOA), that combines Improved Dynamic Opposite Learning (IDOL) with an adaptive encircling prey stage. Although improving exploration-exploitation balance, the improvement drastically increases the computational time and complexity of the algorithm. To address the issues of poor local search capability and local optima entrapment, Liu et al. (2023) suggested a Whale Optimization Algorithm with Combined mutation and Removing similarity (CRWOA). Despite the improved convergence speed and solution quality as compared to other algorithms, the population diversity still drops sharply during later iterations, which makes the algorithm prone to stagnation. Qu et al. (2024) proposed the Spiral-Enhanced Whale Optimization Algorithm, which incorporates a non-linear time-varying self-adaptive perturbation strategy and an Archimedean spiral structure. This improved solution accuracy of the algorithm but increased the complexity of the algorithm since the disturbance factor introduced needs complex tuning. Gao et al. (2021) proposed the Skew Tent Nonlinear Whale Optimization Algorithm (STNWOA) to address problems of local optima trapping and slow convergence speed. The improved algorithm however was tested only on a few benchmark functions and its performance across diverse problem types is not confirmed. Therefore, there remains the need to improve the WOA to holistically address the problems of premature convergence, local optima entrapment and proper exploration-exploitation balance while maintaining simplicity and fast convergence

speeds.
This study introduces an improved WOA, termed CWOA-IW, which incorporates chaotic mapping and inertia weight to address these deficiencies. The initial population is generated with a cubic chaotic map, enhancing diversity, and reducing the risk of premature convergence. Inertia weight is incorporated into the position-update mechanism to help the algorithm escape local optima and dynamically balance exploration and exploitation. The proposed CWOA-IW is then applied to the profit maximization problem for generating companies, taking into account the various limitations and complexities of power system operations. The remainder of this paper is structured as follows: The objective function for the profit maximization problem is formulated in Section **2**. The conventional whale optimization algorithm is described in Section 3. The proposed CWOA-IW using chaotic mapping and inertia weight theories is presented in Section 4. The developed profit maximization tool is described in Section 5. Section 6 presents the benchmark functions and the power system test beds used to test the efficacy of the improved model and the optimization tool. The results of the improved CWOA-IW algorithm and the profit maximization tool with a comparative analysis against other optimization algorithms is shown in Section 7. Conclusions are drawn in Section 8.

2. Problem Formulation

With the transition from a traditionally regulated market to a deregulated one, the objective function of GENCOs shifts solely from minimizing cost to maximizing profits, while ensuring grid stability and reliability under operational and market constraints such as forecasted demand, fluctuating electricity prices and generation limits (Abdi, 2021; Shukla et al., 2015). The elements of the objective function and constraints associated with the problem are covered in this section.

2.1 Objective function

The GENCO's profit is defined as the difference between the total revenue obtained from the sale of electricity at market price and its total operating costs, expressed in Equation (1).

$$Maximize\ PF = TR - TC \tag{1}$$

PF is the profit of the GENCO, TC is the total operating cost of the GENCO and TR is the total revenue of the GENCO. The total operating cost (TC) of the GENCO is expressed as a function of the fuel cost of power generated by each unit at each time *t*, the start-up cost and the commitment status of each unit as expressed in Equation (2).

$$TC = \sum_{t=1}^{T} \sum_{i=1}^{N} [F_i(Pg_i^t) + SUC_{i,t}\ ].X_i^t \tag{2}$$

T is the scheduling time horizon, t is the time index, N is the total number of thermal generating units and i is the generating unit index. F_i is the fuel cost function of unit i, Pg_i^t is the power output of unit i at time t, $SUC_{i,t}$ is the start-up cost of unit i at time t and X_i^t is the commitment status of unit i at time t.

The total revenue (TR) obtained by a GENCO from selling power is expressed as a function of the power generated by each unit at each time *t*, the forecasted market price of electricity at that time, and each generating unit's commitment status, and is given by Equation (3).

$$TR = \sum_{t=1}^{T} \sum_{i=1}^{N} \left(Pg_i^t . FSP_t\right) . X_i^t \tag{3}$$

where FSP_t is the forecasted market price at time t.

2.2 Constraints

Generating companies cannot increase profit infinitely and are met with limitations that influence how they operate. The constraints used in this study are:

2.2.1 System demand constraint

Throughout the whole scheduling period, GENCOs produce power such that the total power output of committed units is either equal to or less than the power demand at each time interval. The system demand constraint is mathematically modelled as Equation (4).

$$\sum_{i=1}^{N} Pg_i^t . X_i^t \leq PD \quad (4)$$

where PD is the load demand at time t.

2.2.2 Unit generation limit constraint

There are inherent limits on the maximum and minimum power that each generating unit can produce when committed. The generation bounds for committed units are defined as Equation (5).

$$P_{gi}^{min} \leq Pg_i^t \leq P_{gi}^{max} \quad (5)$$

P_{gi}^{min} is the minimum power generation limit of unit i and P_{gi}^{max} is the maximum power generation limit of unit i.

2.2.3 Unit minimum up/down time

Each generating unit must satisfy minimum-up time and minimum-down time constraints. Once a unit is committed, it must remain on for a set period (minimum up time), and once shut down, it must remain off for a set period (minimum down time). The minimum up/down time constraints are expressed in Equation (6).

$$T_i^{on} \geq T_i^{up} ; T_i^{off} \geq T_i^{down} \quad (6)$$

where $T_i^{on}$and T_i^{off} represent the on and off durations of unit i respectively, and T_i^{up} and T_i^{down} represent the minimum up and down times of unit i respectively.

2.2.4 Unit ramp up/down rates

The ramp rate of a generating unit refers to the maximum change in output power that operators can apply within a given time interval. These limits are defined by the ramp-up and ramp-down constraints, which are modelled as Equation (7).

$$Pg_i^t - Pg_i^{t-1} \leq UR_i ; Pg_i^{t-1} - Pg_i^t \leq DR_i \quad (7)$$

Pg_i^t is the power output of generating unit i at time t, Pg_i^{t-1} is the power output of generating unit i at the previous time period, UR_i is the ramp-up limit of unit i and DR_i is the ramp-down limit of unit i.

3. Whale Optimization Algorithm

The Whale Optimization Algorithm is a well-known optimization technique inspired by nature that has applications in data science, engineering, medicine, and economics (Nasiri & Khiyabani, 2018; Pham et al., 2020; Wei et al., 2025; Zhou & Hao, 2025). The algorithm was proposed in 2016 by Seyedali Mirjalili and

Andrew Lewis, and is inspired by the distinctive hunting behaviour of humpback whales, particularly their bubble-net feeding approach (Mirjalili & Lewis, 2016). This behaviour involves whales creating bubbles in a spiral pattern to encircle and trap prey. In WOA, a set of candidate solutions, referred to as whales, are initialized randomly within defined boundary conditions. The position of each whale is updated iteratively using analytic systems which mimic two key behaviours: search for prey (exploration) and encircling prey or bubble-net attacking (exploitation). The position update is guided by parameters such as a random coefficient vector (A), a random number (r) between 0 and 1, and a logarithmic spiral constant (b), as shown in the position update equations. During iterations, the algorithm evaluates the fitness of each whale against the given objective function, updating the best-known solution until an optimal solution is found or a stopping criterion, such as a maximum number of iterations, is met. The simplicity and effectiveness of WOA have led to its rapid adoption for solving complex optimization problems.

3.1 Encircling Prey

The initial phase of the whales' hunting strategy involves encircling their prey. WOA treats the current optimal whale, denoted as $\vec{X}^*$, as the target prey or as close to the optimum. All other whales adjust their positions based on $\vec{X}^*$ using Equation (8) and (9) (Mirjalili & Lewis, 2016) is

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \quad (8)$$

$$\vec{D} = \left|\vec{C} \cdot \vec{X}^*(t) - \vec{X}(t)\right| \quad (9)$$

$\vec{A}$ and $\vec{C}$ represent coefficient vectors and t is the current iteration. In each iteration, $\vec{X}$ is updated if a better solution is found.

The vectors $\vec{A}$ and $\vec{C}$ are calculated with Equation (10) and (11) respectively.

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \quad (8)$$

$$\vec{C} = 2 \cdot \vec{r} \quad (9)$$

$\vec{r}$ is a random vector in [0,1] and $\vec{a}$ is linearly reduced from 2 to 0 across iterations (in both exploration and exploitation phases).

3.2 Bubble-net Attacking Strategy

The bubble-net attacking strategy of humpback whales is modelled as the exploitation phase (Kaveh & Ghazaan, 2017). During this stage, whales encircle their prey by exhaling bubbles in a circular pattern, gradually narrowing the bubble ring to trap the prey in a confined area. The whale then ascends in a spiral trajectory to capture the prey. This behaviour is mathematically represented using two key mechanisms: the Shrinking Encircling mechanism and the Spiral Updating Position. The shrinking encircling mechanism is implemented by reducing the value of the control parameter $\vec{a}$, which limits the movement range and simulates the tightening of the search space. The spiral update position uses a spiral equation to mimic the whale's helical movement toward the prey. Together, these mechanisms guide individual whales toward the best-known position, enhancing local search capability and refining solution accuracy. Update of the whale at this stage is done using Equation (12).

$$\vec{X}(t+1) = \overrightarrow{D'} \cdot e^{bl} \cdot cos(2\pi l) + \vec{X}^*(t) \quad (10)$$

The whales simultaneously swim in a spiral pattern and in a shrinking circle around the prey. To model this behaviour, a probability of 50% is assumed for choosing between either movement in updating the position of whales. The mathematical model for updating positions by the whales at this stage is given in Equation (13).

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A} \cdot \vec{D} & if\ p < 0.5 \\ \vec{D'} \cdot e^{bl} \cdot cos(2\pi l) + \vec{X}^*(t) & if\ p \geq 0.5 \end{cases} \quad (11)$$

3.3 Search for prey

At this point, when $|A| > 1$, the current whale randomly selects an individual whale from the present population to update its position to conduct a global search, thereby preventing the population from converging early on a locally optimum solution. Its mathematical model is similar to Equation (8) and (9), except that the optimal individual is replaced by a randomly chosen one.

$$\vec{X}(t+1) = \vec{X}_{rand}(t) - \vec{A} \cdot \vec{D} \quad (14)$$

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_{rand}(t) - \vec{X}(t)\right| \quad (15)$$

$\vec{A}$ and $\vec{C}$ are coefficient vectors, t indicates the current iteration, $\vec{X}_{rand}$ is the position vector of the randomly selected whale and $\vec{X}$ is the position vector of the current whale.

4. Proposed Chaotic Whale Optimization Algorithm with Inertia Weight

Similar to other metaheuristic algorithms, WOA exhibits limitations that reduce its accuracy and effectiveness in tackling specific optimization tasks. Previous studies and critical reviews (Gharehchopogh & Gholizadeh, 2019; Mohammed et al., 2019; Nadimi-shahraki et al., 2022) show that WOA has inefficient search mechanisms (Nadimi-Shahraki et al., 2022), often resulting in premature convergence (Liu et al., 2023), poor exploration-exploitation balance (Cao et al., 2023), stagnation away from optimal regions (Sun et al., 2019) and low population diversity (Gao et al., 2021). These performance deficiencies can often be attributed to the algorithm's controlling parameters and stages, particularly the initialization process and the mechanisms that govern exploration and exploitation.

The initialization stage in WOA, which typically relies on uniform random population generation, lacks strategic distribution and diversity enhancement mechanisms. As a result, the algorithm may begin with a poorly distributed population, which affects its ability to effectively explore the search space and contributes to low population diversity and early stagnation. Furthermore, the control parameters, particularly the linearly decreasing coefficient a, the random vector r, and the spiral shape parameter b, play a pivotal role in steering the search behaviour. The linear adaptation of a, intended to shift the algorithm gradually from exploration to exploitation, often fails to respond dynamically to the problem landscape, thereby leading to poor search strategies and unbalanced transitions between global and local search phases.

When the value of a reduces too quickly, exploration is prematurely abandoned, increasing the risk of premature convergence; if a remains large for too long, the algorithm may stagnate far from optimal regions due to insufficient exploitation. These shortcomings, coupled with static parameter control and simplistic agent movement strategies, limit WOA's performance in complex or high-dimensional optimization problems. As evidenced in various studies, refining the initialization phase and adopting adaptive control parameter schemes are essential for mitigating these issues and enhancing the overall robustness and accuracy of the algorithm.

Another critical factor shaping WOA's performance is its dependence on the current best whale during the position update of the entire population. During exploitation, the movements of all whales are primarily directed by the best solution identified thus far. While this leader-driven strategy facilitates rapid convergence toward potentially optimal regions of the search space, it simultaneously increases the risk of premature

convergence—particularly when the current best solution resides within a suboptimal region in the search space (Gharehchopogh & Gholizadeh, 2019).
To address these shortcomings of the standard WOA relating to population diversity, premature convergence, local optima entrapment and poor exploration-exploitation balance, two theories are applied: Chaotic mapping and Inertia weight.

Pseudocode of the WOA algorithm.

```
Initialize the whale's population Xi (i = 1, 2, …, n)
Calculate the fitness of each search agent
X*=the best search agent
while (t < maximum number of iterations)
    for each search agent
    Update a, A, C, l, and p
        if (p<0.5)
            if (|A|< 1)
                Update the position of the current search agent by the Eq. (8)
            else if (|A≥1|)
                Select a random search agent (X_rand)
                Update the position of the current search agent by the Eq. (14)
            end if
        else if (p≥0.5)
                Update the position of the current search by the Eq. (12)
        end if
        end for
        Check if any search agent goes beyond the search space and amend it
        Calculate the fitness of each search agent
        Update X* if there is a better solution
        t=t+1
end while
return X*
```

4.1 Chaotic mapping

The initial population's quality and diversity greatly affect the performance of metaheuristic algorithms. The standard WOA relies on random distributions, which may not sufficiently explore the solution space. To address this, chaotic mapping techniques are incorporated into the initialization phase of the algorithm. Due to its deterministic and ergodic properties, the chaotic map yields a more diverse initial population in the search space (Gao et al., 2021).
In this study, the cubic chaotic map is utilized to produce the initial population. The chaotic sequence is modelled in Equation (16).

$$X_i = \rho X_{i-1}\left(1 - {X_{i-1}}^2\right),\ X_i \in (0,1) \tag{12}$$

The chaotic parameter $\boldsymbol{\rho}$ quantifies how well the chaotic map distributes points over time. It governs the sequence's chaotic and ergodic behaviour. If $\boldsymbol{\rho}$ is too large, the sequence may diverge or become overly chaotic and unstable. Conversely, if $\boldsymbol{\rho}$ is too small, the sequence may exhibit reduced ergodicity and tend toward periodic behaviour. After conducting sensitivity analysis, the value of $\boldsymbol{\rho}$ is set to 2.59 for optimal ergodic characteristics
The chaotic number X_i, is mapped to the ith initial individual whale in the search space to generate initial populations.

4.2 Inertia weight

To further tune and balance the exploration and exploitation ability, an inertia weight factor is introduced in WOA to scale the influence of the current best whale on generating the positions of individual whales in the exploitation phase. The inertia weight coefficient is defined in Equation (17).

$$w = w_{max} - \frac{(w_{max} - w_{min}) \cdot current\ iteration}{max\ number\ of\ iterations} \tag{13}$$

The parameters w_{max} and w_{min}, representing the maximum and minimum values of the inertia weight respectively, are set to 0.9 and 0.4 after sensitivity analysis. The formula shows that during the early stages of optimization, the weight coefficient is large, allowing for larger search steps and preventing local optima trapping. As the optimization progresses, the weight coefficient decreases, enabling a more refined local search that enhances both the accuracy and convergence speed. The new position update equations are modelled in Equation (18) and (19). The update is done depending on the value of parameter *p*. When *p* is greater or equal to 0.5, the whales update their position using Equation (19). However, when *p* is less than 0.5, the whales update their position using Equation (18).

$$\vec{X}(t+1) = w \cdot \vec{X}^*(t) - \vec{A} \cdot \vec{D} \tag{14}$$

$$\vec{X}(t+1) = \overrightarrow{D'} \cdot e^{bl} \cdot cos(2\pi l) + w \cdot \vec{X}^*(t) \tag{15}$$

$$\vec{X}(t+1) = \begin{cases} w \cdot \vec{X}^*(t) - \vec{A} \cdot \vec{D} & if\ p < 0.5 \\ \overrightarrow{D'} \cdot e^{bl} \cdot cos(2\pi l) + w \cdot \vec{X}^*(t) & if\ p \geq 0.5 \end{cases} \tag{16}$$

The flowchart of CWOA-IW incorporating the cubic chaotic map and inertia weight is shown in Figure 1.

5. Profit Maximization Tool

Using the improved CWOA-IW algorithm, the proposed optimization tool for solving the profit maximization problem follows a structured procedure to maximize GENCO profits while adhering to system and operational constraints. The process begins with the input of test system data, which includes each generating unit's generation limits, fuel cost coefficients, start-up costs, ramping rates, and minimum up and down times. In addition, the power demand and market pricing data over the scheduling horizon are provided as inputs to the tool.

Following this, the population initialization phase is carried out. Here, an initial set of candidate solutions (representing the power dispatch schedules of the generating units within their defined limits) is generated using the cubic chaotic map technique. This ensures a diverse starting population for the algorithm. Each possible solution is then assessed in the objective function evaluation stage, where the profit of the generating units is computed. The solution that yields the highest profit, along with its associated power dispatch schedule, is recorded as the current best.

Subsequently, the parameter updating stage is performed. In this step, the CWOA-IW parameters (a, A, C, l, p and w) are updated according to their respective governing equations. These updated parameters guide the position updating process, during which the solutions are adjusted either with reference to the current best solution or in relation to randomly selected solutions, thereby balancing exploration and exploitation.

To ensure feasibility, constraint handling techniques are applied to the updated solutions. If any constraints such as generation limits, ramp rates, or minimum up/down times are violated, penalties are imposed on the profit values. This adjustment directs the search towards solutions that satisfy all system requirements. Once adjustments are made, the objective function is re-evaluated, allowing the algorithm to determine the profit associated with the updated solutions.

This iterative cycle of parameter updating, position updating, constraint handling, and re-evaluation continues until the termination criterion is met, typically determined by a maximum iteration number. At the end of the process, the tool returns the optimal power dispatch schedule for the generating units along with the maximum profit achievable under the given market and operational conditions. The flowchart illustrating the developed profit maximization tool using CWOA-IW is shown in Figure 2.

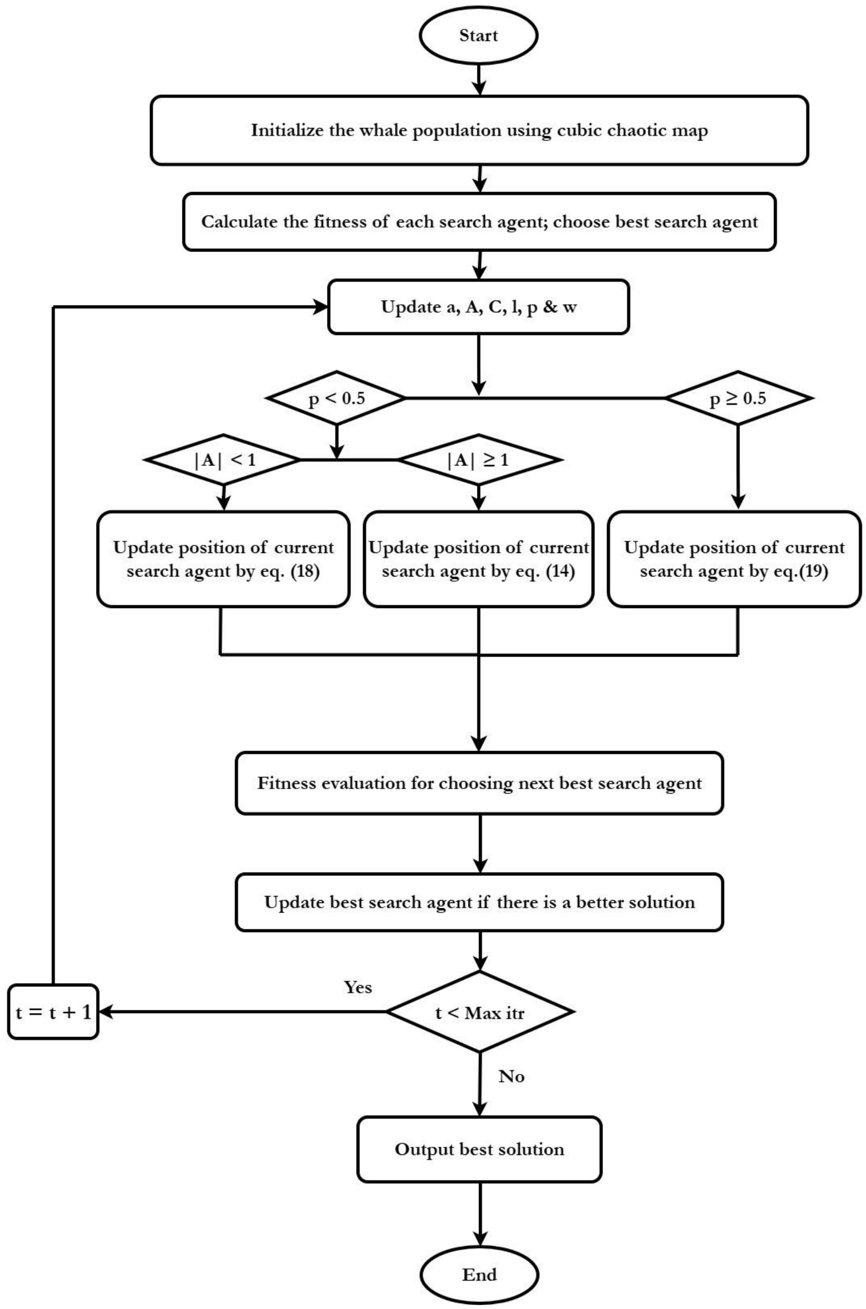

Figure 1 Flowchart of proposed CWOA-IW

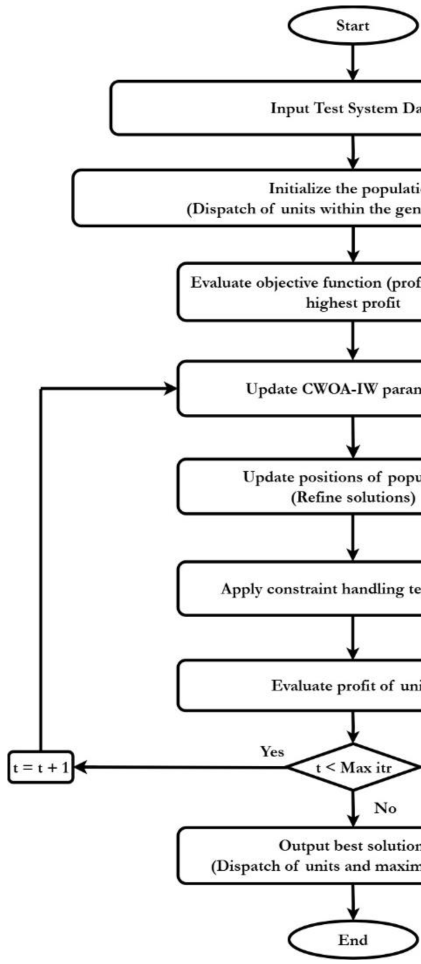

Figure 2 Flowchart describing profit maximization process

6. Testing of the Improved Algorithm and Optimization Tool

6.1 Benchmark Functions

The CWOA-IW algorithm's efficacy was assessed using 23 classical benchmark functions obtained from (Mirjalili & Lewis, 2016). These functions fall into three categories: unimodal, multimodal and fixed dimension multimodal functions. Functions F1-F7 are unimodal since they have only one global optimum and are often used to assess the exploration capabilities of the algorithm. Functions F8-F13 are multimodal functions and functions F14 - F23 are fixed dimension multimodal functions, both with numerous local optima whose number increases exponentially with the dimensions. A detailed description of all 23 benchmark functions is presented in Table 1.

The enhanced Chaotic Whale Optimization Algorithm with Inertia Weight (CWOA-IW) is compared with the base WOA, the Grey Wolf Optimizer (GWO) and the Particle Swarm Optimizer (PSO). All simulations were carried out in MATLAB R2022a on a computer with these specifications: Lenovo 20L8A01RUK Intel (R) Core (TM) i5-8250U CPU @ 1.60GHz and 8GB RAM. Sensitivity analysis was performed to obtain optimum parameter tuning in testing the algorithms. The specific parameters of the proposed CWOA-IW and compared algorithms are shown in Table 2.

Table 1 Description of benchmark functions

Function	Description	Dim	Range	f_{min}
F1	$F1=\sum_{i=1}^{d}x_i^2$	30	[− 100,100]	0
F2	$F2=\sum_{i=1}^{d}\lvert x_i\rvert+\prod_{i=1}^{d}\lvert x_i\rvert$	30	[− 10,10]	0
F3	$F3=\sum_{i=1}^{d}\left(\sum_{j=1}^{i}x_j\right)^2$	30	[− 100,100]	0
F4	$F4=\max\{\lvert x_i\rvert, 1\le i\le d\}$	30	[− 100,100]	0
F5	$F5=\sum_{i=1}^{d-1}\left[100\left(x_{i+1}-x_i^2\right)^2+(x_i-1)^2\right]$	30	[− 30,30]	0
F6	$F6=\sum_{i=1}^{d}([x_i+0.5])^2$	30	[− 100,100]	0
F7	$F7=\sum_{i=1}^{d}ix_i^4+rand[0,1)$	30	[− 1.28,1.28]	0
F8	$F8=\sum_{i=1}^{d}\left(x_i\,sin\left(\sqrt{\lvert x_i\rvert}\right)\right)$	30	[− 500,500]	-418.9829*d
F9	$F9=\sum_{i=1}^{d}\left[x_i^2-10\,cos\,2\,\pi x_i+10n\right]$	30	[− 5.12,5.12]	0
F10	$F10=-20\exp\left(-0.2\sqrt{\frac{1}{d}\sum_{i=1}^{d}x_i^2}\right)-\exp\left(\frac{1}{d}\sum_{i=1}^{d}cos\,2\,\pi x_i\right)+20+\exp(1)$	30	[− 32,32]	0
F11	$F11=\frac{1}{4000}-\sum_{i=1}^{d}x_i^2-\prod_{i=1}^{d}\cos\frac{x_i}{\sqrt{i}}+1$	30	[− 600,600]	0
F12	$F12=\frac{\pi}{d}[10\sin(\pi y_1)]+\sum_{i=1}^{d-1}(y_1-1)^2\left[1+10\sin^2(\pi y_{1+1})+\sum_{i+1}^{d}u(x_i,10,100,4)\right]$	30	[− 50,50]	0
F13	$F13=0.1\left(\sin^2(3\pi x_1)+\sum_{i+1}^{d}(x_i-1)^2[1+sin^2(3\pi x_1+1)]+(x_d-1)^2+sin^2(2\pi x_d)\right)+\sum_{i=1}^{d}u(x_i,5,100,4)$	30	[− 50,50]	0
F14	$F14=\left[\frac{1}{500}+\sum_{j=1}^{25}\frac{1}{j+\sum_{i=1}^{2}\left(x_i-a_{ij}\right)^6}\right]^{-1}$	2	[− 50,50]	0.998
F15	$F15=\sum_{i-1}^{11}\left[a_i-\frac{x_1\left(b_i^2+b_ix_2\right)}{b_i^2+b_ix_3+x_4}\right]^2$	4	[− 65.536,65.536]	0.0003075
F16	$F16=4x_1^2-2.1x_1^4+\frac{1}{3}x_1^6+x_1x_2-4x_2^2+4x_2^4$	2	[-5,5]	-1.0316
F17	$F17=\left(x_2-\frac{5.1}{4\pi^2}x_1^2+\frac{5}{\pi}x_1-6\right)^2+10\left(1-\frac{1}{8\pi}\right)\cos x_1+10$	2	[-5, 10]	0.398
F18	$F18=[1+(x_1+x_2+1)^2(19-14x_1+3x_1^2-14x_2+6x_1x_2+3x_2^2)]*[30+(2x_1-3x_2)^2*(18-32x_i+12x_1^2+48x_2-36x_1x_2+27x_2^2)]$	2	[-2,2]	3
F19	$F19=-\sum_{i=1}^{4}c_i\exp\left(-\sum_{i=1}^{3}a_{ij}\left(x_j-p_{ij}\right)^2\right)$	3	[0,1]	-3.86
F20	$F20=-\sum_{i=1}^{4}c_i\exp\left(-\sum_{i=1}^{6}a_{ij}\left(x_j-p_{ij}\right)^2\right)$	6	[0,1]	-3.32
F21	$F21=-\sum_{i=1}^{5}\left[(X-a_i)(X-a_i)^T+c_i\right]^{-1}$	4	[0,10]	-10.1532
F22	$F22=-\sum_{i=1}^{7}\left[(X-a_i)(X-a_i)^T+c_i\right]^{-1}$	4	[0,10]	-10.4028
F23	$F23=-\sum_{i=1}^{10}\left[(X-a_i)(X-a_i)^T+c_i\right]^{-1}$	4	[0,10]	-10.5363

Table 2 Design parameters

Parameter	Algorithms			
	CWOA-IW	WOA	GWO	PSO
Number of iterations	500	500	500	500
Number of runs	30	30	30	30
Number of search agents	30	30	30	30
$\vec{a}$	2 to 0	2 to 0	2 to 0	NA
ρ	2.59	NA	NA	NA
w_{max}	0.9	NA	NA	NA
w_{min}	0.4	NA	NA	NA

The comparative analysis parameters used were the Optimal Value, the Average Optimal Value, the Standard Deviation and the Mean Absolute Error.

6.2 Description of Power System Test Beds and System Data

The developed optimization tool is examined using three standard test systems to evaluate its effectiveness. The number of iterations was set to 500 and the number of search agents set to 30. Algorithm performance is assessed in terms of solution quality and convergence speed, and the results are compared with existing optimization methods to demonstrate its capability of obtaining higher profit values. The three test systems comprise a 3-unit 10-bus system (Ravichandran & Subramanian, 2020), the IEEE-39 bus system with 10 generating units(Dhaliwal & Dhillon, 2021), and the IEEE-118 bus system with 54 generating units (Illinois Institute of Technology, 2015) representing small, medium and large-scale test systems respectively. Detailed descriptions of the test system data are provided Tables 3, 4 and 5.

Table 3 Description of 3 Generator test system

Gen No.	P_{min} (MW)	P_{max} (MW)	a(constant) ($/h)	b (linear) ($/MWH)	c(quadratic) ($/MW^{2}h)	Startup cost ($)	ramp up/down (MW/h)	min up/down time(h)
G1	100	600	500	10	0.002	450	100	3
G2	100	400	300	8	0.0025	400	100	3
G3	50	200	100	6	0.005	300	50	3

Table 4 Description of 10 Generator test system

Gen No.	P_{min} (MW)	P_{max} (MW)	a(constant) ($/h)	b(linear) ($/MWh)	c(quadratic) ($/MW^{2}h)	Startup cost ($)	ramp up/down (MW/h)	min up/down time(h)
G1	150	455	1000	16.19	0.00048	4500	113.75	8
G2	150	455	970	17.26	0.00031	5000	113.75	8
G3	20	130	700	16.6	0.002	550	32.5	5
G4	20	130	680	16.5	0.00211	560	32.5	5
G5	25	162	450	19.7	0.00398	900	40.5	6
G6	20	80	370	22.26	0.00712	170	20	3
G7	25	85	480	27.74	0.00079	260	21.25	3
G8	10	55	660	25.92	0.00413	30	13.75	1
G9	10	55	665	27.27	0.00222	30	13.75	1
G10	10	55	670	27.79	0.00173	30	13.75	1

Table 5 Description of 54 Generator test system

Gen No.	P_{min} (MW)	P_{max} (MW)	a(constant) ($/h)	b(linear) ($/MWh)	c(quadratic) ($/MW²h)	Startup cost ($)	ramp up/down (MW/h)	min up/down time(h)
G1	5	30	31.67	26.2438	0.069663	40	15	1
G2	5	30	31.67	26.2438	0.069663	40	15	1
G3	5	30	31.67	26.2438	0.069663	40	15	1
G4	150	300	6.78	12.8875	0.010875	440	150	8
G5	100	300	6.78	12.8875	0.010875	110	150	8
G6	10	30	31.67	26.2438	0.069663	40	15	1
G7	25	100	10.15	17.82	0.0128	50	50	5
G8	5	30	31.67	26.2438	0.069663	40	15	1
G9	5	30	31.67	26.2438	0.069663	40	15	1
G10	100	300	6.78	12.8875	0.010875	100	150	8
G11	100	350	32.96	10.76	0.003	100	175	8
G12	8	30	31.67	26.2438	0.069663	40	15	1
G13	8	30	31.67	26.2438	0.069663	40	15	1
G14	25	100	10.15	17.82	0.0128	50	50	5
G15	8	30	31.67	26.2438	0.069663	40	15	1
G16	25	100	10.15	17.82	0.0128	50	50	5
G17	8	30	31.67	26.2438	0.069663	40	15	1
G18	8	30	31.67	26.2438	0.069663	40	15	1
G19	25	100	10.15	17.82	0.0128	59	50	5
G20	50	250	28	12.3299	0.002401	100	125	8
G21	50	250	28	12.3299	0.002401	100	125	8
G22	25	100	10.15	17.82	0.0128	50	50	5
G23	25	100	10.15	17.82	0.0128	50	50	5
G24	50	200	39	13.29	0.0044	100	100	8
G25	50	200	39	13.29	0.0044	100	100	8
G26	25	100	10.15	17.82	0.0128	50	50	5
G27	100	420	64.16	8.3391	0.01059	250	210	10
G28	100	420	64.16	8.3391	0.01059	250	210	10
G29	80	300	6.78	12.8875	0.010875	100	150	8
G30	30	80	74.33	15.4708	0.045923	45	40	4
G31	10	30	31.67	26.2438	0.069663	40	15	1
G32	5	30	31.67	26.2438	0.069663	40	15	1
G33	5	20	17.95	37.6968	0.028302	30	10	1
G34	25	100	10.15	17.82	0.0128	50	50	5
G35	25	100	10.15	17.82	0.0128	50	50	5
G36	150	300	6.78	12.8875	0.010875	440	150	8
G37	25	100	10.15	17.82	0.0128	50	50	5
G38	10	30	31.67	26.2438	0.069663	40	15	1
G39	100	300	32.96	10.76	0.003	440	150	8
G40	50	200	6.78	12.8875	0.010875	400	100	8
G41	8	20	17.95	37.6968	0.028302	30	10	1

G42	20	50	58.81	22.9423	0.009774	45	25	1
G43	100	300	6.78	12.8875	0.010875	100	150	8
G44	100	300	6.78	12.8875	0.010875	100	150	8
G45	100	300	6.78	12.8875	0.010875	110	150	8
G46	8	20	17.95	37.6968	0.028302	30	10	1
G47	25	100	10.15	17.82	0.0128	50	50	5
G48	25	100	10.15	17.82	0.0128	50	50	5
G49	8	20	17.95	37.6968	0.028302	30	10	1
G50	25	50	58.81	22.9423	0.009774	45	25	2
G51	25	100	10.15	17.82	0.0128	50	50	5
G52	25	100	10.15	17.82	0.0128	50	50	5
G53	25	100	10.15	17.82	0.0128	50	50	5
G54	25	50	58.81	22.9423	0.009774	45	25	2

7. Results and Discussion

7.1 Optimal Value, Mean Optimal Value, Standard Deviation and Mean Absolute Error

Table 6 presents the optimal values, mean optimal values, standard deviations (SD), and mean absolute errors (MAE) obtained by WOA, PSO, GWO, and the proposed CWOA-IW across the 23 classical benchmark functions. The results demonstrate that CWOA-IW achieves superior performance in most test cases. Specifically, CWOA-IW attained the best optimal values in 5 out of 8 unimodal functions and 4 out of 6 multimodal functions, outperforming WOA, PSO, and GWO. Furthermore, CWOA-IW successfully reached the known global optimum for all fixed-dimension multimodal functions.

In terms of average optimal performance, CWOA-IW produced the best mean optimal values in 16 out of the 23 benchmark functions, whereas GWO and PSO achieved this in only 2 functions each, and WOA in none. All algorithms recorded identical mean optimal values for 3 functions. These results highlight the proposed algorithm's ability to consistently produce high-quality solutions.

Regarding robustness and precision, CWOA-IW achieved the lowest standard deviation in 16 of the 23 benchmark functions, compared to 0 for WOA, 1 for GWO, and 6 for PSO. Similarly, CWOA-IW obtained the lowest MAE in 15 of the 23 functions, outperforming WOA (0), GWO (3), and PSO (4). Notably, CWOA-IW and GWO observed identical MAE values for function F19. These findings confirm that CWOA-IW offers superior consistency and accuracy in locating near-optimal solutions. Overall, CWOA-IW demonstrated the most effective and reliable performance among all the compared algorithms.

7.2 Convergence Behaviour

The figures below show the convergence curves of the four algorithms for selected benchmark functions. It can be seen in functions F1, F3, F4, F9 and F11 that the curve of CWOA-IW rapidly decreases as the number of iterations increase and obtains the best optimal values. This is indicative of the excellent exploitation ability of CWOA-IW, its ability to avoid local minima and its higher optimization accuracy. Convergence towards the optimum in the final iterations can be seen in F7 and F10. This shows that the algorithm kept searching the search space for good solutions. It can also be seen in functions F8, F17 and F21 that CWOA-IW obtains the optimal value in the shortest time as compared to the other algorithms. Overall, CWOA-IW exhibits a superior convergence behaviour with faster convergence, higher accuracy and stronger global search capability as compared to WOA, GWO and PSO.

Table 6 Comparison of optimization results obtained for the benchmark functions

Function		CWOA-IW	WOA	GWO	PSO
f1	Optimum Value	**1.1103E-260**	1.4821E-87	7.4222E-255	3.8144E-14
	Mean	**2.3131E-244**	1.3264E-73	4076.7702	1.9490E-06
	Standard Deviation	**0**	6.7732E-73	2940.3352	7.6881E-06
	Mean Absolute Error	**2.3131E-244**	1.3264E-73	4076.7702	1.9490E-06
f2	Optimum Value	**4.0295E-137**	4.9554E-58	6.0120E-137	0.0013
	Mean	**3.2034E-130**	3.5276E-51	5.9607E-128	0.0579
	Standard Deviation	**8.3185E-130**	1.0923E-50	3.0894E-127	0.0894
	Mean Absolute Error	**3.2034E-130**	3.5276E-51	5.9607E-128	0.0579
f3	Optimum Value	**2.4693E-188**	16061.8282	2.7373E-187	13.4267
	Mean	**7.7711E-184**	42535.9013	2.4956E-06	89.4264
	Standard Deviation	**0**	16924.7007	1.0284E-05	63.1512
	Mean Absolute Error	**7.7711E-184**	42535.9013	2.4956E-06	89.4264
f4	Optimum Value	**1.2175E-114**	0.0837	3.9994E-100	0.8938
	Mean	**6.1775E-99**	51.9006	5.0620E-07	2.1200
	Standard Deviation	**3.3831E-98**	26.5786	6.3060E-07	0.8789
	Mean Absolute Error	**6.1775E-99**	51.9006	5.0620E-07	2.1200
f5	Optimum Value	27.2469	27.2295	25.9896	**1.9859**
	Mean	27.8744	28.1624	**27.1213**	61.3549
	Standard Deviation	**0.3051**	0.4397	0.8578	90.8315
	Mean Absolute Error	27.8744	28.1624	**27.1213**	61.3549
f6	Optimum Value	0.0753	0.0687	0.1011	**1.5898E-11**
	Mean	0.2650	0.3695	0.7402	**2.7299E-06**
	Standard Deviation	0.1155	0.2163	0.4037	**1.0057E-05**
	Mean Absolute Error	0.2650	0.3695	0.7402	**2.7299E-06**
f7	Optimum Value	**8.3101E-07**	3.4604E-05	0.0003	0.0126
	Mean	**9.8937E-05**	2.7459E-03	0.0016	0.0278
	Standard Deviation	**8.3604E-05**	3.4929E-03	0.0008	0.0122
	Mean Absolute Error	**9.8937E-05**	2.7459E-03	0.0016	0.0278
f8	Optimum Value	**-12569.4798**	-12568.9808	-12566.5036	-8206.8712
	Mean	**-12281.2736**	-10386.1810	-6398.9191	-6581.7763
	Standard Deviation	782.7635	2017.0787	1406.9593	**701.8604**
	Mean Absolute Error	**288.2264**	2183.3190	6170.5809	5987.7237
f9	Optimum Value	**0**	**0**	**0**	20.8941
	Mean	**0**	5.6843E-15	2.2012	50.3780
	Standard Deviation	**0**	2.2884E-14	2.7835	14.6799
	Mean Absolute Error	**0**	5.6843E-15	2.2012	50.3780
f10	Optimum Value	**4.4409E-16**	**4.4409E-16**	8.8818E-16	7.3692E-08
	Mean	**1.8652E-15**	3.6415E-15	9.8987E-14	1.5253
	Standard Deviation	**1.7702E-15**	2.3511E-15	2.5440E-14	0.6926
	Mean Absolute Error	**1.8652E-15**	3.6415E-15	9.8987E-14	1.5253
f11	Optimum Value	**0**	**0**	**0**	1.7620E-11
	Mean	**0**	3.7007E-18	0.0063	0.0311
	Standard Deviation	**0**	2.0270E-17	0.0129	0.0304
	Mean Absolute Error	**0**	3.7007E-18	0.0063	0.0311
f12	Optimum Value	0.0022	0.0045	0.0059	**8.9545E-14**
	Mean	**0.0090**	0.0214	0.0427	0.1037
	Standard Deviation	**0.0034**	0.0170	0.0223	0.1722
	Mean Absolute Error	**0.0090**	0.0214	0.0427	0.1037
f13	Optimum Value	0.0345	0.1145	0.0991	**3.0888E-14**
	Mean	0.1948	0.4672	0.6607	**0.0809**
	Standard Deviation	**0.0910**	0.2254	0.2762	0.2322
	Mean Absolute Error	0.1948	0.4672	0.6607	**0.0809**

f14	Optimum Value	**0.9980**	**0.9980**	**0.9980**	**0.9980**
	Mean	**0.9980**	2.9615	4.1999	3.1648
	Standard Deviation	**1.1959E-10**	3.2333	3.9479	2.7497
	Mean Absolute Error	**0.0020**	1.9635	3.2011	2.1660
f15	Optimum Value	**0.0003**	**0.0003**	**0.0003**	**0.0003**
	Mean	**0.0003**	0.0006	0.0025	0.0043
	Standard Deviation	**2.9265E-05**	0.0003	0.0061	0.0116
	Mean Absolute Error	**4.0789E-05**	0.0003	0.0022	0.0040
f16	Optimum Value	**-1.0316**	**-1.0316**	**-1.0316**	**-1.0316**
	Mean	**-1.0316**	**-1.0316**	**-1.0316**	**-1.0316**
	Standard Deviation	0.0001	5.8702E-09	1.0395E-05	**6.6486E-16**
	Mean Absolute Error	8.2980E-05	2.8452E-05	**2.8437E-05**	2.8453E-05
f17	Optimum Value	**0.3979**	**0.3979**	**0.3979**	**0.3979**
	Mean	**0.3979**	**0.3979**	**0.3979**	**0.3979**
	Standard Deviation	1.9292E-06	7.9698E-05	1.4228E-06	**0**
	Mean Absolute Error	1.3466E-06	2.2612E-05	1.2356E-06	**9.3465E-11**
f18	Optimum Value	**3.0000**	**3.0000**	**3.0000**	**3.0000**
	Mean	**3.0000**	**3.0000**	**3.0000**	**3.0000**
	Standard Deviation	0.0001	0.0002	3.3917E-05	**2.0384E-15**
	Mean Absolute Error	0.0001	5.3346E-05	2.8450E-05	**7.7138E-14**
f19	Optimum Value	**-3.8628**	**-3.8628**	**-3.8628**	**-3.8628**
	Mean	**-3.8622**	-3.8574	-3.8610	-3.8628
	Standard Deviation	0.0009	0.0078	0.0024	**2.7101E-15**
	Mean Absolute Error	**0.0023**	0.0043	**0.0023**	0.0028
f20	Optimum Value	**-3.3220**	**-3.3220**	**-3.3220**	**-3.3220**
	Mean	**-3.3212**	-3.2004	-3.2516	-3.2903
	Standard Deviation	**0.0007**	0.1322	0.0757	0.0535
	Mean Absolute Error	**0.0014**	0.1198	0.0704	0.0326
f21	Optimum Value	**-10.1529**	-10.1514	-10.1528	**-10.1532**
	Mean	**-9.7991**	-8.3017	-9.2238	-5.8990
	Standard Deviation	**1.2898**	2.5601	2.1476	3.6041
	Mean Absolute Error	**0.3541**	1.8515	0.9294	4.2542
f22	Optimum Value	**-10.4028**	-10.4020	**-10.4027**	**-10.4029**
	Mean	-10.2061	-7.8140	**-10.2253**	-7.5190
	Standard Deviation	0.9676	3.0296	**0.9630**	3.6209
	Mean Absolute Error	0.1967	2.5888	**0.1775**	2.8839
f23	Optimum Value	**-10.5362**	-10.5339	-10.5363	-10.5364
	Mean	**-10.5248**	-6.4305	-9.9935	-6.8461
	Standard Deviation	**0.0147**	3.2069	2.0582	3.7918
	Mean Absolute Error	**0.0115**	4.1058	0.5428	3.6903

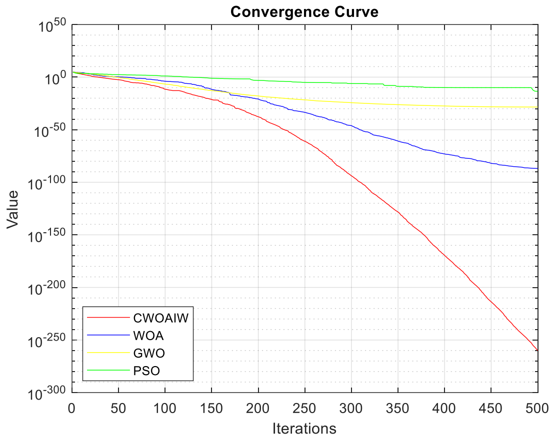

Figure 3 Convergence Curves for F1

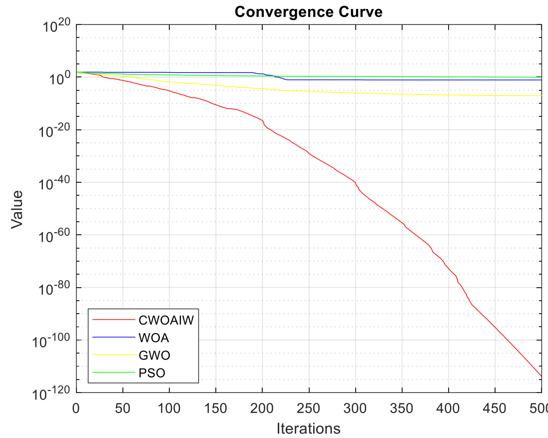

Figure 4 Convergence Curves for F2

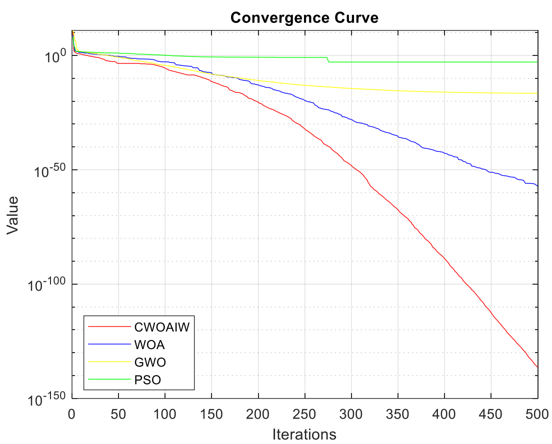

Figure 5 Convergence Curves for F3

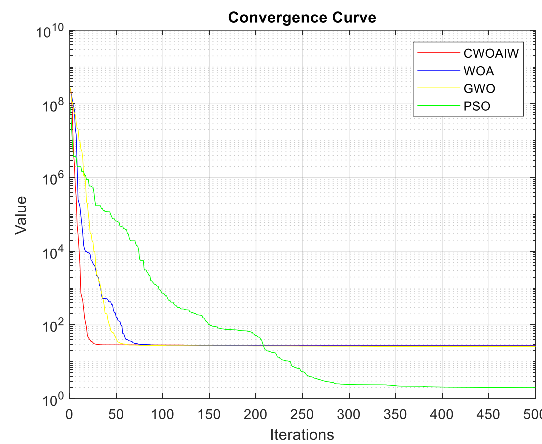

Figure 6 Convergence Curves for F4

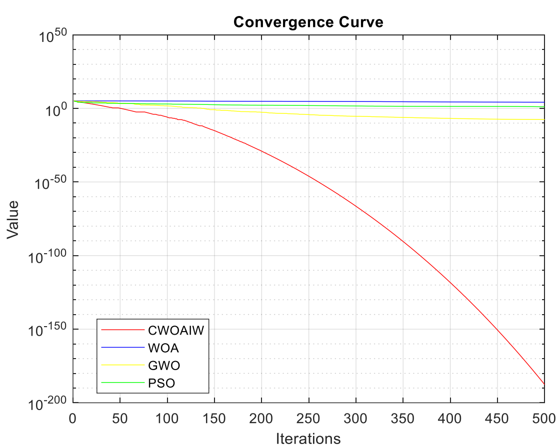

Figure 7 Convergence Curves for F5

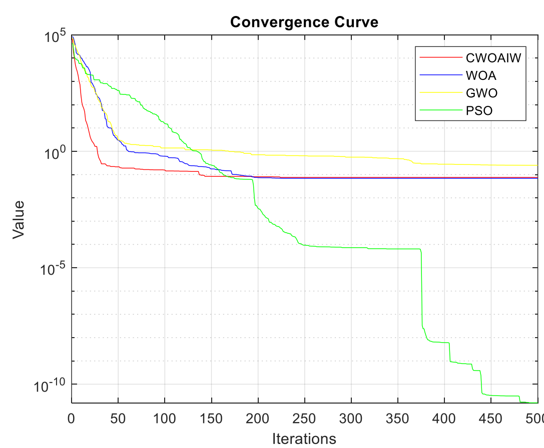

Figure 8 Convergence Curves for F6

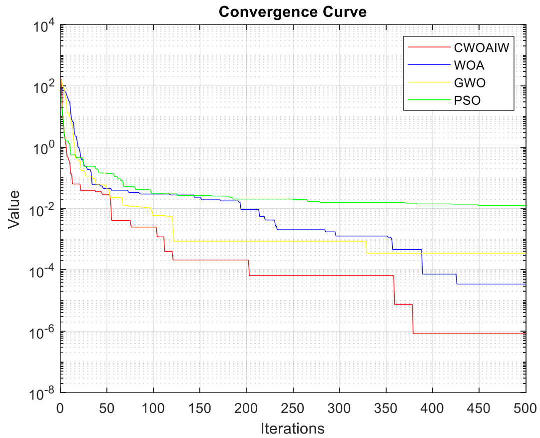

Figure 9 Convergence Curves for F7

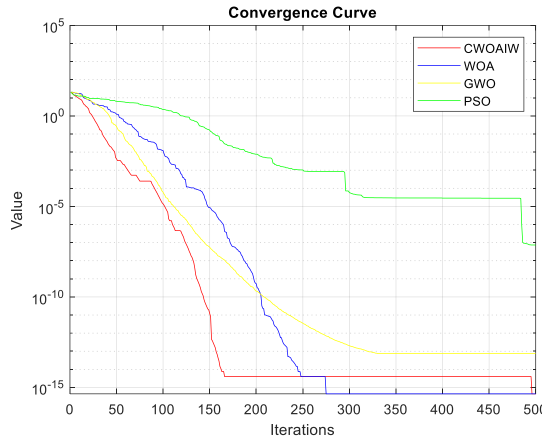

Figure 10 Convergence Curves for F8

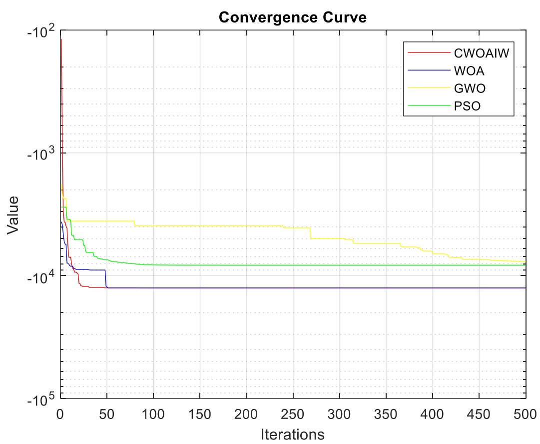

Figure 11 Convergence Curves for F9

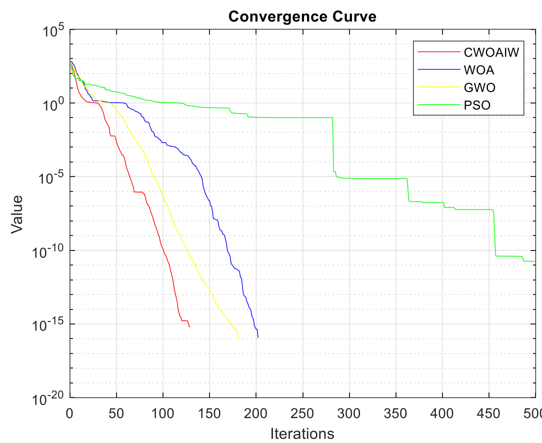

Figure 12 Convergence Curves for F10

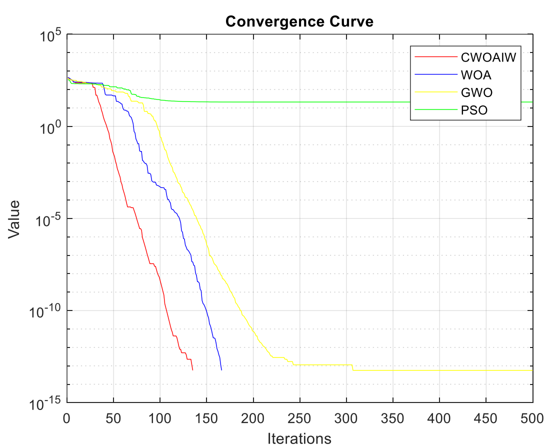

Figure 13 Convergence Curves for F11

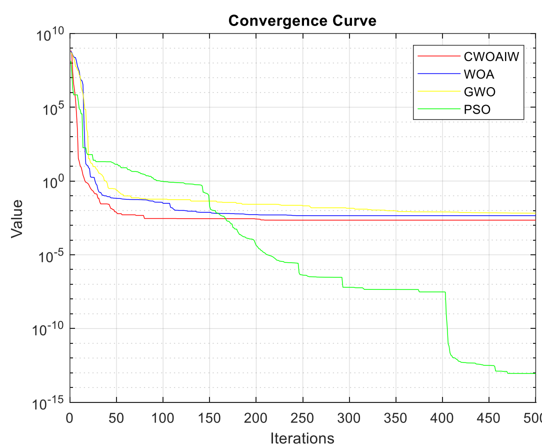

Figure 14 Convergence Curves for F12

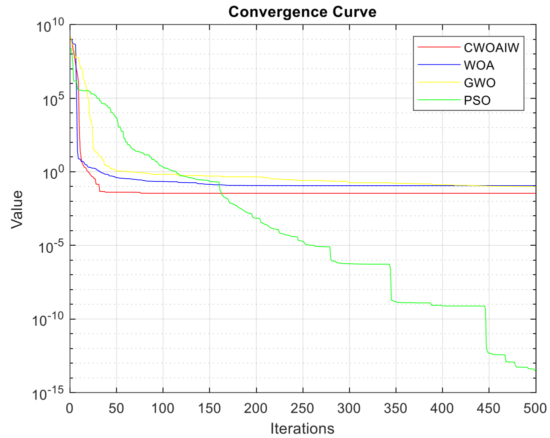

Figure 15 Convergence Curves for F13

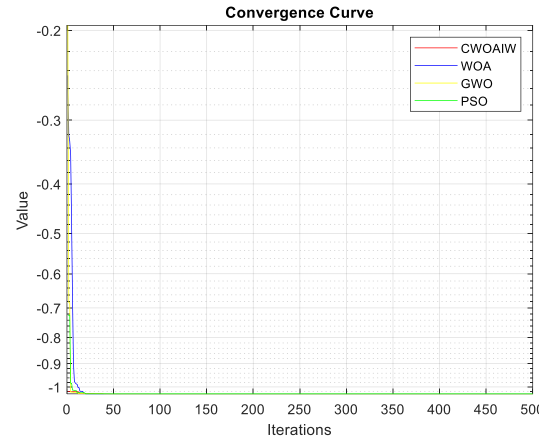

Figure 16 Convergence Curves for F14

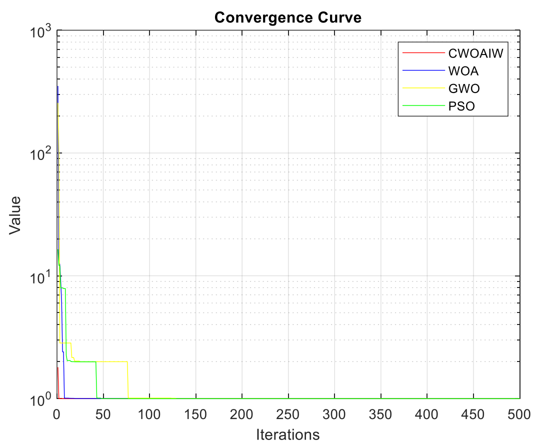

Figure 17 Convergence Curves for F15

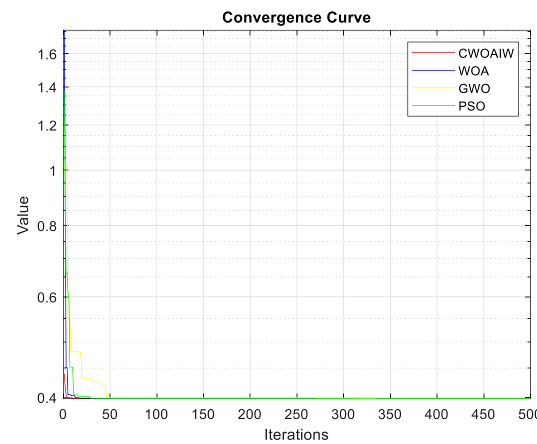

Figure 18 Convergence Curves for F16

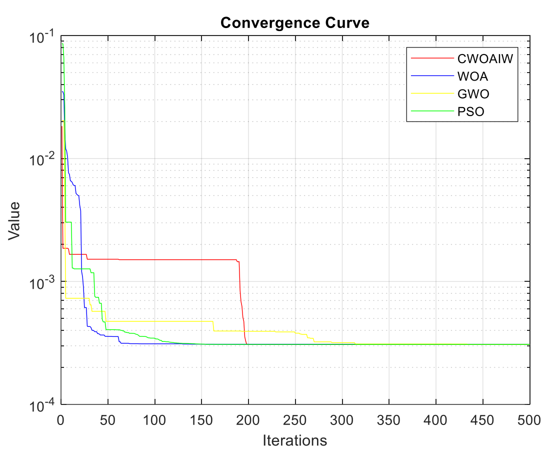

Figure 19 Convergence Curves for F17

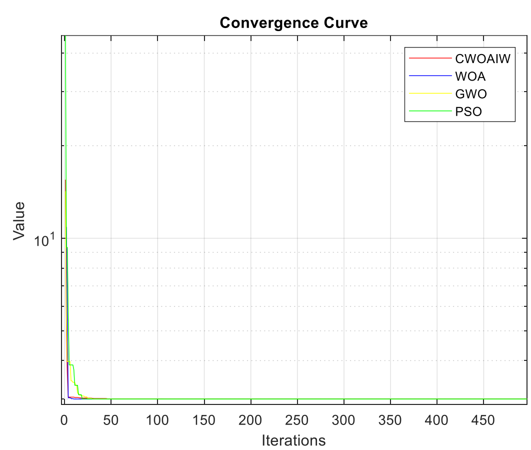

Figure 20 Convergence Curves for F18

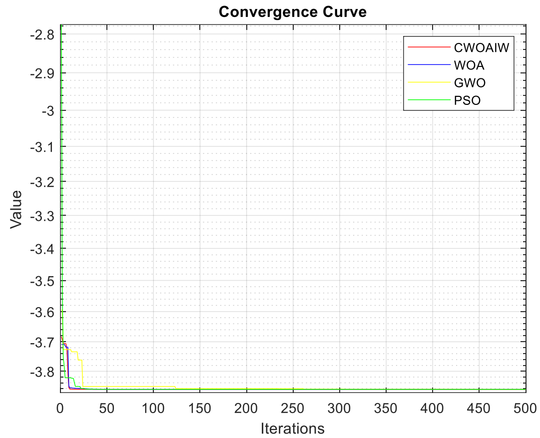

Figure 21 Convergence Curves for F19

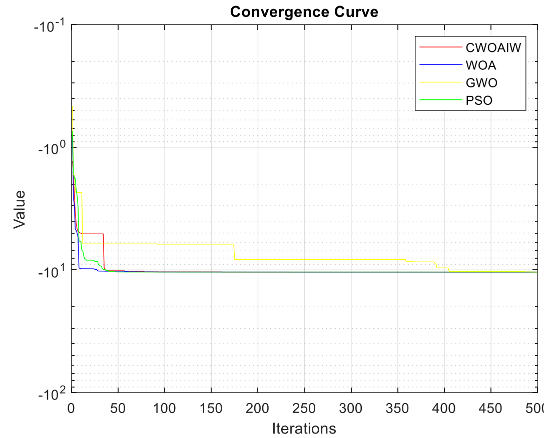

Figure 22 Convergence Curves for F20

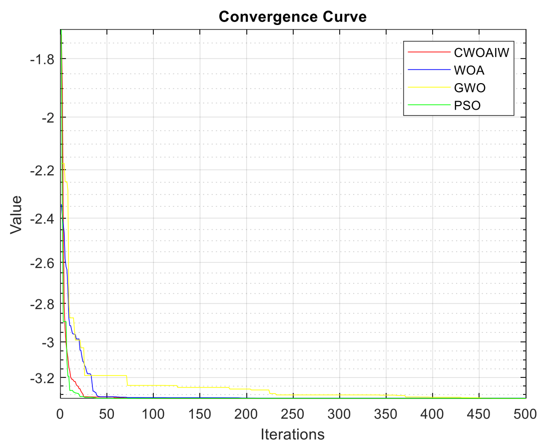

Figure 23 Convergence Curves for F21

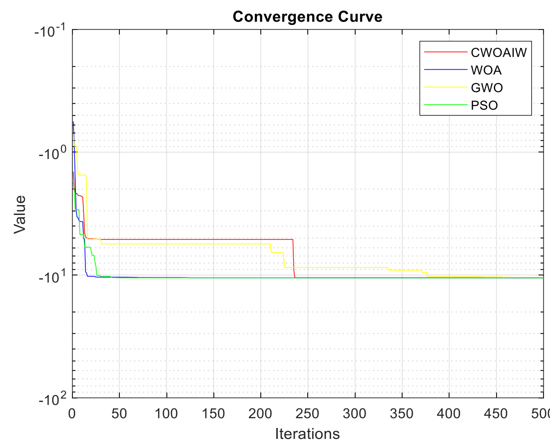

Figure 24 Convergence Curves for F22

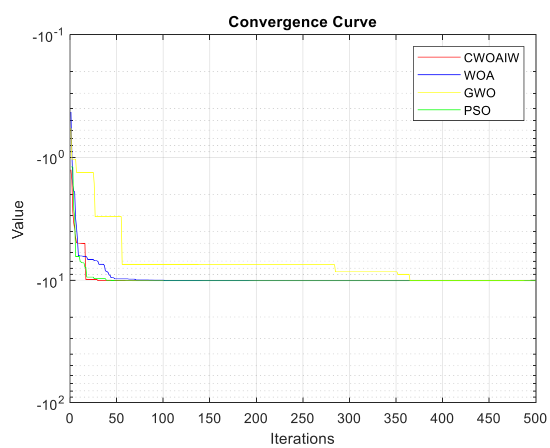

Figure 25 Convergence Curves for F23

7.3 Wilcoxon Signed-Rank Test

The statistical significance of the proposed CWOA-IW, GWO, PSO and WOA was evaluated using the Wilcoxon signed-rank test at a 5% significance level. Table X shows that CWOA-IW exhibits a significant improvement over the standard WOA, with a p-value of 0.000281. CWOA-IW also shows a marginal improvement in performance over PSO, with a p-value of 0.0447. No statistically significant difference is observed when compared with GWO, suggesting comparable performance on this benchmark suite. The win-lose/tie counts further support these findings, with CWOA-IW achieving higher wins against all other algorithms. These results show that CWOA-IW provides consistent and superior performance over the benchmark suit compared to the other algorithms.

Table 7 Wilcoxon Signed Test Results for Algorithms

Algorithm	p-values	n/w/l/t
CWOA-IW vs WOA	0.000281	23/19/2/2
CWOA-IW vs PSO	0.0447	23/13/10/0
CWOA-IW vs GWO	0.3382	23/14/8/1

7.4 Power Generation

The power demand and market pricing data for the 3 standard test systems were obtained from(Dhaliwal & Dhillon, 2021; Ravichandran & Subramanian, 2020). Tables 8, 9 and 10 show the optimal scheduled generation for all units at each hour as obtained by CWOA-IW.

Table 8 Load profile & Market price data for 3 Generator test system

H(h)	Power Demand (MW)	Power Generation (MW)	Prices ($/h)
1	170	170	10.55
2	250	250	10.35
3	400	400	9.00
4	520	520	9.45
5	700	700	10.00
6	1050	900	11.25
7	1100	1000	11.30
8	800	800	10.65
9	650	650	10.35
10	330	330	11.20
11	400	400	10.75
12	550	500	10.60
TOTAL	6920	6620	

7.5 Profit

Table 11 presents the profits achieved by each algorithm across the test systems, demonstrating their effectiveness in solving the complex problem of profit maximization for GENCOs under various constraints. The percentages in brackets show the profit reduction relative to the profits achieved by the CWOA-IW algorithm. Table 11 indicates that the proposed **CWOA-IW algorithm** achieved the highest profits across all generator systems, clearly outperforming WOA, GWO, and PSO. The percentages in brackets represent how much lower each competing algorithm's profit was compared to CWOA-IW. For example, in the 3-generator system, WOA, GWO, and PSO achieved profits that were 69.9%, 176.6%, and 401.0% lower, respectively, showing a significant advantage for CWOA-IW. Although the performance gap narrows in the 54-generator system (0.45% for WOA, 35.7% for GWO, and 3.6% for PSO), CWOA-IW still produces the highest and most consistent profits. This demonstrates its robustness, scalability, and superior convergence characteristics in solving the GENCO profit maximization problem. Figures 26-28 give a graphical representation of the values in Table 11.

The proposed CWOA-IW achieves superior results across the benchmark suite, showing a better balance between exploration and exploitation, and a lower tendency for local optima entrapment. These characteristics are crucial for profit maximization for generating companies due to the non-convex search space and highly constrained nature of the task. Consequently, the improved capabilities of the proposed CWOA-IW demonstrated in the benchmark functions translate into higher profits when applied to practical power system test beds, including the 3 unit 10-bus system, the IEEE-39 bus system and the IEEE-118 bus system.

Table 9 Load profile & Market price data for 10 Generator test system

H(h)	Power Demand (MW)	Power Generation (MW)	Prices ($/h)
1	700	700	22.15
2	750	750	22.00
3	850	830	23.10
4	900	766.2	22.65
5	1000	821.2	23.25
6	1100	640	22.95
7	1150	697.9	22.50
8	1200	560.7	22.15
9	1300	1086.8	22.80
10	1400	1331.4	29.35
11	1450	1275.6	30.15
12	1500	1460.4	31.65
13	1400	1283.1	24.60
14	1300	1138.1	24.50
15	1200	1200	22.50
16	1050	1050	22.30
17	1000	1000	22.25
18	1100	1100	22.05
19	1200	1200	22.20
20	1400	1346.1	22.65
21	1300	1293.1	23.10
22	1100	1100	22.95
23	900	900	22.75
24	800	800	22.55
TOTAL	27050	24330.6	

Table 10 Load profile & Market price data for 54 Generator test system

H(h)	Power Demand (MW)	Power Generation (MW)	Prices ($/h)
1	2800	2800	22.15
2	3000	3000	22.00
3	3400	3400	23.10
4	3800	3800	22.65
5	4000	4000	23.25
6	4400	4400	22.95
7	4600	4600	22.50
8	4800	4800	22.15
9	5200	5200	22.80
10	5600	5600	29.35
11	5800	5800	30.15
12	6000	5600	31.65
13	5600	5200	24.60
14	5200	4800	24.50
15	4800	4200	22.50
16	4200	4000	22.30
17	4000	4400	22.25
18	4400	4800	22.05
19	4800	5600	22.20
20	5600	5200	22.65
21	5200	4400	23.10
22	4400	3600	22.95
23	3600	3200	22.75
24	3200	5600	22.55
TOTAL	108400	108134	

Table 11 Simulation Results for Profit Maximization Tool

ALGORITHM	3 GENERATOR SYSTEM		10 GENERATOR SYSTEM		54 GENERATOR SYSTEM	
CWOA-IW	**$4,229.33**		**$9,325.62**		**$828,289.99**	
WOA	$2,489.30	**(69.9%)**	$6,728.73	**(39%)**	$824,556.51	**(0.45%)**
GWO	$1,529.12	**(176.59%)**	$6,532.94	**(43.16%)**	$610,464.10	**(35.68%)**
PSO	$844.15	**(401.02%)**	$3,867.71	**(141.81%)**	$799,272.39	**(3.63%)**

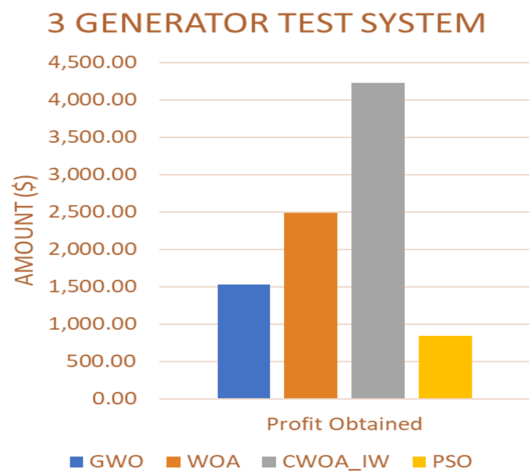

Figure 26 Profit Results for 3 Generator test system

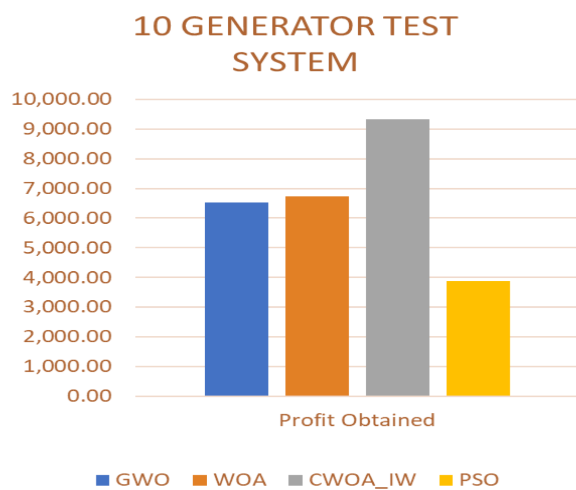

Figure 27 Profit Results for 10 Generator test system

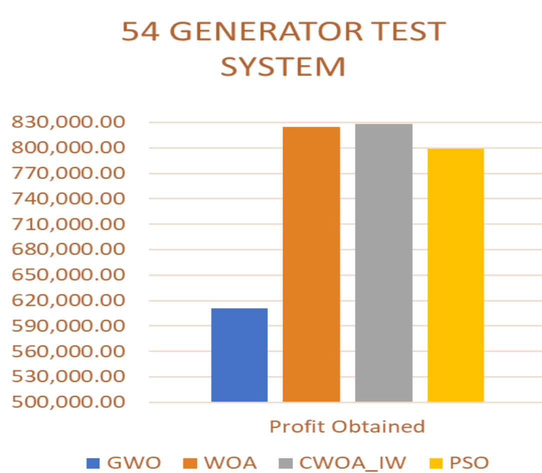

Figure 28 Profit Results for 54 Generator test system

8. Conclusion

This study proposes an enhanced Whale Optimization Algorithm using Chaotic Mapping and Inertia Weight (CWOA-IW) to address the limitations of standard WOA, namely premature convergence, poor population diversity, and exploration-exploitation imbalance. CWOA-IW achieves a more diverse population distribution through the integration of a cubic chaotic map during initialization, while the introduction of an inertia weight enhances its convergence behaviour and search adaptability throughout the optimization process.

Experimental results on classical benchmark functions demonstrate the superior performance of CWOA-IW in terms of convergence behaviour and solution quality. Furthermore, when applied to the profit maximization problem of GENCOs, the improved algorithm optimizes the generation scheduling under the tested market and operational constraints. The improved algorithm achieved higher profits compared to conventional metaheuristic algorithms such as WOA, GWO and PSO for three power system test beds. This suggests CWOA-IW's robustness and scalability for real-world electricity market operations. Overall, CWOA-IW provides a promising and scalable optimization framework for solving complex engineering and power system optimization problems.

Declaration of Ethical Standards

As the authors of this study, we declare that this study complies with all ethical standards.

Credit Authorship Contribution Statement

Kofi Afum Danso: Software and Writing. Peter Asigri: Conceptualization and Supervision. Nicholas Kwesi Prah II: Supervision and Editing. Daniel Kwegyir: Review and Editing. Richeson Akwanfo: Methodology. Mawuli Kweku Afenu: Software. Nana Ama Abaka Mensah: Writing. Adwoa Darkoa Addi-Oppey: Writing. Daniel Opoku: Review and Supervision.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

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Data Availability

The data used are publicly available datasets obtained from published literature.

References

Abdel-Basset, M., Abdel-Fatah, L., & Sangaiah, A. K. (2018). Metaheuristic algorithms: A comprehensive review. In *Computational Intelligence for Multimedia Big Data on the Cloud with Engineering Applications* (pp. 185–231). Elsevier. https://doi.org/10.1016/B978-0-12-813314-9.00010-4

Abdi, H. (2021). Profit-based unit commitment problem: A review of models, methods, challenges, and future directions. In *Renewable and Sustainable Energy Reviews* (Vol. 138). Elsevier Ltd. https://doi.org/10.1016/j.rser.2020.110504

Abdollahzadeh, B., Gharehchopogh, F. S., & Mirjalili, S. (2021). African vultures optimization algorithm: A new nature-inspired metaheuristic algorithm for global optimization problems. *Computers and Industrial Engineering, 158*(May), 107408. https://doi.org/10.1016/j.cie.2021.107408

Ayyarao, T. S. L. V., Ramakrishna, N. S. S., Elavarasan, R. M., Polumahanthi, N., Rambabu, M., Saini, G., Khan, B., & Alatas, B. (2022). War Strategy Optimization Algorithm: A New Effective Metaheuristic Algorithm for Global Optimization. *IEEE Access*, *10*, 25073–25105.

Benaissa, B., Kobayashi, M., Al Ali, M., Khatir, T., & El Amine Elaissaoui Elmeliani, M. (2024). Metaheuristic optimization algorithms: An overview. *HCMCOUJS-Advances in Computational Structures*, *14*(1), 34–62. https://doi.org/10.46223/HCMCOUJS

Cao, D., Xu, Y., Yang, Z., Dong, H., & Li, X. (2023). An enhanced whale optimization algorithm with improved dynamic opposite learning and adaptive inertia weight strategy. *Complex and Intelligent Systems*,

9(1), 767–795. https://doi.org/10.1007/s40747-022-00827-1
Deepa, R., & Venkataraman, R. (2021). Enhancing Whale Optimization Algorithm with Levy Flight for coverage optimization in wireless sensor networks. *Computers and Electrical Engineering*, *94*. https://doi.org/10.1016/j.compeleceng.2021.107359
Dhaliwal, J. S., & Dhillon, J. S. (2019). Profit based unit commitment using memetic binary differential evolution algorithm. *Applied Soft Computing Journal*, *81*. https://doi.org/10.1016/j.asoc.2019.105502
Dhaliwal, J. S., & Dhillon, J. S. (2021). A synergy of binary differential evolution and binary local search optimizer to solve multi-objective profit based unit commitment problem. *Applied Soft Computing*, *107*. https://doi.org/10.1016/j.asoc.2021.107387
Durga, P., & Gayathri, K. (2024). Chaotic Sea-Horse Optimizer for Profit-Based Unit Commitment to Maximize the Profit of GENCOs in Restructured Power System Considering Reserve Allocation. *Indian Journal Of Science And Technology*, *17*(39), 4048–4057. https://doi.org/10.17485/IJST/v17i39.2795
Gao, P., Ding, H., & Xu, R. (2021). Whale Optimization Algorithm Based on Skew Tent Chaotic Map and Nonlinear Strategy. *Academic Journal of Computing & Information Science*, *4*(5). https://doi.org/10.25236/ajcis.2021.040513
Ghadi, M. J., Itami Karin, A., Baghramian, A., & Hosseini Imani, M. (2016). Optimal power scheduling of thermal units considering emission constraint for GENCOs' profit maximization. *International Journal of Electrical Power and Energy Systems*, *82*, 124–135. https://doi.org/10.1016/j.ijepes.2016.03.011
Gharehchopogh, F. S., & Gholizadeh, H. (2019). A comprehensive survey: Whale Optimization Algorithm and its applications. *Swarm and Evolutionary Computation*, *48*, 1–24. https://doi.org/10.1016/j.swevo.2019.03.004
Gilvaei, M. N., Imani, M. H., Ghadi, M. J., Li, L., & Golrang, A. (2021). Profit-based unit commitment for a GENCO equipped with compressed air energy storage and concentrating solar power units. *Energies, 14*(3). https://doi.org/10.3390/en14030576
Illinois Institute of Technology. (2015). Index of /Data. http://motor.ece.iit.edu/data/
Kaveh, A., & Ghazaan, M. I. (2017). Enhanced whale optimization algorithm for sizing optimization of skeletal structures. *Mechanics Based Design of Structures and Machines*, *45*(3). https://doi.org/10.1080/15397734.2016.1213639
Kennedy, J., Eberhart, R., & gov, bls. (1995). *Particle Swarm Optimization*.
Krishna, P. V. R., & Sao, S. (2016). An Improved TLBO Algorithm to Solve Profit Based Unit Commitment Problem under Deregulated Environment. *Procedia Technology*, *25*, 652–659. https://doi.org/10.1016/j.protcy.2016.08.157
Kumar, V., Naresh, R., & Sharma, V. (2023). Profit based unit commitment problem solution using metaheuristic optimisation approach. *International Journal of Systems Science: Operations and Logistics*, *10*(1). https://doi.org/10.1080/23302674.2022.2037026
Lin, L., & Gen, M. (2009). Auto-tuning strategy for evolutionary algorithms: Balancing between exploration and exploitation. *Soft Computing*, *13*(2), 157–168. https://doi.org/10.1007/s00500-008-0303-2
Liu, J., Shi, J., Hao, F., & Dai, M. (2023). A novel enhanced global exploration whale optimization algorithm based on Lévy flights and judgment mechanism for global continuous optimization problems. *Engineering with Computers*, *39*(4). https://doi.org/10.1007/s00366-022-01638-1
Mirjalili, S., & Lewis, A. (2016). The Whale Optimization Algorithm. *Advances in Engineering Software*, *95*, 51–67. https://doi.org/10.1016/j.advengsoft.2016.01.008
Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey Wolf Optimizer. *Advances in Engineering Software*, *69*, 46–61. https://doi.org/10.1016/j.advengsoft.2013.12.007
Mohammed, H. M., Umar, S. U., & Rashid, T. A. (2019). A Systematic and Meta-Analysis Survey of Whale Optimization Algorithm. In *Computational Intelligence and Neuroscience* (Vol. 2019). https://doi.org/10.1155/2019/8718571
Nadimi-shahraki, M. H., Fatahi, A., Zamani, H., Mirjalili, S., & Oliva, D. (2022). Hybridizing of Whale and Moth-Flame Optimization Algorithms to Solve Diverse Scales of Optimal Power Flow Problem. *Electronics (Switzerland)*, *11*(5). https://doi.org/10.3390/electronics11050831
Nadimi-Shahraki, M. H., Zamani, H., & Mirjalili, S. (2022). Enhanced whale optimization algorithm for medical feature selection: A COVID-19 case study. *Computers in Biology and Medicine*, *148*. https://doi.org/10.1016/j.compbiomed.2022.105858

Nasiri, J., & Khiyabani, F. M. (2018). A whale optimization algorithm (WOA) approach for clustering. *Cogent Mathematics & Statistics*, *5*(1). https://doi.org/10.1080/25742558.2018.1483565

Pham, Q. V., Mirjalili, S., Kumar, N., Alazab, M., & Hwang, W. J. (2020). Whale Optimization Algorithm with Applications to Resource Allocation in Wireless Networks. *IEEE Transactions on Vehicular Technology*, *69*(4). https://doi.org/10.1109/TVT.2020.2973294

Putz, D., Schwabeneder, D., Auer, H., & Fina, B. (2021). A comparison between mixed-integer linear programming and dynamic programming with state prediction as novelty for solving unit commitment. *International Journal of Electrical Power and Energy Systems, 125*(June 2020), 106426. https://doi.org/10.1016/j.ijepes.2020.106426

Qu, S. Z., Liu, H., Xu, Y., Wang, L., Liu, Y., Zhang, L., Song, J., & Li, Z. (2024). Application of spiral enhanced whale optimization algorithm in solving optimization problems. *Scientific Reports*, *14*(1), 24534. https://doi.org/10.1038/s41598-024-74881-9

Ravichandran, S., & Subramanian, M. (2020). Profit maximization of GENCO's using an elephant herding optimization algorithm. *Studies in Informatics and Control*, *29*(1), 131–140. https://doi.org/10.24846/v29i1y202013

Sahoo, A., & Hota, P. K. (2019). Moth Flame Optimization Algorithm based Optimal Strategic Bidding in Deregulated Electricity Market. *IEEE Region 10 Annual International Conference, Proceedings/TENCON, 2019-October*, 2105–2110. https://doi.org/10.1109/TENCON.2019.8929290

Senthilvadivu, A., Gayathri, K., & Asokan, K. (2018). Exchange Market algorithm based Profit Based Unit Commitment for GENCOs Considering Environmental Emissions. In *International Journal of Applied Engineering Research* (Vol. 13).

Shehab, M., Sihwail, R., Daoud, M., Al-Mimi, H., & Abualigah, L. (2024). Nature-Inspired Metaheuristic Algorithms: A Comprehensive Review. *International Arab Journal of Information Technology*, *21*(5), 815–831. https://doi.org/10.34028/iajit/21/5/4

Shukla, A., Lal, V. N., & Singh, S. N. (2015). Profit-based unit commitment problem using PSO with modified dynamic programming. *2015 18th International Conference on Intelligent System Application to Power Systems, ISAP 2015*. https://doi.org/10.1109/ISAP.2015.7325550

Sudhakar, A. V. V., Karri, C., & Jaya Laxmi, A. (2017). Profit based unit commitment for GENCOs using Lagrange Relaxation–Differential Evolution. *Engineering Science and Technology, an International Journal, 20*(2), 738–747. https://doi.org/10.1016/j.jestch.2016.11.012

Sun, Y., Yang, T., & Liu, Z. (2019). A whale optimization algorithm based on quadratic interpolation for high-dimensional global optimization problems. *Applied Soft Computing Journal*, *85*. https://doi.org/10.1016/j.asoc.2019.105744

Tomar, V., Bansal, M., & Singh, P. (2023). Metaheuristic Algorithms for Optimization: A Brief Review. *Engineering Proceedings*, *59*(1). https://doi.org/10.3390/engproc2023059238

Wang, J., Bei, J., Song, H., Zhang, H., & Zhang, P. (2023). A whale optimization algorithm with combined mutation and removing similarity for global optimization and multilevel thresholding image segmentation [Formula presented]. *Applied Soft Computing*, *137*. https://doi.org/10.1016/j.asoc.2023.110130

Wei, J., Gu, Y., Yan, Y., Li, Z., Lu, B., Pan, S., & Cheong, N. (2025). LSEWOA: An Enhanced Whale Optimization Algorithm with Multi-Strategy for Numerical and Engineering Design Optimization Problems. *Sensors*, *25*(7). https://doi.org/10.3390/s25072054

Xue, J., & Shen, B. (2023). Dung beetle optimizer: a new meta-heuristic algorithm for global optimization. In *Journal of Supercomputing* (Vol. 79, Issue 7). https://doi.org/10.1007/s11227-022-04959-6

Zhou, Y., & Hao, Z. (2025). Multi-Strategy Improved Whale Optimization Algorithm and Its Engineering Applications. *Biomimetics*, *10*(1). https://doi.org/10.3390/biomimetics10010047