AN IMPROVED WILD HORSE OPTIMIZER ALGORITHM FOR ELECTRIC VEHICLE CHARGING STATIONS COMBINATED DISTRIBUTED GENERATION AND BATTERY STORAGE SYSTEM

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ABSTRACT

The rapid development of electric vehicles (EV) has increased the load on charging stations (CS), placing significant pressure on distribution power systems, particularly with adverse effects on voltage stability, peak loads, and high power losses. In this study, we propose a solution combining the deployment of distributed generation (DG) and battery energy storage systems (BESS) to support electric vehicle charging stations (EVCS) in distribution networks. The objective is to minimize power losses and maintain stable operating voltage. An improved algorithm, the Chaotic Wild Horse Optimizer (CWHO), derived from the original Wild Horse Optimizer (WHO), is proposed to achieve better solutions for the problem model. The standard IEEE 33-bus distribution network is used for testing and simulating solutions with Matlab R2022a under two scenarios: integrating DG and BESS over a 24-hour framework and increasing the EVCS intensity factor. The results are compared with previous studies to demonstrate the effectiveness and superiority of the improved CWHO algorithm for the EVCS optimization problem.

Keywords: *Electric vehicle, Distributed system, Power system, EVCS, BESS.*

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1. INTRODUCTION

In recent years, the consumption of fossil fuels has grown as the transportation and power generation sectors have expanded [1]. These resources not only result in significant expenses but also contribute to greenhouse gas (GHG) emissions, negatively impacting the environment [2]. Amid growing concerns about global warming, the electrification of vehicles has raised awareness of electric vehicle (EV) adoption, and renewable energy sources (RES) have become increasingly important. The goal is to reduce GHG emissions from the global energy sector by 50% by 2050 [3]. The integration of distributed generation (DG) and battery energy storage systems (BESS) in distribution networks with EV charging stations (EVCS) has proven to be a promising solution, offering multiple practical benefits. This approach not only optimized RES utilization but also maintains voltage stability and power flow during operation. Especially with fluctuating load demands, DG power injection ensures stable system voltage, minimizing the negative impacts of peak load or severe load variations [4]. Additionally, BESS also played a vital role in maintaining energy reserves during power fluctuations from DG, ensuring stability and continuity in power supply during sudden demand surges. Furthermore, BESS provides flexible power dispatch as needed, reducing dependence on conventional energy sources and improving RES utilization efficiency [5]. These combined factors enhance the performance of distribution networks, optimize energy usage, lower costs, and protect the environment.

Recent studies on EVCS optimization include integrating DG and restructuring distribution networks using the Whale Optimization Algorithm (WOA) improved system efficiency, meet EV charging demands, minimize power losses, and enhance operational capabilities [5]. Optimal placement of EVCS with Vehicle-to-Grid (V2G) provision using the Symbiotic Organisms Search (SOS) algorithm enhances operational efficiency, minimizes power losses, and optimizes grid supply through V2G techniques [6]. Particle Swarm Optimization (PSO) has been used to determine the optimal location and capacity of EVCS for unbalanced radial distribution systems (URDS) [7]. The Mexican Axolotl Optimization (MAO) and Wild Horse Optimizer (WHO) algorithms have been applied to identify the placement of EV parking lots with distribution systems [8]. Other techniques include PSO [9], optimal energy storage allocation using Genetic Algorithm (GA) [10], and determining the optimal location, capacity, and number of DG units through a Chaotic Random Segment Search (CSFS)-enhanced algorithm in distribution grids, proposing models to deploy various DG units to improve voltage quality at nodes [12]. However, the proposed solutions lack integration and fail to fully leverage the advantages of individual models, operating only in isolated frameworks without high synchronization, especially for large-scale problems with multiple constraints. Additionally, existing search algorithms did not achieve optimal results compared to advanced and improved algorithms.

In this paper, we proposed an improved CWHO algorithm based on the original WHO algorithm [13], combined with chaotic search functions to effectively address the optimization of DG and BESS deployment in distribution systems integrated with EVCS. The objective was to minimize power losses and maintain stable operational voltage. This improvement enhances search efficiency and delivers better results compared to the original WHO and previously published Chaotic Equilibrium Optimizer (CEO) algorithms. The model has been simulated on the IEEE-33 bus distribution network using Matlab R2022a, with four test scenarios and three different power coordination levels. The main contributions of the study can be summarized as follows:

- Proposing an improved algorithm CWHO, which was more efficient than the original WHO algorithm;
- Developing an EVCS optimization model in distribution networks that incorporated DG and BESS deployment;
- Applying Matlab R2022a to simulate and solve the optimization problem effectively;
- Suggesting a practical solution for the real-world development of EVCS systems.

2. PROBLEM MODEL

2.1. Objective function

$$F = \min(P_{LT}) \tag{1}$$

where P_{LT} is the system power loss total.

2.2. Constraints

Power Balance

$$\begin{aligned} &P_{SUB} + \sum_{j=1}^{N_b}\left(P_{PV,j} + P_{WT,j}\right) \\ &= \sum_{j=1}^{N_b}(P_{L,j} + P_{CS,j} + P_{BESS,j} + P_{LT,j}) \quad j = 1,2,...,N_b; \end{aligned} \tag{2}$$

$$\begin{aligned} &Q_{SUB} + \sum_{j=1}^{N_b}\left(Q_{PV,j} + Q_{WT,j}\right) \\ &= \sum_{j=1}^{N_b}(Q_{L,j} + Q_{CS,j} + Q_{BESS,j} + Q_{LT,j}) \quad j = 1,2,...,N_b; \end{aligned} \tag{3}$$

where, N_b is node.

P_{SUB}, Q_{SUB}: active, reactive power emitted from the grid.

$P_{PV,j}$, $Q_{PV,j}$: active, reactive power from PV.

$P_{WT,j}$, $Q_{WT,j}$: active, reactive power WT.

$P_{L,j}$, $Q_{L,j}$: total power of active and reactive power of the load.

$P_{CS,j}$, $Q_{CS,j}$: total active, reactive power of the CS.

$P_{BESS,j}$, $Q_{BESS,j}$: total active, reactive power of the BESS.

$P_{LT,j}$, $Q_{LT,j}$: total active, reactive power losses.

Voltage Constraints

Voltage limit:

$$V_t^{min} \le V_i \le V_t^{max}; i = 1,2,...,N_b \qquad 0.95 \le V_i \le 1.05 \tag{4}$$

Where, V_t^{min}, V_t^{max} indicate the lower and upper voltage, respectively.

Power limits:

$$P_{CS,i}^{min} \le P_{CS,i} \le P_{CS,i}^{max}; i = 1,2,...,n \tag{5}$$

$$P_{DG,i}^{min} \le P_{DG,i} \le P_{DG,j}^{max}; i = 1,2,...,n \tag{6}$$

$$P_{BESS,i}^{min} \le P_{BESS,i} \le P_{BESS,i}^{max}; i=1,2,...,n \tag{7}$$

Where:

$P_{CS,i}^{min} = P_{CS,i} = P_{CS,i}^{max}$ when P_{CS} adjustment limits of CS;

$P_{DG,i}^{min} = P_{DG,i} = P_{DG,i}^{max}$ when P_{DG} adjustment limits of DG;

$P_{BESS,i}^{min} = P_{BESS,i} = P_{BESS,i}^{max}$ when P_{BESS} adjustment limits of BESS;

$P_{CS,i}^{min}, P_{DG,i}^{min}, P_{BESS,i}^{min}$ minimum active power of CS, DG, and BESS at node i;

$P_{CS,i}^{max}, P_{DG,i}^{max}, P_{BESS,i}^{max}$ maximum active power of CS, DG, and BESS at node i;

n the number CS, DG, and BESS integrated and connected into the power grid.

3. THE CWHO ALGORITHM FOR EVCS PROBLEMS

3.1. Wild Horse Optimizer (WHO)

Wild Horse Optimizer (WHO) was a metaheuristic algorithm inspired by the behavior of wild horses in nature [13]. WHO was a dynamic mechanism that simulates how wild horses move, search, and select a leader within a herd, where group members interact and compete to find the best position, similar to how wild horses behave in their natural environment.

3.2. Creating an initial population

Generate an initial random group [13]:

$$(\vec{x}) = \left\{\vec{x_1}, \vec{x_2}, ..., \vec{x_n}\right\} \tag{8}$$

The objective function assesses the random group to identify the target value:

$$(\vec{O}) = \left\{O_1, O_2, ..., O_n\right\} \tag{9}$$

First, divide the population into several smaller groups:

- If there are N members, the possible number of groups is G=[N×PS], where PS represents the proportion of stallions in the population, utilized as a control parameter.
- There are G leaders, and the remaining members (N-G) are evenly distributed within the groups.

3.3. Grazing behaviour

To simulate this process, the formula used to describe the movement is:

$$X_{i,G}^{j} = 2Z\cos(2\pi RZ) \times (\text{Stallion}^{j} - X_{i,G}^{j}) + \text{Stallion}^{j} \tag{10}$$

Where, $X_{i,G}^{j}$ is the present position of a member within the group, the location of the stallion, Z is the adaptation mechanism determined according to (11), R is a random variable within the interval of [−2,2].

$$\begin{aligned} &P = \vec{R_1} < TDR, IDX = (P == 0), \\ &Z = R_2 \Theta IDX + \vec{R_3} \Theta (\sim IDX) \end{aligned} \tag{11}$$

Where P is a vector of values 0 and 1, $\vec{R_1}$, $\vec{R_3}$ is a randomly distributed vector with uniform distribution in [0,1], R_2 is a random variable within the interval of [0,1], IDX the indices of the elements in the random vector $\vec{R_1}$ satisfies the condition (P==0), TDR is an adaptation parameter that begins with a value of 1 and progressively decreases based on (12), the final value will be 0.

$$TDR = 1 - ier \times \left(\frac{1}{maxier}\right) \tag{12}$$

where ier present iteration and maxier the maximum iteration count of the algorithm.

3.4. Horse mating behaviour

To model the mating behavior between horses, the following equation is used:

$$\begin{aligned} &X_{G,k}^{p} = \text{Crossover}(X_{G,i}^{q}, X_{G,j}^{z}), \\ &i \neq j \neq k, q = z = end;\ \text{Crossover} = \text{Mean} \end{aligned} \tag{13}$$

where $X_{G,k}^{p}$ the position of the horse p in group k, which was determined by the position of the horse q in group i and the horse z in group j.

3.5. Group leadership

The leaders compete for their group to dominate the waterhole, and other groups are not allowed to use the waterhole until the dominant group leaves.

$$\overline{\text{Stallion}_{G_i}} = \begin{cases} 2Z\cos(2\pi RZ) \times (WH - \text{Stallion}_{G_i}) + WH & \text{if } R_3 > 0.5 \\ 2Z\cos(2\pi RZ) \times (WH - \text{Stallion}_{G_i}) - WH & \text{if } R_3 \leq 0.5 \end{cases} \tag{14}$$

where, $\overline{\text{Stallion}_{G_i}}$ the next position of the group leader i, WH the position of the waterhole, Stallion_{G_i} the current position of the group leader i, Z the adaptation mechanism calculated according to the equation (11), and R is a random variable within the interval of [−2, 2].

3.6. Exchange and selection of leaders

The leader is selected arbitrarily to ensure the randomness of the algorithm. Then, the leader is chosen based on fitness. If a member has better fitness than the leader, their positions are swapped according to the equation (15) [13].

$$\text{Stallion}_{G_i} = \begin{cases} X_{G,i} & \text{if } cost(X_{G,i}) < cost(\text{Stallion}_{G_i}) \\ \text{Stallion}_{G_i} & \text{if } cost(X_{G,i}) > cost(\text{Stallion}_{G_i}) \end{cases} \tag{15}$$

where, $t(X_{G,i})$ and $t(\text{Stallion}_{G_i})$ is the fitness value of the colt and the stallion.

3.7. Chaotic Wild Horse Optimizer (CWHO)

The WHO algorithm was originally based on the foraging behavior of wild horses. The addition of the chaotic function to the WHO algorithm was a significant improvement aimed at enhancing the performance of the algorithm in global optimization. The chaotic function is used to adjust the movement positions of the wild horses, generating unpredictable jumps that help the algorithm search for optimal solutions more effectively. This not only increased the search capability but also ensured diversity and continuous improvement in the optimization process. The two main equations of the WHO combined with the chaotic map are presented.

$$X_i^{new} = X_i + \alpha \times (X_{best} - X_i) + \beta \times (rand(0,1) - 0.5) + \gamma \times C_i \quad (16)$$

where α and β the control parameters; X_{best} the best current position of the wild horse; rand(0,1) as random number in the range of [0, 1], γ the control parameter for the chaotic component; c_i the chaotic component, for which 10 chaotic functions can be used [14].

$$X_i = \begin{cases} X_i^{new} & \text{if } f(X_i^{new}) < f(X_i) \\ X_i & \text{otherwise} \end{cases} \quad (17)$$

If the newly discovered position yields a better objective function value than the current position, the wild horse will shift to that new position.

3.8. Application of the CWHO Algorithm for the EVCS problems

Step 1: Define the components of the EVCS charging and discharging scheduling problem, including the objective, objective function, and constraints.

Step 2: Randomly initialize a population for the CWHO algorithm.

Step 3: Calculate and evaluate the objective function for each horse in the population based on its current position.

Step 4: Randomly select a group leader in the initial stage to enhance diversity. In later stages, the leader is chosen based on fitness, selecting the horse with the best fitness as the leader.

Step 5: Update positions: The leader moves towards the waterhole, and other horses move according to the leader with a random factor.

Step 6: Swap positions if a horse has better fitness than the leader, swapping their positions.

Step 7: Maintain diversity by adding the chaotic component to the positions of the horses to avoid premature convergence, using equation (16).

Step 8: Check the stopping condition. If the maximum number of iterations or the required fitness threshold is reached, stop the algorithm. If not, return to Step 4.

Step 9: Save the best position and fitness in the population as the optimal result.

4. SIMULATION RESULTS

In this section, the improved CWHO algorithm is simulated and tested with 10 different chaotic search functions, with a total of 300 iterations, aiming to minimize power loss applied to the IEEE 33-bus network. The results are compared to select the best performing improved algorithm for the problem model. Through the simulation search process, the convergence characteristics shown in Fig. 1 clearly indicate that the best solution belongs to CWHO10. Therefore, CWHO10 is proposed as the suitable algorithm for solving the EVCS problem.

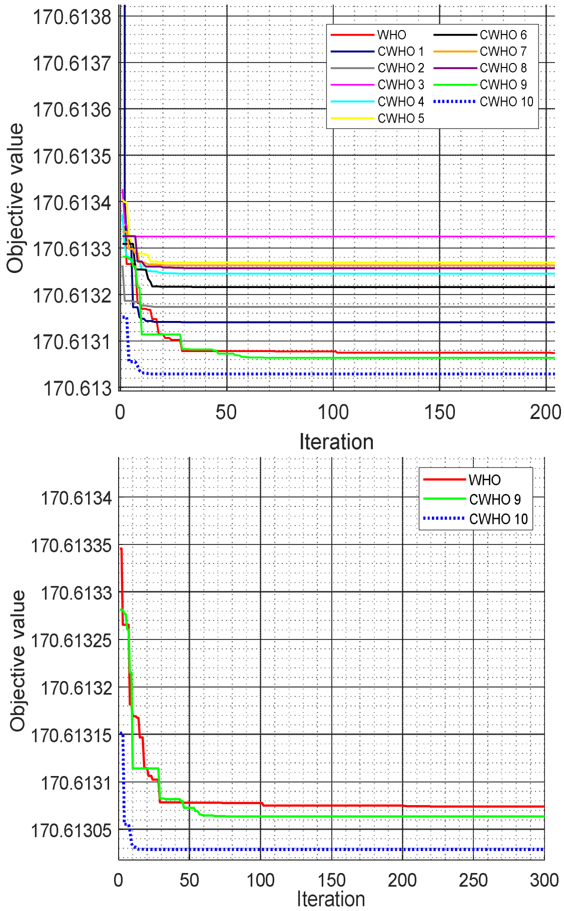

Fig. 1. The convergence characteristic of CWHO

4.1. Integrated Energy Dispatch Solutions in Distribution Networks

To further demonstrate the effectiveness of the improved CWHO10 compared to WHO in the EVCS problem, the model is tested in three cases.

- Case 1: The system integrates only DG.
- Case 2: The system integrates DG and BESS.
- Case 3: The system integrates EVCS, DG, and BESS.

Input parameters for simulating the cases

The power of 7 EVCS is fixed at nodes 3, 7, 9, 19, 22, 24, 26. At the same time, 3 DG units are placed at nodes 14, 18, 32, and the BESS system is located at nodes 8 and 27.

This setup minimizes power loss, stabilizes voltage, optimizes energy from DG and renewable sources, and enhances system efficiency [15, 16].

The power of solar (PV) and wind (WT) energy sources over a 24-hour frame is presented in Table 1 to simulate and test the power dispatch, with the WT and PV sources referenced according to the following parameter set [17].

Table 1. The typical output power of wind and solar power sources

Hour	PVs	WTs	Hour	PVs	WTs
12--1 am	0	0.25	12--1	1	0.71
1--2	0	0.235	1--2	0.95	0.805
2--3	0	0.23	2--3	0.83	0.91
3--4	0	0.235	3--4	0.72	0.96
4--5	0	0.22	4--5	0.55	0.86
5--6	0.05	0.225	5--6	0.3	0.81
6--7	0.1	0.19	6--7	0.13	0.7
7--8	0.27	0.17	7--8	0.05	0.585
8--9	0.5	0.25	8--9	0	0.415
9--10	0.7	0.37	9--10	0	0.325
10--11	0.9	0.47	10--11	0	0.29
11--12 pm	0.95	0.62	11--12 am	0	0.265

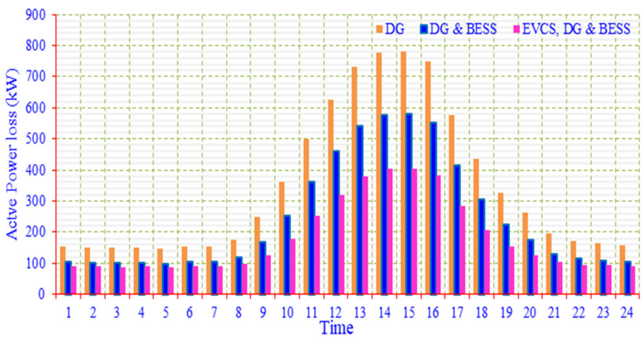

Fig. 2. The total power loss across the three cases surveyed

The simulation results presented in Fig. 2 clearly show that in case 1, where only DG is utilized, the system experiences the largest power loss, nearly double that of case 3, which integrates EVCS, DG, and BESS. Case 2 has lower losses than case 1, but still higher than case 3. Therefore, it can be inferred that the proposed model performs effectively satisfies the power balance constraints when DG and BESS are efficiently dispatched. This solution also provided more stability as BESS plays a key role in quickly responding to power fluctuations to maintain stability, while voltage is consistently maintained at a high level in all cases.

Case 1: DG was the sole energy source, providing base load over 24 hours. The highest load occurs during the off-peak hours (1-8 AM, 7-12 PM), especially during peak hours, leading to significant losses when relying solely on DG.

Case 2: DG was supported by BESS, reducing losses compared to Case 1, particularly during peak hours (9 AM - 6 PM). BESS adds power quickly, reducing the burden on DG and saving costs. However, the limited capacity of BESS makes it challenging to meet large load fluctuations, but it is still an effective balancing solution.

Case 3: The fully integrated system exhibits the lowest losses, particularly during peak hours (1-3 PM). EVCS helps with management and efficient distribution, reducing the load on DG and making good use of BESS in a flexible manner. This solution was highly effective and reliable for the development and implementation of EVCS.

4.2. Power Dispatch According to the Charging Levels for the EVCS System

In this part, the charging intensity coefficients are established to evaluate the coordination and power dispatching capability of the EVCS, DG, and BESS components, in order to test the flexibility and efficiency of the improved CWHO10 algorithm. Three load levels are considered in [18], with the BESS parameters maintained as in (4.1), and the EVCS and DG power fixed for both the charging and discharging modes.

As the load increases, the BESS discharges to support grid demand, while it charges when surplus power was available. At low and medium charge levels, the BESS primarily stores surplus powers, with values of -0.5MW and -0.275MW, respectively. During heavy charging, high EVCS demand and insufficient DG supply led the BESS to discharge 0.209MW. Total power lossed across consumption stages are 94.06kW, 95.24kW, and 108.58kW, respectively. In simulations, the CWHO algorithm consistently outperforms WHO and CEO in terms of power loss, charging power, and system stability, demonstrating its effectiveness for EVCS optimization with integrated DG and BESS. Moreover, voltage stability is maintained within 0.95 (pu) to 1.1 (pu) across all surveyed nodes, effectively addressing fluctuations, peak loads, and localized overloads. This highlights the technical robustness of the CWHO algorithm for addressing real-world challenges in EVCS management.

Table 2. Simulation results across the three charging levels

Charging level	Total EVCS capacity (MW)	Total power DG	BESS Power (MW)				Power loss (kW)		
			WHO		CWHO		CEO	WHO	CWHO
Low charging	1.562	0.61	-0.5	-0.5	-0.5	-0.5	94.05847	94.0585	94.0583
Average charging	3.124	0.61	-0.4014535	-0.2755482	-0.4017864	-0.2751151	95.23819	95.2382	95.2382
Heavy charging	4.9984	0.61	-0.1078503	0.210255	-0.1077630	0.2097027	108.5799	108.5800	108.5798

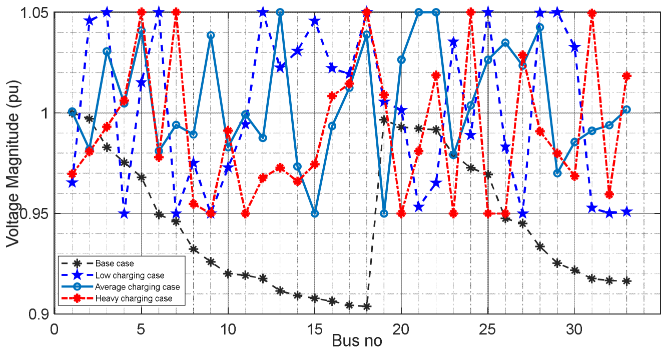

Fig. 3. The voltage node values at the three charging levels

5. CONCLUSION

The simulation results conducted across three scenarios and three levels of power dispatch for the EVCS system demonstrated that the improved CWHO10 algorithm provides practical effectiveness in optimizing the coordination of power for the EVCS model in a distribution network integrated with DG and BESS. Each applied solution proved the superiority of CWHO when compared to the original WHO and previously published CEO algorithms. In the proposed simulation cases, the integration of DG, BESS, and EVCS shows superior and more stable performance compared to other solutions. Therefore, this solution is recommended for implementation in the development of EVCS infrastructure in practice.

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