

# WILD HORSE OPTIMIZER ALGORITHM FOR DETERMINED OPTIMAL PLACEMENT OF ELECTRIC VEHICLE CHARGING STATIONS IN DISTRIBUTION NETWORKS

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## ABSTRACT

The rapid development of electric vehicle charging stations (EVCS) has increased pressure on the power system, especially the distribution network (DN), and solutions to mitigate these negative impacts are always a priority. This study proposed a model for determining the optimal location of EVCS within DNs with the goal of minimizing installation costs and power losses, while maintaining node voltage stability. The Wild Horse Optimization (WHO) algorithm is applied to the problem, and a standard IEEE 34-node network is used for simulation and verification. MATLAB R2022a software used to retrieve results for two scenarios: with and without Vehicle-to-Grid (V2G) optimization. Power losses reached 221.695 kW and 206.097 kW respectively, and the minimum node voltage reached 0.94758 pu, significantly better than previously published GWO results. These results demonstrate that the problem model is appropriate and applicable to calculating EVCS infrastructure development.

## 1. INTRODUCTION

Environmental issues have always been a major concern for nations striving for stability and sustainability. Among these, the transportation sector is one of the primary contributors to CO<sub>2</sub> emissions, leading to global warming and climate change [1], [2], [3]. In recent years, the integration of bidirectional converters into the power grid for V2G applications of electric vehicles (EVs) has received significant attention due to its potential benefits. This technology holds great potential for optimizing power grid development. Despite its many outstanding advantages, the rapid increase in the number of EVCS has created significant pressure and negative impacts on the power grid [4], particularly in DN. Therefore, proposing solutions to mitigate these impacts was

an essential concern. Recent studies have introduced effective solutions for the development of EVCS systems, including: optimizing the placement of EVCS in DNs using the JAYA optimization algorithm: this model aims to minimize installation costs and power losses, demonstrating the effectiveness of optimal placement [5]. Application of the Arithmetic Optimization Algorithm (AOA), identifies optimal EVCS locations in DNs and proves effective in reducing power losses and improving the operation of Charging Stations (CS) [6]. Optimizing EV parking spots in Smart Grids: Considers charging power demands and used the Cuckoo Optimization Algorithm (COA) with sequential Monte Carlo simulation, demonstrating the economic efficiency of power coordination for both investors and vehicle

owners [7]. The optimal placement of EVCS in Microgrids uses an embedded hybrid optimizer to maximize distributed energy source capacity [8]. Dispatching EVCS in DN integrated with Distributed Generation DG employs a hybrid Genetic Algorithm and Particle Swarm Optimization (GA-PSO) to minimize power losses and voltage deviation indices, showing high efficiency in DG mobilization for EVCS systems [9]. Dispatching EVCS integrated with DG: considers load convergence characteristics and used a novel chaotic student psychology based optimization (CSPBO) algorithm. Tested on IEEE 33-bus and real world 136 bus networks in Brazil, this method demonstrates optimal power dispatch and effective utilization of renewable energy sources [10]. The optimal placement of Electric Vehicle Fast Charging Stations (EVFCS) in DNs using V2G technology: applies the Grey Wolf Optimization (GWO) algorithm, achieving minimized installation costs and power losses [11]. The optimal EVCS placement in real world DNs demonstrated superior performance in minimizing installation costs and power losses using the Particle Swarm Optimization (PSO) algorithm [12].

These studied highlight the effectiveness of the proposed solutions across various scenarios. However, for a more comprehensive and precise evaluation, it is necessary to explore and compare multiple search algorithms to achieve higher efficiency, especially by leveraging recent robust and innovative search tools.

In this study, we proposed a new WHO and powerful search algorithm belonging to the meta-heuristic group [13]. This algorithm is applied to the optimization problem of determining the optimal placement of EVCS in DN. The problem is analyzed under two scenarios: without V2G and with V2G applied to EVCS. The results are simulated and validated using Matlab R2022a software on the standard IEEE 34-bus distribution network. The effectiveness of the proposed approach is demonstrated through

comparisons and evaluations against the previously published GWO algorithm [14].

The main contributions of this study can be summarized as follows:

- The proposed an efficient WHO algorithm for the EVCS optimization problem.
- Applying and validating the proposed method through simulations using MATLAB software.
- The proposed solution for the practical development of the EVCS system.

## 2. PROBLEM MODEL

The number of EVs varies at different times across CS locations, and the land prices in urban areas are significantly higher than in surrounding regions. This leads investors to be cautious before making decisions, particularly regarding factors such as location, installation costs, and power loss costs when deploying CS. These factors will directly impact the project's costs and profitability.

### 2.1. Number of CS

The number of CS is calculated using the formula provided in [15]:

$$N_{CS} = \frac{P_{EV} \times N \times T_C}{t \times H \times \theta \times C_{CS}} \quad (1)$$

Where,  $P_{EV}$  is the average power of each EV,  $N$  is the total number of EVs charged each day,  $T_C$  is the charging time to fully charge an EVs,  $t$  is the service time of the CS,  $C_{CS}$  is the power of the CS,  $\theta$  is the charging efficiency,  $H$  is the load demand factor of the CS.

### 2.2. V2G technology

This is a solution that provides numerous positive impacts for the operation of distribution networks, particularly in regulating the bidirectional power flow from the grid to G2V and from V2G during the charging and discharging process of EVs. In this study, the proposed solution seeks to determine the bidirectional power flow throughout the grid connection of EVs, optimizing the systems efficiency.

$$P_{CS}^i = (N_{EV}^{G2V} \times R_{ch}) - (N_{EV}^{V2G} \times R_{dis}) \quad (2)$$

Where,  $P_{CS}^i$  is the power added to node  $i$  due to the installation of additional CS  $N_{EV}^{G2V}$  and  $N_{EV}^{V2G}$  represents the number of EVs at the G2V and V2G nodes;  $R_{ch}$  and  $R_{dis}$  represents the charging and discharging rates of an EV battery, respectively.

### 2.3. Formulas for the optimization problem

The optimal location and size of CS in the distribution network are determined through the following equations:

#### 2.3.1. Objective function

The objective function of the problem is to minimize the installation costs of CS ( $IC$ ) and the power loss costs ( $C_{Ploss}$ ) [15]. In this case, the installation costs consist of fixed costs, land rental costs, and development costs for the CS, expressed through the following formula:

$$IC_i = C_{FIX} + 100 \times ND \times C_{LAND}^i + 4 \times C_p \times C_{DEV} \quad (3)$$

Where,  $C_{FIX}$  is the fixed cost of the CS,  $ND$  is the proposed planning duration in days,  $C_{LAND}^i$  is the land rental cost per square meter at node  $i_{th}$  for 5 years,  $C_p$  is the unit cost of each connector,  $C_{DEV}$  is the development cost of the connection process.

The power loss cost ( $C_{Ploss}$ ) is determined as follows:

$$C_{Ploss} = P_{loss} \times C_e \quad (4)$$

Where,  $C_e$  is the electricity price.

The objective function  $OF$  in the model is expressed as follows:

$$OF = \text{Min} \left( w_1 \times \sum_{i=1}^{Nb} IC_i \times Z_i + w_2 \times \sum_{j=1}^N P_{loss} \times C_e \right) \quad (5)$$

Where,  $w_1$  and  $w_2$  are the positive constants;  $Z_i = 1$  when the CS is connected to the  $i_{th}$  node.

#### 2.3.2. Constraints

The constraints for the CS location problem are implemented as follows:

#### - Power balance

$$P_{SUB} = \sum_{i=1}^{Nb} P_{Di} + P_{loss} + \sum_{i=1}^{N_{CS}} P_{CSi} \quad (6)$$

$$Q_{SUB} = \sum_{i=1}^{Nb} Q_{Di} + Q_{loss} + \sum_{i=1}^{N_{CS}} Q_{CSi} \quad (7)$$

Where,  $P_{SUB}$ ,  $P_{Di}$ ,  $P_{loss}$  and  $P_{CSi}$  are the active power from the source transformer, the active power demand at node  $i_{th}$ , the total active power loss, and the active power of the CS at node  $i_{th}$ , respectively;  $Q_{SUB}$ ,  $Q_{Di}$ ,  $Q_{loss}$  and  $Q_{CSi}$  are the reactive power from the source transformer, the reactive power at node  $i_{th}$ , the total reactive power loss, and the reactive power of the CS at node  $i_{th}$  (in this case  $Q_{CS} = 0$ ).

#### - Voltage limits

$$V^{Min} < V_i < V^{Max}, i = 1, 2, \dots, Nb \quad (8)$$

#### - Current limits

$$I^{Min} < I_j < I^{Max}, j = 1, 2, \dots, N_r \quad (9)$$

Where,  $N_r$  the number of branches in the distribution network.

### 2.4. The WHO algorithm

The WHO was a metaheuristic algorithm inspired by the behavior of wild horses in nature [13]. The WHO was a dynamic mechanism that simulates how wild horses move, search, and select leaders within a herd, where the members interact and compete to find the best position, similar to wild horses in the natural environment.

The wild horse optimizer consists of five main steps as follows:

- **Generate the initial population**

A randomly generated initial population.

$$(\bar{X}) = \{\bar{x}_1, \bar{x}_2, \dots, \bar{x}_n\} \quad (10)$$

The objective function evaluates the population:

$$(\bar{O}) = \{O_1, O_2, \dots, O_n\} \quad (11)$$

First, divide the population into several smaller groups:

If  $N$  the members, the number of groups  $G = \lfloor N \times PS \rfloor$ , Where  $PS$  the percentage of stallions in the population, used as a control parameter.

The leaders  $G$ , and the remaining members  $(N-G)$  are evenly distributed into the groups.

- **Herding behavior**

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

$$X_{i,G}^j = 2Z \cos(2\pi RZ) \times (Stallion^j - X_{i,G}^j) + Stallion^j \quad (12)$$

Where,  $X_{i,G}^j$  the current position of the member in the group,  $Stallion^j$  the position of the stallion,  $Z$  the adaptation mechanism calculated by (13),  $R$  a random number in the range of  $[-2, 2]$ .

$$P = \overline{R_1} < TDR, IDX = (P == 0), \quad (13)$$

$$Z = R_2 \ominus IDX + \overline{R_3} \ominus (\square IDX)$$

Where,  $P$  a vector consisting of values 0 and 1,  $\overline{R_1}$  and  $\overline{R_3}$  are a random number in  $[0,1]$ ,  $R_2$  is a random vectors uniformly distributed in  $[0,1]$ ,  $IDX$  indexes of the random vector  $\overline{R_1}$  returns that satisfy the condition  $(P = 0)$ ,  $TDR$  an adaptive parameter that starts with a value of 1 and decreases during the execution of the algorithm according to (14) and at the end of the execution of the algorithm reaches 0.

$$TDR = 1 - iter \times \left( \frac{1}{\max iter} \right) \quad (14)$$

Where,  $iter$  the current iteration and  $\max iter$  the maximum number of iterations.

- **The mating behavior of horses.**

To simulation the mating behavior of horses, the following formula is used:

$$X_{G,k}^p = \text{Crossover}(X_{G,i}^q, X_{G,j}^z), \quad (15)$$

$$i \neq j \neq k, q = z = \text{end}$$

$$\text{Crossover} = \text{Mean}$$

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

- **Group leadership**

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

$$\overline{Stallion_{G_i}} = \begin{cases} 2Z \cos(2\pi RZ) \times (WH - Stallion_{G_i}) + WH & \text{if } R3 > 0.5 \\ 2Z \cos(2\pi RZ) \times (WH - Stallion_{G_i}) - WH & \text{if } R3 \leq 0.5 \end{cases} \quad (16)$$

Where,  $\overline{Stallion_{G_i}}$  the next position of the leader of group  $i$ ,  $WH$  the position of the waterhole,  $Stallion_{G_i}$  is the current position of the leader of group  $i$ ,  $Z$  the adaptive mechanism calculated by equation (13), and  $R$  a random number in the range  $[-2, 2]$ .

- **Exchange and selection of leaders**

First, the leader is randomly selected to ensure the randomness of the algorithm. After that, the leader is chosen based on fitness. If a member has a better fitness than the leader, their positions will be swapped according to equation (17) [13].

$$\overline{Stallion_{G_i}} = \begin{cases} X_{G,i} & \text{if } \text{cost}(X_{G,i}) < \text{cost}(Stallion_{G_i}) \\ Stallion_{G_i} & \text{if } \text{cost}(X_{G,i}) > \text{cost}(Stallion_{G_i}) \end{cases} \quad (17)$$

Where,  $t(X_{G,i})$  and  $t(Stallion_{G_i})$  the fitness values of the foal and the stallion.

## 2.5. Applying WHO for the EVCS problem

**Step 1:** Identify the components of the EVCS charging and discharging scheduling problem according to formulas (3), (4), (5), (6), (7), (8), (9).

**Step 2:** Randomly initialize a population for the WHO algorithm using formula (10).

**Step 3:** Calculate and evaluate the objective function in the population based on the current position using formula (11).

**Step 4:** Select a random group leader in the early stages. In later stages, select the horse with the best fitness as the leader.

**Step 5:** Update the position.

**Step 6:** Swap positions if a horse has better fitness than the leader using formula (17).

**Step 7:** Check the stopping condition. If the maximum number of iterations is reached or fitness meets the required threshold, stop the algorithm. If not, return to Step 4.

**Step 8:** Save the best position and fitness in the population as the optimal result.

### 3. THE SIMULATION RESULTS

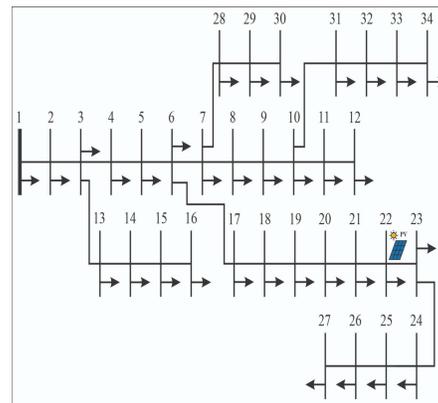
#### 3.1. The testing simulation

To evaluate the search quality of WHO on the problem model, the test results were run through 50 independent simulations to retrieve results and compared them with 6 other algorithms, including: An augmentation Runge Kutta optimizer (RUN) [16], Seagull Optimization Algorithm (SOA) [17], Grey Wolf Optimization (GWO) [15], Ant Lion Optimizer (ALO) [18], Moth Swarm Algorithm (MSA) [19], and Gradient-based optimizer (GBO) [20]. The data parameters are used for simulation cases in Table 1 and Figure 1. The simulation results presented in Figure 2 showed that among the 7 search algorithms, 3 algorithms provided good results, such as RUN, MSA and WHO. Among these 3 algorithms, WHO demonstrated superior and more stable performance throughout the testing process as results presented in Table 2. This evidence supported the proposal that WHO was suitable for solved the EVCS problem.

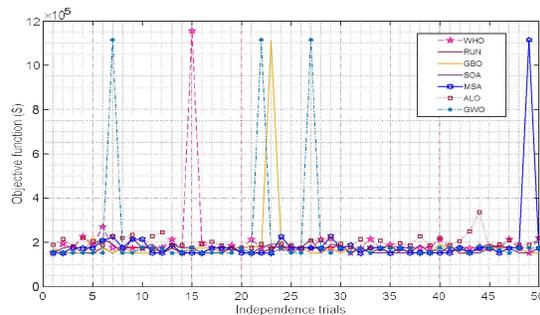
**Table 1. Data used for EVCS planning [15]**

Parameter	Value
Number of EVs ( $N_{EV}$ )	1,000
Charging time ( $t_{ch}$ )	0.33 Hour
Service time of RCS ( $t_{sv}$ )	18 Hour
Capacity of CS ( $C_{CS}$ )	480 kW
Fixed cost of CS ( $C_{fix}$ )	21,900 \$

Parameter	Value
Development cost of connector ( $C_{dev}$ )	109.5 \$
Average power for each EV ( $P$ )	96 kW
Connector capacity ( $C_p$ )	96 kW
Electricity price ( $C_e$ )	0.11 \$/kWh
Planning period ( $ND$ )	1,825 days
Charging efficiency ( $f_{ch}$ )	0.9
Load factor of a CS ( $d_{lf}$ )	0.95



**Figure 1. Diagram of DN IEEE 34-bus**



**Figure 2. The simulation results verify and compare the algorithms**

**Table 2. Target comparison value through applied algorithms**

Functions	Fitness value (Min)	Fitness value (Average)	Fitness value (Max)	Standard deviation	CPU time (s)
ALO	168,045.9	171,549.9	171,695.9	715.251	12.241
MSA	166,220.9	171,257.9	171,695.9	1,067.898	12.072
WHO	<b>164,408.2</b>	<b>171,112.2</b>	<b>171,695.9</b>	<b>1,286.092</b>	<b>12.153</b>
RUN	166,220.9	168,994.9	171,695.9	1,377.361	33.613
GBO	169,870.9	170,856.4	171,695.9	909.5753	11.548
SOA	168,045.9	169,834.4	171,695.9	575.9603	11.409
GWO	169,870.9	171,440.6	171,695.9	632.9384	11.721

**3.2. Scenario 1: Without the V2G technology**

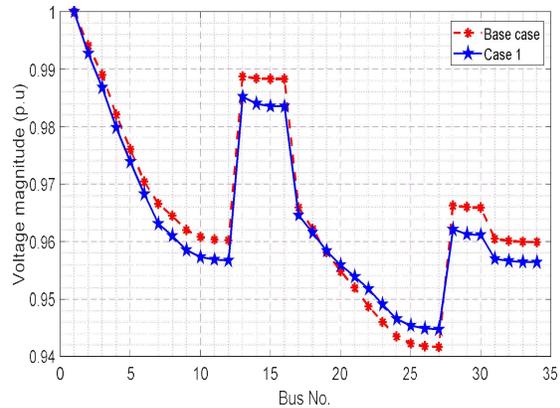
In this case, the location of the EVCS is determined without applying the V2G technology. The results obtained from the simulation process were evaluated and compared with GWO. The results were assessed over 20 independent runs, demonstrating the superior effectiveness and search capability of the proposed solution. The input parameters for the simulation in this case were applied as in [15].

The results presented in Table 3 clearly highlight the superior performance too general of WHO in optimizing the EVCS location. Specifically, this algorithm achieves the lowest power loss value at 221.695 kW, compared to 235.634 kW for the GWO method and 221.6947 kW for the baseline case, where the CSs are installed at nodes 2, 13, 15, and 29. Additionally, the voltage quality at the nodes in the system is significantly improved, reaching a minimum of voltage magnitude at 0.94495 p.u, which was higher than the baseline case. The installation cost was also lower, at only 345,217 (\$) compared to 348,867 (\$), which demonstrated the superiority of the proposed solution over the methods used for comparison. This indicates that the proposed solution not only meets the technical constraints effectively but also achieved optimization goals and enhanced the operational efficiency of the system.

**Table 3. Optimal results without V2G**

	Base case	GWO	WHO
Power loss (kW)	221.6947	235.634	221.695
Min Voltage (pu)	0.9417	0.94481	0.94495
EVCS locations	-	2, 13, 14, 29	2, 13, 15, 29
Installation cost (\$)	-	348,867	345,217
Power loss cost due to EVCS (\$)	-	50,278	291,953
Objective value (\$)	-	199,572.5	198,257.6

The node voltage intensity presented in Figure 3 illustrated a significant improvement compared to the proposed GWO method [14], confirmed that the solution effectively meets the established objectives and constraints while demonstrating that stability is maintained.



**Figure 3. Voltage profile without V2G**

**3.3. Scenario 2: Considering V2G technology**

In this scenario, the EVCS is integrated with V2G technology, an advanced solution that optimizes energy used and enhanced operational efficiency, leading towards smart grid technology. The V2G technology not only allowed the EVCS to provide power to EVs, but also enables it to discharge power back into the grid when necessary, effectively regulating any negative impacts. This helps to mitigate energy consumption from fluctuating loads and peak loads, maintaining the stability of power quality.

The results presented in Table 4 once again demonstrate the effectiveness of the WHO algorithm in optimizing the installation locations of EVCSs at nodes 2, 3, 13, and 15. In this case, the power loss value was only 206.097 kW, lower than the 207.158 kW of the GWO method, highlighting the strong search capability of WHO. Additionally, the voltage quality in the system has also been significantly improved, with a value of voltage magnitude at 0.94758 pu at node 27, showing the stability of the algorithm.

**Table 4. The simulation results consider V2G technology**

	Base case	GWO	WHO
Power loss (kW)	221.6947	207.158	206.097
Min Voltage (pu)	0.9417	0.94752	0.94758
EVCS locations	-	2, 3, 14, 15	2, 3, 13, 15
Installation cost (\$)	-	361,642	363,467
Power loss cost due to EVCS (\$)	-	-52,620	-56,360
Objective value (\$)	-	154,510.7	153,553.4

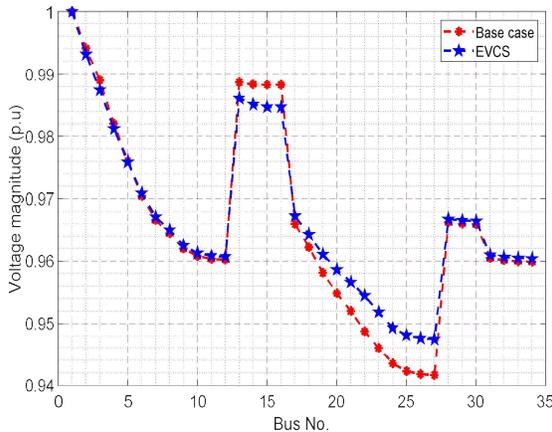
**Figure 4. Voltage profile with V2G**

Figure 4 illustrated the voltage intensity values at the nodes, confirming the superior performance of WHO compared to the previously published GWO [14].

#### 4. CONCLUSION

Through the simulation results, it can be affirmed that the proposed WHO algorithm this algorithm is proposed by other people, for determining the EVCS locations in the DN with integrated DG provides practical benefits. The results also demonstrated its superiority when compared to the previously published GWO method. The objective functions of minimizing power loss, optimizing land rental costs, and improving voltage quality all achieved better results than GWO. The simulation results on Matlab 2022a confirmed the accuracy and

reliability of WHO, making it a powerful computational tool for the development of EVCS infrastructure in practice.

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## ỨNG DỤNG THUẬT TOÁN TỐI ƯU HÓA NGỰA HOANG ĐỂ XÁC ĐỊNH VỊ TRÍ TỐI ƯU CÁC TRẠM SẠC XE ĐIỆN TRONG MẠNG LƯỚI PHÂN PHỐI

### TÓM TẮT

*Sự phát triển nhanh chóng của các trạm sạc xe điện (EVCS) đã làm tăng áp lực lên hệ thống điện, đặc biệt là mạng phân phối, việc đề xuất các giải pháp giảm thiểu những tác động tiêu cực luôn được quan tâm. Nghiên cứu này đề xuất một mô hình xác định vị trí tối ưu EVCS trong mạng phân phối với mục tiêu cực tiểu chi phí lắp đặt và tổn thất điện năng, duy trì ổn định điện áp nút. Thuật toán Tối ưu hóa Ngựa Hoang (WHO) được áp dụng cho bài toán, mạng điện chuẩn IEEE 34 nút được sử dụng mô phỏng kiểm tra, kết hợp phần mềm MATLAB R2022a truy xuất kết quả với hai kịch bản có xét và không có xét kỹ thuật Vehicle-to-Grid (V2G). Công suất tổn thất đạt 221,695 (kW), 206,097 (kW) lần lượt, điện áp nút tối thiểu đạt 0,94758 p.u, vượt trội hơn khi so sánh với GWO đã công bố trước đó. Kết quả này chứng minh mô hình bài toán là phù hợp và có thể áp dụng để tính toán phát triển hạ tầng EVCS.*

**Từ khóa:** Hệ thống lưu trữ năng lượng pin (BESS), hệ thống điện, mạng lưới phân phối, sạc EVCS, WHO