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Research Article

Improved Grey Wolf Optimization Algorithm for Optimal Allocation Problem of Electric Vehicle Charging Stations

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Abstract:

It is frequently preferred to perform development processes to improve the results of optimization algorithms and increase their performance. Swarm-based metaheuristic optimization algorithms are frequently preferred due to their ease of application and fast results. In this study, the alpha wolf class, also called the wolf leader class in grey wolf optimization (GWO), was improved with chaotic Chebyshev map and named as chGWO. 7 of the standard test functions were used to evaluate the performance of chGWO and the findings were compared with the literature. Based on the comparisons of the algorithms in the literature, the chGWO algorithm gave good results in single-mode benchmark functions. Then, the improved algorithm was applied to the problem of optimum placement of electric vehicle charging stations (EVCSs) in the grid using the IEEE 33-bus test system. It gave better results than the classical GWO algorithm. It was seen that the improved chGWO was advanced and could be used in solving various engineering problems.

1. Introduction

Optimization algorithms are important tools to find the best solution for various problems. These algorithms are generally divided into two categories: heuristic optimization algorithms and mathematical optimization algorithms. Among the meta-heuristic optimization algorithms such as Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA), GWO, Salp Swarm Optimization (SSO), Artificial Bee Colony (ABC), and Atom Search Algorithm (ASA) [1]. In particular, the use of optimization algorithms in solving engineering optimization problems is increasing steadily. Optimization algorithms have been successfully used in various applications, from the optimization of concrete-weighted dams to the speed control of brushless direct current motors [2,3]. The use of these algorithms has enabled more suitable results to be obtained in engineering problems [4]. Additionally, optimization algorithms are widely used in various areas such as multi-object tracking, discovery of classification rules, and diabetes diagnosis [5,6,7,8]. Optimization algorithms are important tools with a wide range of applications. Meta-heuristic optimization algorithms and artificial intelligence algorithms are effectively used in solving engineering problems. The use of these algorithms plays an important role in optimizing problems and finding the best solutions.

Improving optimization algorithms is an important step for solving complex problems. These improvements generally aim to enhance the performance of existing algorithms, improve solution accuracy, or increase convergence speed. Chaotic maps are methods that can increase the diversity of algorithms by providing a balance between randomness and determinism, helping them to avoid local minima [9]. This way, it becomes possible for optimization algorithms to explore a broader search space and find better solutions [10]. Advanced optimization algorithms are used in various applications, from path planning of mobile robots to the optimization of their structures [11,12]. These developments allow algorithms to have a broader range of applications and to adapt better to different problems [13,14]. The use of chaotic maps is one of the methods that helps to find better solutions by increasing the diversity of algorithms and improving optimization processes.

The increasing number of charging stations and their optimal placement are crucial factors in promoting the adoption and efficient operation of electric vehicles (EVs). Research has shown that the appropriate site selection is crucial for the effective use of EVCS [15]. As the number of fast charging stations continues to increase, it is important to strategically place high-capacity stations close to the electrical grid in order to mitigate their negative effects on the network [16,17]. The impact of electric vehicle charging station loads on grid reliability indicators is significant and should be considered when evaluating their effects on the grid [18]. The rising demand for energy storage and the transition to electric drive systems in vehicles are elevating the significance of lithium-ion batteries in energy storage systems, especially in electric vehicles[19]. It focusses on designing solar-powered charging stations for electric vehicles to promote the use of renewable energy and balance energy demand and supply systems [20]. The design and simulation of DC fast chargers for electric vehicles are of great importance in terms of developing charging infrastructure and addressing issues such as cost, speed, and efficiency [21]. Additionally, analysing the integration of EVCSs into residential electricity distribution networks highlights the importance of strategic planning for optimal placement [22]. The optimal integration of EVCSs plays a vital role in supporting the widespread adoption of EVs. Promoting sustainable transportation and reducing dependence on traditional fossil fuel vehicles is one of the key issues, which includes strategic placement, integration with renewable energy sources, and efficient design of charging infrastructure [23,24].

The originality of this study lies in the innovative enhancement of the alpha wolf class, the most critical component of the wolf hierarchy in GWO. The alpha wolf is responsible for making crucial decisions, such as hunting, and it contains the most valuable solutions within the algorithm. By integrating Chebyshev chaotic maps into the alpha class, in this study specifically targeted its improvement, resulting in the development of the chGWO algorithm.

The performance of the chGWO algorithm has been rigorously evaluated using quality test functions F1-F7, demonstrating that it significantly enhances the foundational GWO algorithm. The results indicate that the chGWO consistently outperforms other methods reported in the literature, reinforcing its efficacy as an advanced optimization technique.

Moreover, to illustrate the applicability of the chGWO in solving complex engineering problems, the algorithm was employed to address the optimal placement of EVCSs within the IEEE 33-bus test system. The results obtained from this application further validate the effectiveness of the chGWO algorithm, showcasing its potential to provide superior solutions in practical scenarios. This study not only contributes to the body of knowledge on swarm-based optimization algorithms but also establishes a pathway for future research aimed at enhancing metaheuristic methods in various engineering applications.

The rest of the paper is as follows; Section 2 presents the mathematical model and boundaries of the EVCSs problem. Section 3 presents the results of the benchmark test function for the GWO algorithm, chaotic map, and the improved chGWO algorithm. Section 4 presents results and discusses the cases where the chGWO algorithm is applied to the IEEE 33 bus test system. The conclusion presented in Section 5.

2. Material and Methods

2.1 Mathematical Model of EVCS Allocation Problem

The objective of this study is to minimize active power loss. To determine the optimal power and location of the EVCS, the objective function has been optimized while considering relevant constraints. Power flow, optimal placement of distributed generation systems, and optimal allocation of ancillary services are generally related to minimizing active power losses. In this study, active power loss in the distribution system is used as the objective function.

2.2 Objective function

$$Min\ (F1) \qquad (1)$$

$$F1 = TotalP_{Loss} = \sum_{L=1}^{Nl} P_{Loss} \qquad L=1,2,3\ldots,\ Nl \quad (2)$$

The $TotalP_{Loss}$ shows the total active power losses and, Nl shows the number of lines in the distribution system.

2.3 Problem boundaries

The voltage limits of the buses are given by equation 3.

$$V_i^{min} \le V_i \le V_i^{max}\ ,\ i=1,2,\ldots,m \qquad (3)$$

V_i represents the bus voltage, V_i^{min} and V_i^{max} represent the minimum and maximum bus voltage limits, respectively. m denotes the number of buses. The voltage values throughout the problem have been taken as V_i^{min} = 0.95 pu and V_i^{max} = 1.05 pu. The bus capacity values are given by equation 4.

$$S_{ij} \le S_{ij}^{max},\ i,j=1,2,\ldots,n \qquad (4)$$

S_{ij} shows the power of bus from i to j. S_{ij}^{max}

represents the maximum line power value, while n indicates the number of lines.

2.4 EVCS limits

$$P_{Total_{Load,EVCS}} = 2 * P_{Load,EVCS} \quad (5)$$

$P_{Load,EVCS}$ shows the electrical load of the EVCS.

3. Grey Wolf Optimization Algorithm (GWO)

The Grey Wolf Optimization (GWO) algorithm is inspired by the social hierarchy and hunting behavior of grey wolves. The hierarchy is composed of alpha, beta, delta, and omega wolves, each playing a specific role within the pack. Figure 1 shows the hierarchy of wolves [25].

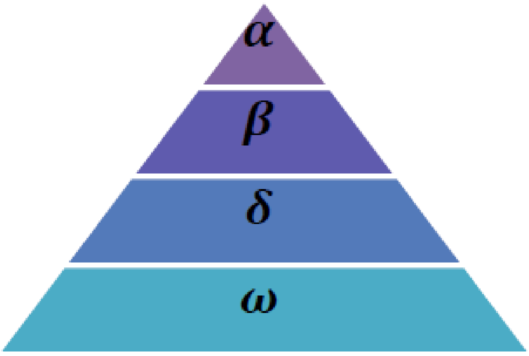


Figure 1. *The hierarchy of grey wolves [25].*

3.1 Social hierarchy

Alpha is the leader of the pack, responsible for making decisions and commanding the group. Beta, the second in command, assisting the alpha and enforcing the pack's discipline. Delta wolves that follow the alpha and beta but dominate the omega wolves. This category includes hunters, sentinels, and elders. Omega, the lowest-ranked wolves, submitting to all others and playing a passive role.

3.2 Mathematical modelling in GWO:

The social hierarchy is modelled by considering the best solution as the alpha (α), the second-best as beta (β), and the third-best as delta (δ). The rest of the solutions are omega (ω), and they follow α, β, and δ during the optimization process.

$$\vec{D} = \left|\vec{C}.\vec{X_p}(t) - \vec{X}(t)\right| \quad (6)$$

$$\vec{X}(t+1) = \vec{X_p}(t) - \vec{A}.\vec{D} \quad (7)$$

t shows the current iteration, the vectors $\vec{A}$ and $\vec{C}$ represent the coefficients, $\vec{X_p}(t)$ denotes the position vector of the prey, and $\vec{X}$ represents the position vector of the grey wolf.

The vectors $\vec{A}$ and $\vec{C}$ are calculated as given below.

$$\vec{A} = 2\vec{a}.\vec{r_1} - \vec{a} \quad (8)$$

$$\vec{C} = 2.\vec{r_2} \quad (9)$$

The components of vector $\vec{a}$ have linearly decreased from 2 to 0 over the iterations, and r_1 and r_2 are random vectors in the range [0,1].

3.3 Encircling prey

Grey wolves encircle their prey during hunting. This behavior is modeled using mathematical equations that update the wolves' positions based on the prey's location. The positions are adjusted using coefficients $\vec{A}$ and $\vec{C}$, which depend on random vectors and the iteration process.

3.4 Hunting

The alpha, beta, and delta wolves guide the hunting process by leading the search agents (candidate solutions) towards the prey. The positions of the search agents are updated based on the top three solutions at each step.

$$\vec{D_\alpha} = \left|\vec{C_1}.\vec{X_\alpha} - \vec{X}\right|, \vec{D_\beta} = \left|\vec{C_2}.\vec{X_\beta} - \vec{X}\right|, \vec{D_\delta} = \left|\vec{C_3}.\vec{X_\delta} - \vec{X}\right| \quad (10)$$

$$\vec{X_1} = \vec{X_\alpha} - \vec{A_1}(\vec{D_\alpha}), \vec{X_2} = \vec{X_\beta} - \vec{A_2}(\vec{D_\beta}), \vec{X_3} = \vec{X_\delta} - \vec{A_3}(\vec{D_\delta}) \quad (11)$$

$$\vec{X}(t+1) = \frac{\vec{X_1} + \vec{X_2} + \vec{X_3}}{3} \quad (12)$$

3.5 Attacking prey (exploitation)

The wolves attack the prey when it stops moving, and this is modeled by reducing the parameter a, which causes the wolves to converge towards the prey's position. When $|\vec{A}|$ is between -1 and 1, the wolves approach the prey.

3.6 Searching for prey (exploration)

During the search, wolves move away from the prey if $|\vec{A}| > 1$, allowing for exploration. This mechanism helps the GWO avoid being trapped in local optima and encourages global exploration of the search space. The GWO algorithm balances exploration and exploitation by adjusting the values of vector $\vec{A}$ is reduced by vector $\vec{a}$ over iterations. The algorithm continues until a stopping criterion is met, such as a maximum number of iterations or a desired fitness level.

GWO mimics the social behavior and hunting strategies of grey wolves to perform optimization, ensuring a balance between exploration (searching) and exploitation (convergence) [25]. Pseudocode for the GWO algorithm shown in Figure 2.

```
Initialize the grey wolf population Xi (i = 1, 2, ..., n)
Initialize a, A, and C
Calculate the fitness of each search agent
Xα=the best search agent
Xβ=the second best search agent
Xδ=the third best search agent
while (t < Max number of iterations)
    for each search agent
            Update the position of the current search agen
    end for
    Update a, A, and C
    Calculate the fitness of all search agents
    Update Xα, Xβ, and Xδ
    t=t+1
end while
return Xα
```

Figure 2. *Pseudocode for the GWO algorithm [25].*

3.7 Chebyshev chaotic map

The Chebyshev map is an important tool in various fields, primarily in cryptography and computer security. In computational mathematics, it is a special class of functions derived from the expansion polynomials of the cosine and sine functions of multiplicative angles [12]. The Chebyshev map is a family of discrete dynamical systems defined by a specific mathematical formula. It has been proven to be topologically conjugate to tent-like maps via a conjugacy function and, consequently, conjugate to Bernoulli shifts with N symbols [26]. Additionally, the Chebyshev chaotic map has been used in the development of effective authentication schemes and encryption systems[27]. It has also demonstrated its versatility in the field of cryptography by being used in public key encryption algorithms and signature algorithms [28]. Chebyshev map optimization is a versatile tool with applications in cryptography, computer security, dynamic modeling, and control systems. Its mathematical properties and chaotic behavior make it valuable in various fields, particularly for developing secure authentication schemes, encryption algorithms, and dynamic modeling techniques.

This study aims to enhance the GWO optimization process by augmenting the exploring capability of the alpha wolf through the Chebyshev chaotic map.

3.8 The improved chGWO (chebyshev grey wolf optimization) method

The discovery capability of the GWO algorithm is sometimes insufficient. To improve this, the chaotic map has been modified to enhance the discovery ability of the alpha grey wolf leader, addressing suboptimal outcomes. This improved method, named chGWO (Chebyshev GWO), aims to achieve optimal results for the alpha value. In each iteration, the leader generated was compared with a new leader modified by the chaotic map, and the leader yielding better results was selected to continue in the next iteration. This process is repeated at every iteration. In the standard GWO algorithm, the leader is recalculated in each step to pursue better results.

```
Initialize  the grey  wolf population Xi (i = 1, 2, …, n)
Initialize a, A and C
Calculate the fitness of each search agent
Xα = the best seach agent
Xβ = the second best seach agent
Xδ = the third best seach agent
while  (t < Max number of iteration)
     for  each search agent
               X1= GWO Update the position of the current search agent
        ==>    X1= Chebyshev(1,iter,max_iter, X1) Improve the position of the current search agent
              Update the position of the current search agent
    end for
    Update a, A and C
   Calculate the fitness of all search agents
  Update Xα, Xβ and Xδ
  t=t+1
end while
return Xα
```

Figure 3. *Pseudocode for the chGWO algorithm.*

In the chGWO method, the initial population is generated randomly, just like in the standard GWO. The produced population is given to the GWO for the first iteration. In the iteration, the best values are determined as the values of alpha based on the fitness function obtained from the initial population. The second-best value is assigned to beta, and the third-best value is assigned to the values of delta.

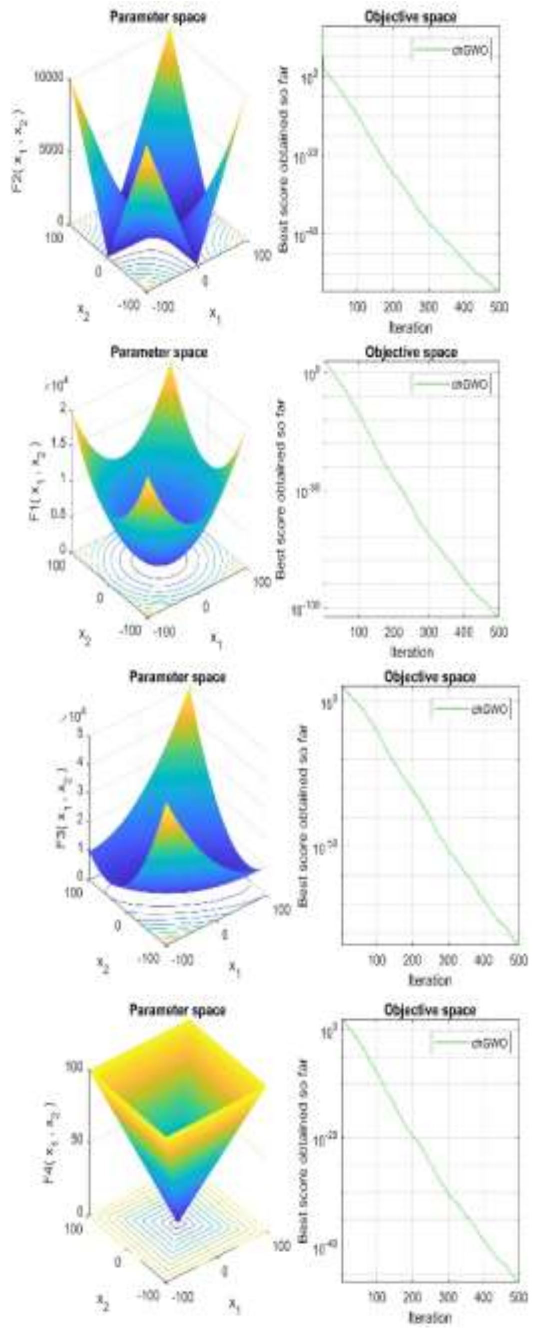
The value of the wolf leader is reproduced using the Chebyshev map and compared with the leader produced during the iteration of the GWO. The value and position of the leader with a better outcome are assigned as the new leader's value and position, and the iteration continues. In this way, by repeating this process for each man, the GWO's reconnaissance capability is enhanced. The pseudocode of the chGWO algorithm is provided in Figure 3.

3.9 Application of chGWO to standard test functions

The improved chGWO algorithm has been applied to the F1-F7 uni-modal test functions to demonstrate its effectiveness. This process has been carried out to test the validity of the chGWO algorithm. The obtained results have been compared with the existing literature. For a fair comparison, the same parameters were selected for all algorithms being compared: a maximum of 500 iterations, a population size of 30, and 30 independent repetitions. The average and standard deviation

Table 1. *F1-F7 Uni-modal test functions*

Function	Dim	Range	fmin
$f_1(x) = \sum_{i=1}^{n} x_i^2$	30	[-100,100]	0
$f_2(x) = \sum_{i=1}^{n}\lvert x_i\rvert + \prod_{i=1}^{n}\lvert x_i\rvert$	30	[-10,10]	0
$f_3(x) = \sum_{i=1}^{n}(\sum_{j-1}^{i} x_j)^2$	30	[-100,100]	0
$f_4(x) = max_i\{\lvert x_i\rvert, 1 \leq i \leq n\}$	30	[-100,100]	0
$f_5(x) = \sum_{i=1}^{n}[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	30	[-30,30]	0
$f_6(x) = \sum_{i=1}^{n}([x_i + 0.5])^2$	30	[-100,100]	0
$f_7(x) = \sum_{i=1}^{n} ix_i^4 + random[0,1)$	30	[-1.28,1.28]	0



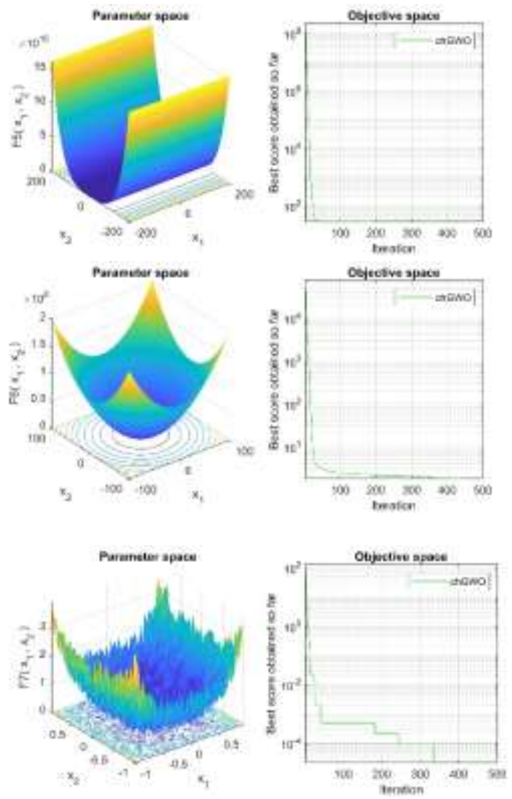


Figure 4. *F1-F7 functions and convergence curves.*

values were calculated based on 30 runs of each algorithm. The results obtained from the chGWO algorithm yielded better outcomes than those from the PSO, DE, GWO, and GSA algorithms. Table 1 provides a list of uni-mode functions F1-F7.

The results obtained by applying the chGWO algorithm to the F1-F7 functions are presented in Table 2. The improved chGWO algorithm has yielded better results compared to the GWO algorithm. The chGWO algorithm has yielded better results for functions other than F5 and F6. Figure 4. The F1-F7 functions and convergence curves are provided.

As can be understood from the results, the chGWO is an effective, and efficient algorithm. It has yielded better results compared to GWO and other algorithms.

3.10 Test system

In this study, the efficiency and validity of the chGWO method were demonstrated by simulating the IEEE 33-bus test distribution system using MATLAB. The MATPOWER package developed by Zimmerman et al. was used to obtain load flow results for the test system [29]. The improved optimization algorithm used a wolf count of 50 and an iteration count of 200.

The IEEE 33-bus test system is a radial distribution system with an active load of 3.72 MW and a reactive load of 2.3 MVAr. Operating at a voltage of 12.66 kV, the system has maximum and minimum

voltages of 1.00 pu and 0.9038 pu, respectively, at bus 18. Initially, there is a loss of 84 kW of active power and 130 kVAr of reactive power. Figure 5 shows the single-line diagram of the modified 33-bus test system.
The MATPOWER package and relevant reference were used for bus and line information [30].

4. Results

To demonstrate the effectiveness of the improved optimization algorithm and to place the EVCSs at optimal values in a 33-bus test system, three different scenarios have been studied.

Case 1: The addition of 2 fixed power and fixed connection bus EVCSs.
Case 2: The addition of 2 EVCSs, which are fixed power and optimal connection bus.
Case 3: The adding of 2 EVCSs where there is optimal connection power and bus.

4.1 Case 1: The addition of 2 fixed power and fixed connection bus EVCSs.

In Case 1, 2 EVCS have been added to the IEEE 33 bus test system. Each EVCS power is fixed and is equal to a load of 1.5 MW. The connection buses numbered 3 and 13 have been selected as the connection buses. These connections are presented in the modified IEEE 33 bus test system and are shown in Figure 5. Table 3 shows the results obtained from GWO and the chGWO algorithms. As can be seen from the table, the active power loss has increased due to the rise in system loads. In the initial state, the active power loss of 201.84 kW has increased to 664.55 kW according to the optimization algorithm results of GWO and chGWO with the integration of EVCSs as additional load into the system. Since the EVCSs were added to the same point with the same strength, both algorithms yielded the same result.

Table 2. *Test functions results.*

F	GWO [25]		PSO [25]		GSA [25]		DE [25]		**chGWO ***	
	ave	*std*	*ave*	*std*	*ave*	*std*	*ave*	*std*	*ave*	*std*
F1	6.59E-28	6.34E-05	0.000136	0.000202	2.53E-16	9.67E-17	8.2E-14	5.9E-14	**6.52E-104**	**1.30E-103**
F2	7.18E-17	0.029014	0.042144	0.045421	0.055655	0.194074	1.5E-09	9.9E-10	**1.643E-55**	**6.292E-55**
F3	3.29E-06	79.14958	70.12562	22.11924	896.5347	318.9559	6.8E-11	7.4E-11	**3.3696-83**	**6.558E-84**
F4	5.61E-07	1.315088	1.086481	0.317039	7.35487	1.741452	0	0	**1.74E-46**	**9.847E-47**
F5	26.81258	69.90499	96.71832	60.11559	67.54309	62.22534	**0**	**0**	27.846	0.66216
F6	0.816579	0.000126	0.000102	8.28E-05	2.5E-16	1.74E-16	**0**	**0**	1.6529	0.3752
F7	0.002213	0.100286	0.122854	0.044957	0.089441	0.04339	0.00463	0.0012	**0.000104**	**7.350E-05**

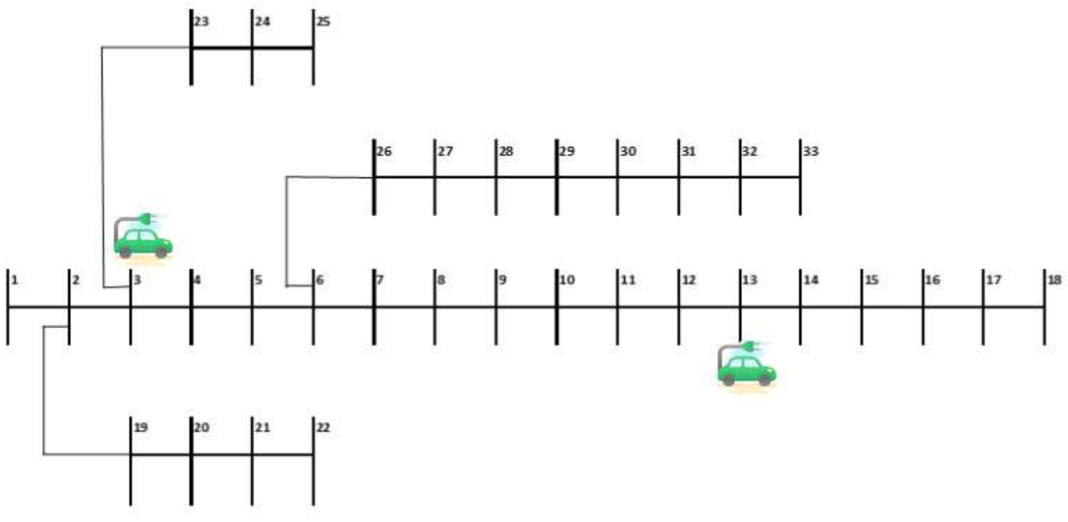


Figure 5. *Modified 33 bus test system*

Tablo 3. *Case 1 results*

	Case 0	Case 1	
		GWO	chGWO
Active Power Loss (kW)	201.84	664.55	664.55
EVCS connection bus		3, 13	3, 13
EVCS load power (MW)		1.5, 1.5	1.5, 1.5

4.2 Case 2: The addition of 2 EVCSs, which are fixed power and optimal connection bus

In Case 2, two EVCSs were added to the IEEE 33-bus test system. Unlike Case 1, the connection powers of the EVCSs were chosen to be equal. The connection buses of the EVCSs were determined using optimization algorithms. Table 4 presents the results obtained from both the GWO and the improved chGWO algorithms. As shown in the table, active power loss increased due to the rise in system loads; however, since the buses were optimally selected by the optimization algorithms, the increase in power loss was not directly proportional to the load increase as in Case 1. Initially, the active power loss of 201.84 kW increased to 297.93 kW according to the GWO algorithm with the integration of additional loads from the EVCSs, while it rose to only 221.39 kW according to the chGWO optimization algorithm. Overall, the improved chGWO algorithm yielded better results than the classical GWO.

4.3 Case 3: The adding of 2 EVCS where there is optimal connection power and bus

Finally, in case 3, 2 EVCSs have been added to the IEEE 33 bus test system. Unlike case 1 and 2, the connection power and connection buses of the EVCSs have been calculated optimally by optimization algorithms.

Table 5 shows the results obtained from the GWO and the improved chGWO algorithms. As can be seen from the table, the active power loss has increased due to the rise in system loads; however, since the connection buses and connection powers were selected as optimal values by the optimization algorithms, there have not been as pronounced increases as in case 1 and case 2.

Tablo 4. *Case 2 results*

	Case 0	Case 2	
		GWO	chGWO
Active Power Loss (kW)	201.84	297.93	221.39
EVCS connection bus		3, 20	2, 2
EVCS load power (MW)		1.5, 1.5	1.5, 1.5

In the initial state, the active power loss of 201.84 kW increased to 207.18 kW according to the GWO algorithm with the integration of additional loads from EVCSs into the system, while according to the chGWO optimization algorithm, it remained at the initial value of 201.84 kW. The improved chGWO algorithm has yielded better results compared to the classical GWO.

Tablo 5. *Case 3 results*

	Case 0	Case 3	
		GWO	chGWO
Active Power Loss (kW)	201.84	207.18	201.84
EVCS connection bus		2, 2	4, 22
EVCS load power (MW)		0.5, 0.5	0.5, 0.5

5. Conclusions

In this study, the effectiveness and performance of the chGWO algorithm, developed based on the GWO, have been examined. Additionally, the success of chGWO has been evaluated in the allocation problem of EVCSs. The results obtained from the study are as follows:

The application of the chGWO algorithm to uni-modal functions; in experiments conducted on F1-F7 uni-modal test functions, it has been observed that the chGWO algorithm yielded better results compared to other popular algorithms such as PSO, DE, GWO, and GSA. The results presented in Table 2 show that the mean and standard deviation values of chGWO are lower than those of the other algorithms. This shows that the problem-solving ability of chGWO and the convergence of the optimized functions have been improved.

The optimal placement of EVCSs; simulations conducted on the IEEE 33 bus test distribution system have demonstrated the effectiveness of the chGWO algorithm in the problem of optimal placement of charging stations. Three different cases were examined, and in each case, it was observed that chGWO performed better than GWO.

Case 1: In the case adding 2 EVCSs fixed power and connection point addition to the test system, since there is only a linear increase in load and the connection buses and connection power are constant, both algorithms yielded the same result.

Case 2: In the case of the addition 2 EVCSs fixed power, and optimally calculated connection buses, it has been determined that the active power loss of chGWO decreases even further compared to case 1, despite the total load in the system increasing.

Case 3: In the case addition of 2 EVCSs calculated optimal connection power and points for the EVCSs by chGWO. It has been observed that chGWO demonstrated a more stable performance compared to GWO in relation to case 1 and 2.

The chGWO algorithm demonstrates that it is an effective tool for optimizing the electric vehicle charging infrastructure. The study demonstrates that the chGWO algorithm can be successfully used in both the optimization of mathematical functions and real-world applications. In future research, the performance of the algorithm on different optimization problems can be examined further, and work can be done on adapting the algorithm for larger-scale applications.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.

- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.

- **Author contributions:** The authors declare that they have equal right on this paper.

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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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