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Optimal Coordination of Directional Overcurrent Relays Using a Modified Grey Wolf Optimization Algorithm Considering Multiple Characteristic Curves

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ABSTRACT

The effective coordination of directional overcurrent relays (DOCRs) is essential for maintaining the stability and dependability of power systems. This work presents a modified grey wolf optimization (MGWO) approach for addressing the DOCR coordination problem. The MGWO algorithm improves the original grey wolf optimization (GWO) by increasing convergence characteristics and balancing the exploration and exploitation stages. This equilibrium is attained by a dimension learning-hunting method and a quadratic reduction in the control parameter during the optimization phase. DOCR coordination is optimized using the MGWO method, using decision factors such as pickup current, time dial setting, and curve type. The goal is to reduce the total operating time of primary relays while maintaining selectivity and shortening the discrimination time between primary and backup relays. The suggested MGWO technique is evaluated on the IEEE 8 bus system with two scenarios and compared to other optimization approaches. The results reveal that MGWO outperforms previous algorithms, achieving improvements in the objective function ranging from 5.52% to 58.19%. Additionally, the DOCR settings created by MGWO are evaluated using ETAP software to assure compliance with operational requirements and prevent violations of DOCR coordination.

Keywords: *Directional Overcurrent Relay Coordination, Grey Wolf Optimization, Multiple Curves, Pickup Current, Time Dial Setting.*

Introduction

Relay coordination is a critical factor in ensuring the optimal operation and reliability of power systems, as it facilitates the rapid isolation of faulted sections while maintaining service to unaffected areas, thus enhancing overall system stability. Over the years, significant advancements have been made in the development of relays for electrical protection. Directional Overcurrent Relays (DOCRs) have proven to be a cost-effective and reliable method for providing both main and secondary protection in power systems. The key parameters controlling DOCR operations are Time Dial (TD) and Pickup Current (IP), and ensuring their optimal coordination is crucial for maintaining system integrity and reliability.

The integration of Distributed Generation (DG) into the distribution network is widely regarded as a sign of progress, bringing improved system performance. Key advantages of DG include higher dependability, decreased energy downtime, and a reduction in overall system losses [1]. However, the introduction of DG, particularly Synchronized-Based DG (SDG), has the potential to alter relay coordination and fault levels in the protection system [2]. This needs the development of new protection coordinating techniques to solve these difficulties while effectively integrating SDGs [3-4].

Advanced optimization techniques have been implemented to tackle challenges in DOCR coordination. Various studies have explored enhanced versions of the Harris Hawk Optimization (HHO) and Water Cycle Algorithm (WCA) [5-6]. Additionally, methods such as the Electromagnetic Field Optimization (EFO) and Firefly Algorithm (FA) have also been utilized [7-8]. Other research has focused on employing modified Genetic Algorithm (GA) and the Particle Swarm Optimization (PSO) to improve DOCR coordination [9-10]. These refined approaches have demonstrated superior performance compared to their original versions.

The Grey Wolf Optimization (GWO) algorithm was first presented by Mirjalili et al. [11] and is a successful metaheuristic approach used to tackle optimization issues in a variety of domains, such as bioinformatics, machine learning, engineering, and medical research [12]. GWO has proven effective in DOCR coordination [13]. However, the classic GWO has slow convergence and a tendency to become caught in local optima. To address these shortcomings, this study presents a Modified GWO (MGWO) strategy for improving DOCR coordination. The proposed MGWO improves on the GWO method by adding a quadratic function based nonlinear convergence factor to accelerate convergence and dimension learning-based hunting to avoid local optima [14].

The paper is organized into four sections: Section II contains the problem formulation for DOCR coordination as well as the MGWO algorithm. Section III explains the findings, their significance, and offers validation and comparisons to other methodologies. Finally, Section IV presents the study's conclusions and a summary of its significant findings.

Coordination Problem Formulation

The formulation of DOCRs coordination issue encompasses four key components: the objective function, relay coordination constraints, relay characteristic constraints, and penalty terms.

Objective Function Formulation (OF)

The main goals of the study are to lower the overall operating duration of all primary relays and to reduce the coordination margin between relay pairs while ensuring the validation of sequential operation among these pairs [6], [15]. These objectives can be expressed as follows:

$$OF_1 = \sum_{i=1}^{M} RT_{i,primer} \quad \text{and} \quad OF_2 = Max(RT_{backup} - RT_{primer} - CTI) \tag{1}$$

$$RT_i = TD_i \times \frac{A}{\left(\left(\frac{IF_i}{IP_i}\right)^B - 1\right) * \beta} \tag{2}$$

$$Tap_i = IP_i \div CT_i \tag{3}$$

Here, M denotes the total number of primary relays, and RT_i represents the operational time of relay R_i. The coefficients A, B, and β correspond to the curve type of R_i based on IEC characteristic curves, with detailed values available in [16]. The pickup current of relay R_i is denoted as IP_i, while TD_i represents the time dial setting for R_i. The fault current passing through relay R_i is indicated as IF_i. Additionally, the tap pickup current is denoted as Tap_i, and the current transformer (CT) ratio for R_i is represented by CT_i. The tap pickup current is calculated using Eq. (3).

Relay Coordination Constraints

The primary and backup relays detect system disturbances at the same time. To avoid mis operation, the backup relay must take over the tripping function in the case that the primary relay malfunctions. The operating time of backup relay (RT_{backup}) is determined by adding the coordination time interval (CTI) to the operating time of primary relay ($RT_{primary}$), ensuring the precision across the two relays. This restriction, which can be stated as follows, is necessary to preserve appropriate relay coordination:

$$RT_{backup} - RT_{primer} \geq CTI \tag{4}$$

The lowest CTI value of 0.3s is employed in this investigation [6].

Relay Characteristics Constraints

The functional and mechanical limitations specified by the relay's specifications are the constraints associated with relay characteristics, as detailed below [17]:

$$RT_i^{min} \leq RT_i \leq RT_i^{max} \tag{5}$$

$$TD_i^{min} \leq TD_i \leq TD_i^{max} \tag{6}$$

$$IP_i^{min} \leq IP_i \leq IP_i^{max} \tag{7}$$

The maximum and minimum operating times of relay R_i are denoted as RT_i^{max} and RT_i^{min} in Eq. (5). Similarly, the maximum and minimum time dial settings for relay R_i are denoted as TD_i^{max} and TD_i^{min}, as defined in Eq. (6). For Eq. (7), the maximum and minimum pickup current values for relay R_i are expressed as IP_i^{max} and IP_i^{min}, respectively. Additionally, the operating time (RT) is bounded between 0.1s and 2s [18]. The TD is constrained between 0.05 and 1.1, while the IP is limited to a range of 0.5 to 2.5 times the CT ratio [19].

Penalty

This study applies a penalty method to address restraints in the DOCR coordination issue. The objective function (OF) is modified by adding a penalty value to deter impractical solutions that disregard relay coordination and characteristic limitations, as outlined in Eq. (8). A high penalty factor ensures strict compliance with the constraints while minimizing the OF value [20].

$$F(x) = 0.5 * (OF_1) + 0.5 * (OF_2) + \sum_{k=1}^{N} Penalty(l) \tag{8}$$

The coefficient for the OF is assigned a value of 0.5 [20], Here, N denotes the total number of relay pairs, and the penalty limit (Penalty(l)) is calculated using the formula below:

$$Penalty(l) = \begin{cases} 0, & if\ (RT_{i\,backup} - RT_{i\,primary}) \geq CTI \\ \xi \left| CTI - (RT_{i\,backup} - RT_{i\,primary}) \right|, & otherwise \end{cases} \tag{9}$$

The penalty factor (ξ) is vital for balancing constraint satisfaction and optimization performance, as improper tuning can affect results [19]. In this study, ξ is set at 1000 to ensure zero penalties in optimal solutions [21]. However, its selection and impact remain underexplored, highlighting the need for further research on its effect on cost and convergence rate in optimization [22].

Proposed MGWO Approach for Coordination Problem

The GWO algorithm is inspired by grey wolves' social structure and hunting behavior, with alpha, beta, and delta wolves guiding omega wolves towards global solutions through three stages: encircling, hunting, and attacking the prey. Encircling: The encircling stage can be represented using Eqs. (10) and (11) [11].

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right| \tag{10}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{11}$$

The prey's location is denoted by $\vec{X}_p$, and the wolf's location by $\vec{X}$. The coefficient $\vec{A}$ and $\vec{C}$ are calculated using Eqs. (12) and (13) [11].

$$\vec{A} = 2\vec{a} \times \vec{r}_1 - \vec{a} \tag{12}$$

$$\vec{C} = 2 \times \vec{r}_2 \tag{13}$$

Where $\vec{r}_1$, $\vec{r}_2$ are random vectors in the range [0,1], and components of $\vec{a}$ decrease linearly from 2 to 0 in the original GWO. The adaptive numbers of $\vec{A}$ and $\vec{a}$ control the balance across searching and refining. When |A| is greater than or equal to 1, the process emphasizes searching, whereas refining dominates when |A| is less than 1. Overemphasis on searching can introduce excessive randomness, resulting in suboptimal outcomes, while excessive exploitation lacks diversity. This study suggests using quadratic functions instead of linear ones to adjust $\vec{a}$ during iterations, as the actual changes follow a nonlinear pattern, which is more effective for GWO [23-24].

T signifies the total number of iterations allowed, while t refers to the iteration currently in progress. A quadratic function is used to adjust the value of $\vec{a}$ throughout the iterations, as shown in Eq. (14).

$$\vec{a} = 2 \times \left(1 - \frac{t}{T}\right)^2 \tag{14}$$

Hunting: Search agents modify their positions in response to the alpha, beta, and delta wolves' locations during the hunting phase. The seeking phase is described by Eqs. (15–17) [11].

$$\begin{aligned} \vec{D}_\alpha &= \left| \vec{C}_1 \times \vec{X}_\alpha - \vec{X} \right|, \\ \vec{D}_\beta &= \left| \vec{C}_2 \times \vec{X}_\beta - \vec{X} \right|, \\ \vec{D}_\delta &= \left| \vec{C}_3 \times \vec{X}_\delta - \vec{X} \right| \end{aligned} \tag{15}$$

$\vec{C}_1$, $\vec{C}_2$, and $\vec{C}_3$ are calculated by Eq. (13).

$$\begin{aligned} \vec{X}_1 &= \vec{X}_\alpha - \vec{A}_1 \times (\vec{D}_\alpha), \\ \vec{X}_2 &= \vec{X}_\beta - \vec{A}_2 \times (\vec{D}_\beta), \\ \vec{X}_3 &= \vec{X}_\delta - \vec{A}_3 \times (\vec{D}_\delta) \end{aligned} \tag{16}$$

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$\vec{X}_{\alpha}$, $\vec{X}_{\beta}$, and $\vec{X}_{\delta}$ represent the three most best solutions at iteration t. The value of $\vec{A}_1$, $\vec{A}_2$, and $\vec{A}_3$ are calculated by Eq. (12), while $\vec{D}_{\alpha}$, $\vec{D}_{\beta}$, and $\vec{D}_{\delta}$ are determined by Eq. (15).

$$\vec{X}_{i-GWO}(t+1) = \frac{\vec{X}_1(t) + \vec{X}_2(t) + \vec{X}_3(t)}{3} \tag{17}$$

Attacking: Wolves initiate an attack by decreasing the number of $\vec{a}$, which also limits the interval of $\vec{A}$. The number of $\vec{A}$ is randomly selected within the interval [-2a, 2a]. When |A| falls below one, the wolves proceed to attack their prey.

Dimension Learning Hunting (DLH) strategy [25]: Eq. (20) calculates the exact spot of each wolf $\vec{X}_i$ (t), considering information from neighboring wolves and a randomly chosen wolf from the population (Pop). The DLH approach generates an alternative potential position $\vec{X}_{i\text{-DLH}}$ (t+1), alongside the position $\vec{X}_{i\text{-GWO}}$ (t+1). The strategy computes the radius $\vec{R}_i$ (t) using the Euclidean distance across the current spot $\vec{X}_i$ (t) and the candidate spot $\vec{X}_{i\text{-GWO}}$ (t+1), as described in Eq. (18).

$$\vec{R}_i(t)=\left\|\vec{X}_i(t) - \vec{X}_{i\text{-GWO}}(t+1)\right\| \tag{18}$$

Using Eq. (19) and the Euclidean distance ($\vec{D}_i$) between $\vec{X}_j$ (t) and $\vec{X}_i$ (t), the adjacent of $\vec{X}_i$ (t), denoted as $\vec{N}_i$ (t), are identified the radius $\vec{R}_i$(t) [25].

$$\vec{N}_i(t)=\left\{\vec{X}_j(t)\middle|\vec{D}_i(\vec{X}_i(t),\vec{X}_j(t)) \leq \vec{R}_i(t),\vec{X}_j(t)\epsilon\text{Pop}\right\} \tag{19}$$

Eq. (20) is used to carry out the learning process from several adjacent solutions, after establishing the neighborhood of $\vec{X}_i$ (t). The d^{th} scope of $\vec{X}_{i\text{-DLH},d}$ (t+1) is calculated by randomly selecting a neighboring solution, $\vec{X}_{n,d}$ (t), from $\vec{N}_i$ (t), and a wolf, $\vec{X}_{r,d}$ (t), from the overall population [25].

$$\vec{X}_{i\text{-DLH},d}(t+1)=\vec{X}_{i,d}(t) + \text{rand} \times \left(\vec{X}_{n,d}(t)-\vec{X}_{r,d}(t)\right) \tag{20}$$

The selection and maintaining phases involve comparing the objective functions of two candidates, $\vec{X}_{i\text{-DLH}}$(t+1) and $\vec{X}_{i\text{-GWO}}$(t+1), using Eq. (21) to determine the stronger candidate [25].

$$\vec{X}_i(t+1)=\begin{cases}\vec{X}_{i\text{-GWO}}(t+1), & \text{if } f(\vec{X}_{i\text{-GWO}}) < f(\vec{X}_{i\text{-DLH}}) \\ \vec{X}_{i\text{-DLH}}(t+1), & \text{otherwise}\end{cases} \tag{21}$$

If the selected candidate's objective function is less than that of $\vec{X}_i$ (t), then $\vec{X}_i$ (t) is substituted by the nominee in order to update the location for $\vec{X}_i$ (t+1). The population's $\vec{X}_i$ (t) stays the same otherwise. The loop count (t) rises by one, and the process keeps going until the highest possible number of iterations (T) is attained. The flowchart in Figure 1 outlines the entire process for resolving the DOCRs coordination issue with the suggested MGWO.

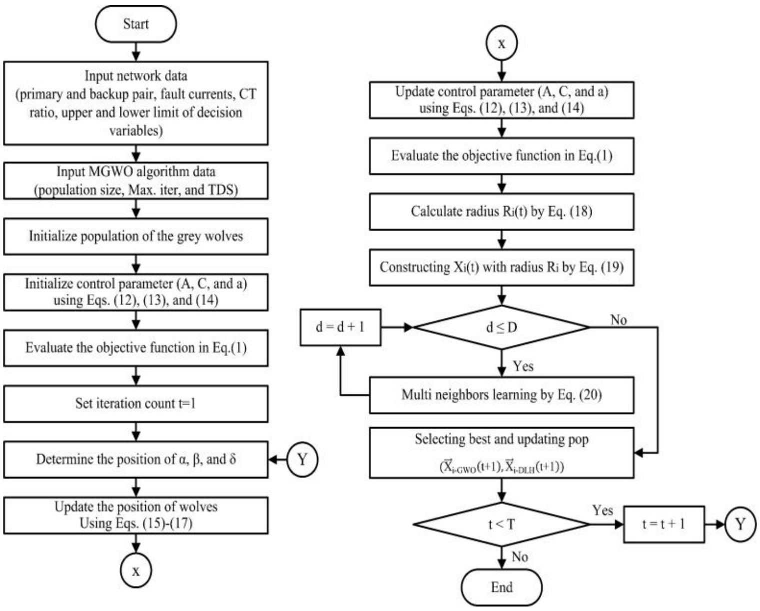

Figure 1. DOCR coordination using the proposed MGWO method.

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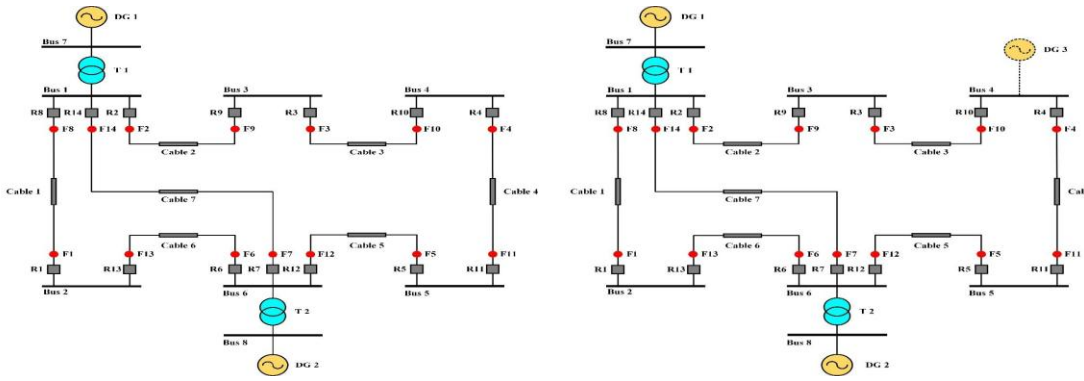
Results and Discussion

The effectiveness of the suggested methodology is evaluated by handling two test systems: the IEEE 8 bus system [26] and the IEEE 8 bus system with a link to another network [27]. Figure 2 shows a single line diagram of the system. The proposed methodology was carried out in the MATLAB environment on a 1.8 GHz PC with 8 GB of RAM running Windows 11.



(a) (b)

Figure 2. Single line schematic of an IEEE 8 bus test system (a) without link to DGs, case-1, and (b) connected to DGs, case-2.

Test system 1: IEEE 8 bus system without DG link

The network comprises eight buses, two generating units, two transformers, and 14 directional overcurrent relays (DOCRs). Each generator unit is rated at 150 MVA, 10 kV, with a reactance of 15%. Similarly, the transformers are rated at 150 MVA, 10 kV, and have a reactance of 4%. Numerical relays featuring a standard inverse (SI) characteristic curve are employed. The current transformer (CT) ratios for relays 3, 7, 9, and 14 are 800:5, whereas all other relays operate with a 1200:5 ratio. Relay coordination was evaluated under three phase fault conditions at various locations. The single line schematic of the system is depicted in Figure 2.a, with fault currents and associated relays given in [21]. Optimization involved 500 iterations and a population size of 50.

The optimal time dial (TD) and pickup current (IP) values determined by the Modified Grey Wolf Optimizer (MGWO) are shown in Table 1. The MGWO achieved significant improvements, reducing OF1 by 0.389s (from 7.043s to 6.654s) and OF2 by 0.054s (from 0.236s to 0.182s) compared to the standard Grey Wolf Optimizer (GWO).

Table 1. TD and IP using GWO and the proposed MGWO for IEEE 8 bus system, case-1.

Relays	GWO		MGWO	
	TD	IP	TD	IP
1	0.059	559.15	0.119	355.67
2	0.320	370.77	0.262	423.01
3	0.307	194.14	0.188	348.71
4	0.080	535.29	0.112	319.79
5	0.076	245.98	0.058	256.06
6	0.241	161.51	0.188	427.66
7	0.284	266.11	0.212	357.08
8	0.256	165.96	0.185	438.53
9	0.051	283.20	0.050	274.79
10	0.073	543.52	0.107	333.69
11	0.148	509.69	0.144	537.82
12	0.242	472.47	0.265	391.65
13	0.074	494.47	0.071	492.80
14	0.289	214.83	0.229	312.83
OF1	7.043		6.654	
OF2	0.236		0.182	

The MGWO objective function values were compared with those from GWO and other algorithms, with the results presented in Table 2 showing significant improvements. Using the same test system and relay locations, MGWO successfully reduced OF1 by 9.259s, 5.106s, 1.244s, and 0.957s compared to the electromagnetism-like mechanism algorithm (EM) [7], harmony search algorithm (HS) [7], water cycle algorithm (WCA) [6], and electromagnetic field optimization (EFO) [7], respectively. Likewise, MGWO achieved reductions in OF2 by 0.191s and 0.071s compared to WCA [6] and EFO [7], respectively. In addition, Figure 3 shows that MGWO finds better solutions and converges faster than GWO. MGWO takes 364 seconds for 239 iterations, while GWO takes 182 seconds for 315 iterations.

Table 2. Comparative evaluation of MGWO and other approaches for IEEE 8 bus system, case-1.

	EM [7]	HS [7]	WCA [6]	EFO [7]	GWO	MGWO
OF1 (s)	15.913	11.760	7.898	7.611	7.043	6.654
OF2 (s)	–	–	0.373	0.253	0.236	0.182

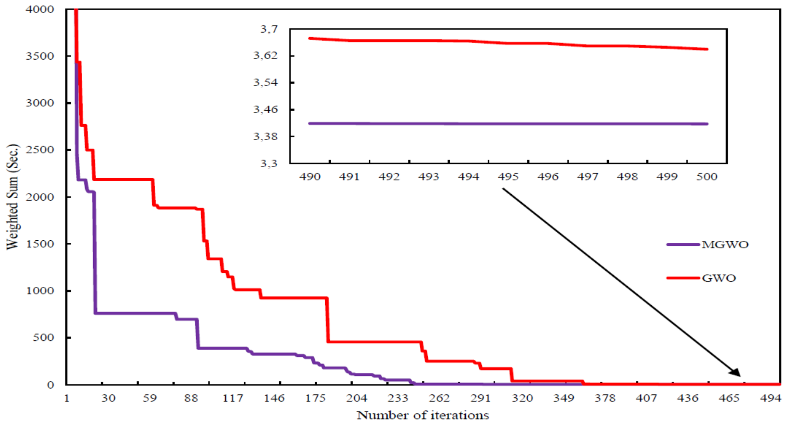


Figure 3. Convergence behavior of MGWO and GWO for IEEE 8 bus system, case-1.

Rather than focusing on optimizing relay placement, this study focused on analyzing various characteristics outlined in the IEC relay standard. The assessment aimed to determine how different relay characteristics influence relay operating times. As illustrated in Figure 4 for the IEC type, the extremely inverse (EI) characteristic typically yielded the lowest objective function (OF) values in most cases, while the standard inverse (SI) characteristic resulted in the highest. Compared to the very inverse (VI), long time inverse (LTI), and SI characteristics, the EI characteristic demonstrated improvements of 46.51%, 66.36%, and 72%, respectively.

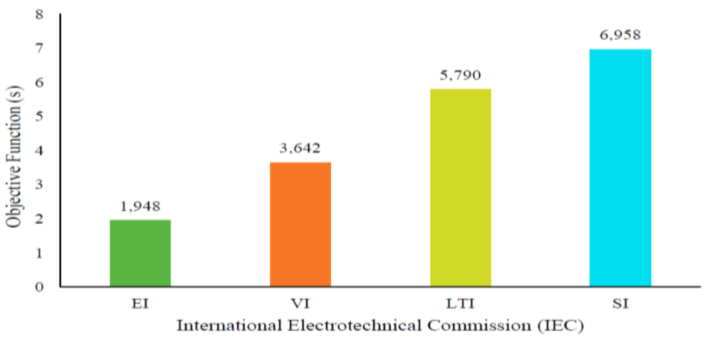


Figure 4. Performance analysis of MGWO across multiple IEC curves for IEEE 8 bus system, case-1.

Table 3 presents a statistical comparison of the baseline GWO and MGWO, detailing the best, worst, and mean values of the objective function for each algorithm. The results show that the MGWO's best objective function values are close to its worst values, highlighting the algorithm's robustness and high performance. Additionally, the lower standard deviation of MGWO compared to GWO further confirms its superior quality and consistency over the original algorithm.

Table 3. Statistical evaluation results for case-1.

Algorithms	OF	Best	Mean	Worst	Standard Deviation	Number of Runs	Violation
GWO	OF1	7.043	8.291	9.962	0.750	28	0
MGWO		6.654	7.698	8.611	0.505	28	0
GWO	OF2	0.236	0.245	0.395	0.071	28	0
MGWO		0.182	0.183	0.233	0.033	28	0

Test system 2: IEEE 8 bus system with DG link

In this test scenario, all details regarding lines, generators, transformers, relay placements, and other related parameters remain identical to those outlined for Case-1 as specified in [26], with an additional external grid modelled as a 400 MVA generator connected at bus 4 shown in Figure 2.b. Fault currents and corresponding relays are given in [28]. Optimization used identical parameters: 500 iterations and a population size of 50.

Table 4 presents the optimal values of TD and IP achieved using the MGWO approach. The OF1 obtained with GWO is 10.626s, while MGWO reduces it to 9.683s, reflecting a reduction of 0.943s. Similarly, the OF2 achieved with GWO is 0.294s, which MGWO lowers to 0.220s, resulting in a decrease of 0.074s.

Table 4. TD and IP using GWO and the proposed MGWO for IEEE 8 bus system, case-2.

Relays	GWO		MGWO	
	TD	IP	TD	IP
1	0.186	366.05	0.138	439.83
2	0.398	359.30	0.331	420.84
3	0.345	249.24	0.280	289.60
4	0.232	457.32	0.179	550.46
5	0.146	505.45	0.109	577.66
6	0.323	418.97	0.235	546.34
7	0.319	340.22	0.305	308.91
8	0.249	564.00	0.302	192.75
9	0.207	322.21	0.226	256.86
10	0.271	383.69	0.272	371.44
11	0.242	520.81	0.218	589.44
12	0.414	325.58	0.296	598.41
13	0.115	531.37	0.112	513.16
14	0.299	393.13	0.288	352.27
OF1	10.626		9.683	
OF2	0.294		0.220	

The objective function values achieved by MGWO were compared with those obtained using GWO and other algorithms, as summarized in Table 5. The results reveal significant improvements with MGWO. Using the same test system and relay locations, the MGWO approach reduced OF1 by 11.115s, 7.647s, 1.327s, and 1.267s compared to the particle swarm optimization (PSO) algorithm [27], modified particle swarm optimization (MPSO) algorithm [27], genetic algorithm (GA) [28], and genetic algorithm-linear programming (GA-LP) [28], respectively. Furthermore, Figure 5 shows that the MGWO technique is more effective in finding the optimal solution and achieves better convergence compared to the GWO technique. MGWO completes the process in 492 seconds with 337 iterations, while GWO takes 246 seconds with 392 iterations.

Table 5. Comparative evaluation of MGWO and other approaches for IEEE 8 bus system, case-2.

	PSO [27]	MPSO [27]	GA [28]	GA-LP [28]	GWO	MGWO
OF1 (s)	20.798	17.330	11.010	10.950	10.626	9.683
OF2 (s)	–	–	–	–	0.294	0.220

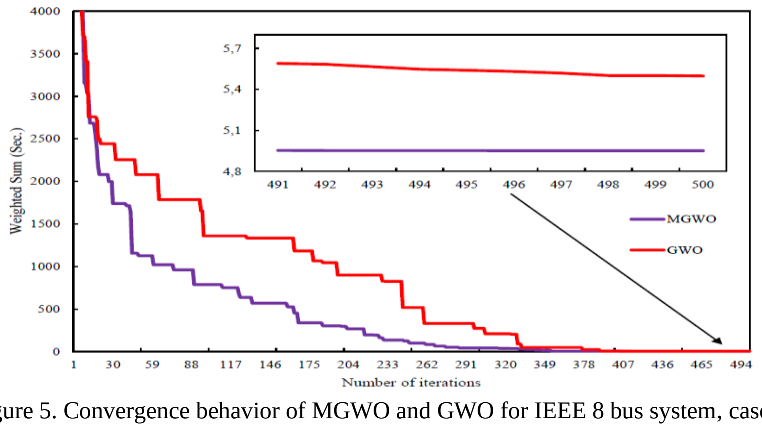


Figure 5. Convergence behavior of MGWO and GWO for IEEE 8 bus system, case-2.

This study analyzed every single curve available in the many characteristics of relay IEC standard. The evaluation was carried out to assess the effect of different relay characteristics on operating times. As shown in Figure 6 for the IEC type, the extremely inverse (EI) characteristic generally produced the lowest objective function (OF) values, while the standard inverse (SI) characteristic resulted in the highest OF. The EI characteristic demonstrated improvements of 53.67%, 78.75%, and 79.72% over the very inverse (VI), long time inverse (LTI), and SI characteristics, respectively.

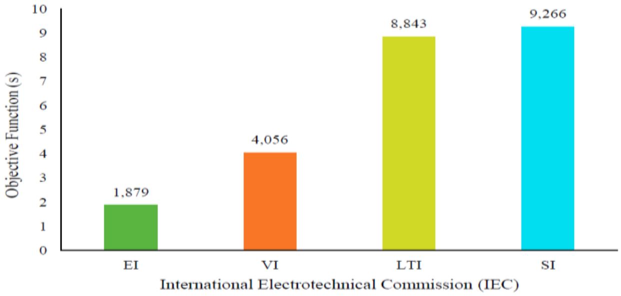


Figure 6. Performance analysis of MGWO across multiple IEC curves for IEEE 8 bus system, case-2.

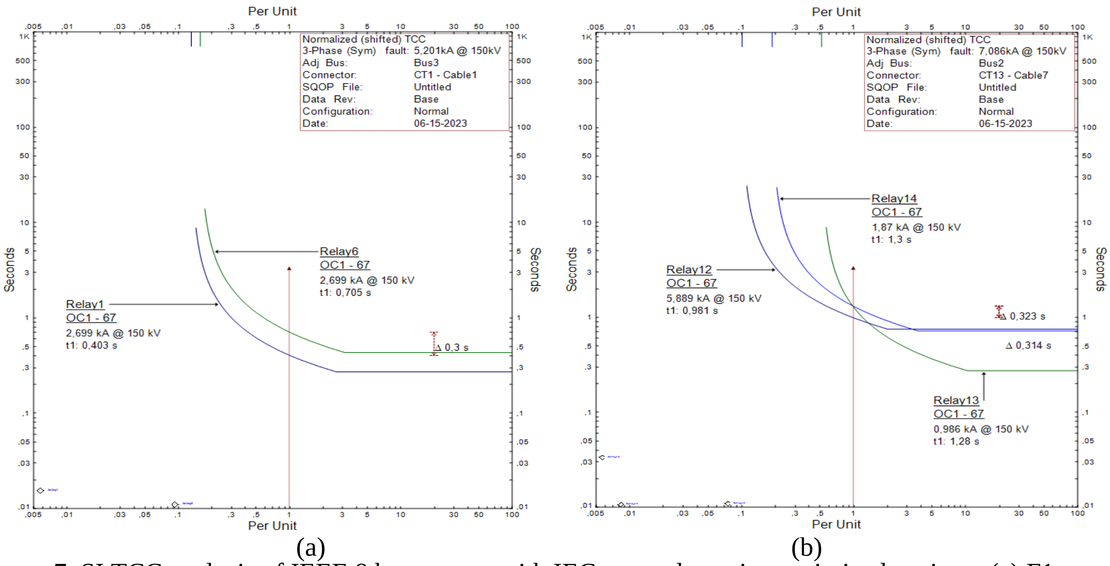
Table 6 presents the statistical analysis comparing the baseline GWO with MGWO, including the best, worst, and mean objective function values obtained by both methods. The results show that the MGWO's best objective function values are close to its worst, highlighting the algorithm's robustness and high quality. Additionally, the MGWO exhibits a lower standard deviation compared to GWO, further emphasizing its superior performance and reliability over the original algorithm.

Table 6. Statistical evaluation results for case-2.

Algorithm	OF	Best	Mean	Worst	Standard Deviation	Number of Runs	Violation
GWO	OF1	10.626	12.413	15.629	1.047	28	0
MGWO		9.683	10.203	10.912	0.374	28	0
GWO	OF2	0.294	0.432	0.622	0.092	28	0
MGWO		0.220	0.289	0.347	0.038	28	0

Verification of MGWO using STAR package of ETAP

In this study, the results were verified using ETAP software, a widely recognized industrial tool for power system analysis. A notable feature of ETAP is its capability to validate DOCR relay coordination settings through the STAR ETAP package. The software includes models for all commonly used DOCR relays in the industry and supports the creation of custom relay models. For this research, pre-built relay models were utilized. ETAP's protection coordination tools ensure relay selectivity and offer time characteristic curves (TCC) for visualizing relay coordination, timing, and current settings. The IEEE 8 bus system was modeled in ETAP using the ALSTOM P125 model. The optimized overcurrent relay settings from the proposed method were applied, using the standard inverse (SI) characteristic for all relays. A three-phase fault analysis was conducted to examine the TCC according to the IEC relay type.



(a) (b)

Figure 7. SI TCC analysis of IEEE 8 bus system with IEC type relay using optimized settings: (a) F1, case-1, and (b) F12, case-2.

Conclusion

This paper introduces a new method for improving the coordination of Directional Overcurrent Relays (DOCRs) by combining the Dimension Learning Based Hunting (DLH) search strategy with a nonlinear convergence factor, yielding a modified Grey Wolf Optimizer (MGWO). The suggested method simplifies DOCR coordination by linearizing the problem, minimizing the search space, and avoiding local optima trapping. The MGWO optimizes the pickup current setting (IP), time dial setting (TD), and curve type while adhering to all limitations.

The method's performance was examined using two cases: an 8-bus system with and without interconnections. The method also optimized relays using various IEC-standard curve types, yielding optimal relay operating times while addressing complex relay characteristics. For both test systems, the approach produced relay operating times of 1.948 seconds and 1.879 seconds for the Extremely Inverse (EI) curve, respectively. In a further test using the Standard Inverse (SI) curve, the approach outperformed baseline GWO and other methods by 5.52% to 58.19% respectively. Including different IEC characteristics (EI, Very Inverse, Long Time Inverse, and SI) in the network improved the solution, with the EI characteristic resulting in the shortest relay operation time. Validation using the ETAP power system simulation validated the technique's efficacy. The primary and backup relays' Time Current Characteristic (TCC) curves did not overlap, guaranteeing correct coordination and preventing mis operation.

Future studies on the MGWO algorithm should address its limitations, such as challenges with computational time and the need for improved convergence accuracy, leaving room for further enhancement. These studies will focus on two main aspects: (1) applying the proposed method to more complex practical scenarios to maximize its advantages, particularly in solving protection coordination problems; and (2) integrating economic factors, such as investment costs and unsupplied energy costs, to improve cost efficiency and support more effective decision-making.

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