The Scientific Temper (2024) Vol. 15 (4): 3261-3271
E-ISSN: 2231-6396, ISSN: 0976-8653
Doi: 10.58414/SCIENTIFICTEMPER.2024.15.4.35
https://scientifictemper.com/

RESEARCH ARTICLE

Improvement of power system operation using a novel hybrid optimization method for optimal allocation of facts devices in radial transmission line

L. Vamsi Narasimha Rao[1,2*], P.S.Prakash[1], M.Veera Kumari[2]

Abstract

This paper presents a novel hybrid heuristic algorithm, termed improved grey wolf optimization and cuckoo search optimization (IGWO-CSO), designed for multi-objective functions. This algorithm aims to optimize the allocation of flexible alternating current transmission systems (FACTS) controllers within power grids, with the objectives of minimizing active power system losses, voltage deviation, and operational costs of the system. In this research work, interline dynamic voltage restorers (IDVR) are utilized as flexible AC transmission system (FACTS) controllers. A comparative analysis is performed with other proposed heuristic optimization algorithms, including particle swarm optimization (PSO), cuckoo search optimization (CSO), grey wolf optimizer (GWO), improved grey wolf optimization (IGWO), and the combined IGWO-CSO algorithms, to confirm and validate the superiority of the proposed technique. The proposed scheme has undergone validation and has been implemented on a 30-bus IEEE electric power system. The numerical results were obtained using MATLAB. The simulation results indicate that the proposed algorithm demonstrates superior performance compared to all other algorithms in attaining the optimal global minimum solutions, characterized by the highest convergence rate.

Keywords: Interline dynamic voltage restorer, Hybrid IGWO-CSO, Multi-objective optimization, Mono-objective optimization, Power loss minimization.

Introduction

The increase in worldwide electricity demand, driven by socio-economic advancements, coupled with limitations on the construction of power generation facilities and transmission infrastructure, has led to a notable disparity between power generation and consumption. As a result, this led to inadequate performance of the power systems, including excessive power losses, congested lines, voltage instabilities, and issues related to reliability and stability. Additionally, numerous critical requirements exhibit high sensitivity to degradations in power quality. Heavy industries, radiation sources, nuclear installations, and hospitals can be classified as critical loads. The reliable on-site power supply of nuclear installations, along with the assurance of power quality, is critical in maintaining the safety of nuclear reactor operations and in safeguarding the public and the environment from radiation hazards. Consequently, the efficient utilization of the grids is essential to achieve high performance in electrical power systems (Gaur *et al*., 2018), (Singh *et al*., 2018). The implementation of reactive power compensation in transmission systems is effective in addressing these issues. Recently, the domain of reactive power compensation has gained significant importance.

When properly planned, the performance of the power system can be significantly enhanced. This includes improvements to the voltage profile, reductions in power system losses, increases in permissible power transfer capability, and enhancements in the stability and reliability of the system (Muhammad *et al*., 2020), (Hema Sekhar *et*

[1]Department of Electrical and Electronics Engineering, Faculty of Engineering and Technology, Annamalai University, Chidambaram, Tamil Nadu, India.

[2]Department of Electrical and Electronics Engineering, Sir C R Reddy College of Engineering, Eluru, Andhra Pradesh, India.

***Corresponding Author:** L. Vamsi Narasimha Rao, Department of Electrical and Electronics Engineering, Faculty of Engineering and Technology, Annamalai University, Chidambaram, Tamil Nadu, India, E-Mail: vamsieee2@gmail.com

How to cite this article: Rao, L.V.N., Prakash, P.S., Kumari, M.V.. (2024). Improvement of power system operation using a novel hybrid optimization method for optimal allocation of facts devices in radial transmission line. The Scientific Temper, **15**(4):3261-3271.

Doi: 10.58414/SCIENTIFICTEMPER.2024.15.4.35

Source of support: Nil

Conflict of interest: None.

Received: 03/10/2024 **Accepted:** 22/10/2024 **Published** : 20/12/2024

al., 2020). The flexible alternating current transmission system (FACTS) is a widely utilized device for reactive power compensation. It encompasses power electronics-based technologies that facilitate improved control of the alternating current system, thereby enhancing the overall performance of the power system. FACTS controllers facilitate the efficient utilization of current power generation and transmission systems, requiring considerably lower investment relative to the expenses associated with constructing new transmission and generation units (Guo *et al*., 2020), (Muhammad *et al*., 2021). The power transmitted through the transmission line is determined by three parameters: the impedance of the line, the voltages at both terminals and the phase angle difference between the buses at each end. FACTS controllers have a substantial impact on these parameters, which play a crucial role in regulating power flow, ensuring voltage remains within acceptable limits, minimizing power losses, and enhancing the power transfer capacity of current transmission lines(Lee *et al*., 2019),(Mitiku *et al*., 2021). Various methods have been utilized across the literature. To determine the suitable size and placement of FACTS controllers, they can be classified into four categories: analytical methods, conventional optimization-based methods, metaheuristic optimization methods, and hybrid methods. The optimal allocation of FACTS represents a nonlinear, multimodal, mixed-integer, and highly constrained problem.

Metaheuristic optimization techniques demonstrate high efficiency in addressing these issues, leading to their widespread application in determining the optimal allocation of FACTS controllers (Singh *et al*., 2020), (Singh *et al*., 2020). Recent studies have employed a range of meta-heuristic methods to identify the optimal allocation of FACTS devices. Optimum placement and capacity of the IDVR using the multi-objective multi-verse optimizer technique. This approach aims to minimize three objective functions simultaneously: voltage deviation, active power loss, and the installation cost of the devices. The IDVR units were installed in the power system. The proposed methodology was executed on the IEEE 30 bus test system. The analysis of the results indicates that the installation of IDVR leads to the most significant reduction in active power losses and voltage deviation. This article introduces a robust and well-established hybrid optimization approach that integrates the IGWO algorithm with the CSO algorithm, referred to as the IGWO-CSO hybrid technique. This technique has not been previously implemented or applied within electric power systems. The novel hybrid IGWO-CSO technique leverages the diversity of wolf behavior inherent in the IGWO technique to enhance the performance of the CSO algorithm. The search agents within the proposed algorithm exhibit a range of social and personal behaviors, which are designed to prevent local optima trapping and enhance convergence speed. A time-varying strategy utilizing nonlinear time-varying coefficients has been implemented to balance the exploitation and exploration phases, thereby preventing the loss of diversity. The research contributions can be summarized as follows: This study introduces a hybrid IGWO-CSO technique designed to enhance the performance of the conventional GWO algorithm. The proposed algorithm has been implemented to enhance power system performance through the strategic allocation of FACTS devices. The allocation of the FACTS device, specifically the IDVR, is optimized to reduce real power losses within the power system, minimize bus voltage deviation, and lower overall system operating costs.

The following outlines the main points of the article.

- Simulations are conducted and analyzed in comparison with multiple optimization algorithms, including PSO, CSO, GWO, and IGWO, to validate the efficacy of the IGWO-CSO.
- The performance of the IGWO-CSO algorithm is validated by comparing the findings with those of other optimization techniques.
- The IGWO-CSO methodology is implemented on IEEE 30 bus systems, both with and without the optimal allocation of the IDVR device, to minimize voltage deviation, active power losses, and operational cost.

IDVR modeling

The schematic network configuration of a two-line or two-feeder IDVR is illustrated in Figure 1. IDVR comprises two DVRs connected by a shared DC connection. The two IDVR DVRs are linked to two distinct feeds by series injection transformers.

The IDVR comprises a control system, a voltage source inverter, and a filter. In Figure 1, V_{b1} and V_{b2} represent the bus voltages of feeder one and feeder 2, respectively. Load 1 and Load 2 are identified as sensitive loads linked to feeder one and feeder 2, respectively. V_{l1} and V_{l2} represent the load voltages of load one and load 2, respectively. When a sag develops at load 1, the DVR 1 injects the voltages. V_{inj1} to ensure that V_{l1} remains equal to V_{s1}.

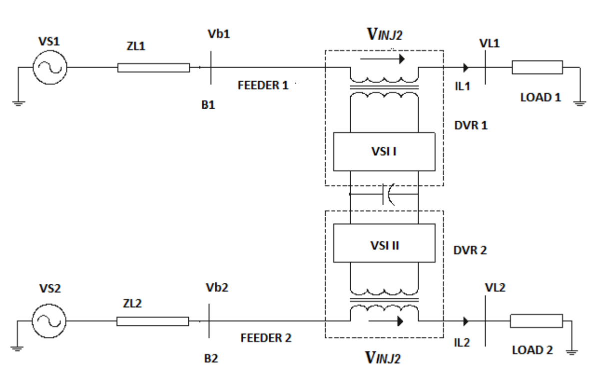

Figure 1: Two feeder diagram of IDVR

Inverter Modeling

Figure 1 illustrates that the voltage sources of two feeders, V_{s1} and V_{s2}, are represented by equations 1 and 2, respectively.

$$V_{s1} = I_1 Z_1 + V_{inj1} + V_{l1} \tag{1}$$

$$V_{s2} = I_2 Z_2 + V_{inj2} + V_{l2} \tag{2}$$

$$\text{Note}: (V_{inj} = V_{DVR})$$

Neglecting losses in both feeders, equations (1) and (2) may be expressed as

$$V_{inj1} = V_{s1} - V_{l1} \tag{3}$$

$$V_{inj2} = V_{s2} - V_{l2} \tag{4}$$

From equations (3) and (4), the voltage injected by the IDVR is the difference between the supply and load voltages of the feeder. Therefore, the inverter voltage rating of the IDVR may be established if the extent of voltage sag requiring compensation by the IDVR is known. Figure 2 illustrates the single-line schematic of one of the feeders seen in Figure 1. According to equations (3) and (4), if $V_s = V_l$, then V_{DVR} = 0, indicating that compensation is unnecessary. Voltage correction is necessary only if $V_s \neq V_l$

The IDVR will initiate voltage compensation when

$$V_L^* < V_s \tag{5}$$

Where $V_L^* = V_L - \left(0.10 * V_L\right)$

Therefore the V_{DVR} is given as

$$V_{DVR} = V_S - V_L^* \tag{6}$$

The voltage rating of the two voltage source inverters depicted in Figure 1 may be determined using equation (6). The voltage rating of the inverter may be obtained using equation (6) alone when the in-phase compensation approach is employed (P. Jayaprakash *et al*., 2014).

The load current exhibits a phase difference with the injected voltage; hence, the DVR must consistently inject both active and reactive power into the load. This study discusses voltage sag avoidance with the IDVR utilizing the in-phase voltage compensation approach. The selection of in-phase methods over other voltage compensation techniques is due to the lower inverter rating associated with in-phase compensation compared to methods such as energy-saving and quadrature compensation methods. According to Figure 3, the actual power of each DVR in the IDVR is

$$P_{DVR} = V_{DVR} \times I_L^* \times \cos\varnothing \tag{7}$$

Where

V_{DVR} : Voltage injected by the DVR

I_L: Load Current

$\cos\varnothing =$ Power Factor

Therefore, using equations (6) and (7), the power and voltage rating of the inverter of IDVR can be determined.

Problem Formulation

This study minimizes three fitness functions while accounting for power system restrictions. The optimization of these fitness functions occurs in two forms: mono-objective function and multi-objective function, as detailed in the subsequent subsections:

Mono-objective function

The active power losses, bus voltage deviation, and system operating cost are optimized individually using a mono-objective function approach. The mathematical formulation of these objectives may be represented as:

Active power loss minimization (PL)

The minimization of active power losses within the power system can be expressed as follows.

$$\min p_L = \min \sum_{k=1}^{NL} G_k [V_i^2 + V_j^2 - 2V_i V_j \cos\left(\delta_{ij}\right)] \tag{8}$$

In this context, G_k denotes the conductance associated with the k^{th} transmission line. NL signifies the total count of transmission lines in the system. Vi and Vj represent the voltage magnitudes at buses i and j, respectively. The term δ_{ij} Indicates the angular difference between the voltages at buses i and j.

Minimization of the bus voltage deviation (VD)

The decrease in bus voltage deviation improves the bus voltages, ensuring they stay within the permissible limits, which can be articulated as:

$$\min VD = \min \sum_{i=1}^{Nl} (V_i - 1.0)^2 \tag{9}$$

In this context, V_i represents the voltage magnitude at the i^{th} bus, while Nl indicates the total count of load buses.

Minimization of the operating cost (OC)

This paper outlines that the operating cost (OC) comprises two components: the cost associated with energy losses and the cost attributed to the investment in FACTS controllers. The objective function necessitates the reduction of energy loss costs by mitigating active power losses through the implementation of FACTS devices while also minimizing the investment costs associated with these devices.

$$\min(C_{PL} + C_{FACTS}) \tag{10}$$

where,

$$C_{PL} = (\text{real power loss}) \times 0.09 \times 365 \times 24 \tag{11}$$

$$C_{FACTS} = C_{IDVR} \tag{12}$$

$$C_{IDVR} = 0.0003S^2 - 0.2691S + 188.22 \tag{13}$$

In this context, C_{PL} and C_{FACTS} denote the annual energy losses and the installation cost of the FACTS controller, expressed in dollars. The value of 0.09 signifies the cost related to power losses, measured in dollars per kilowatt-hour. Figure 365 represents the total number of days in a year, while 24 indicates the number of hours in a day. C_{IDVR} refers to the installation cost of the IDVR devices, measured in dollars per (KVAR). Lastly, S denotes the operating range of the FACTS devices, expressed in (MVAR).

Multi-objective Function

In the mono-objective function form, the objective functions under consideration are optimized concurrently through their combination into One objective function F is presented in equation (14).

$$F = w1 \cdot J1 + w2 \cdot J2 + w3 \cdot J3 \tag{14}$$

In this equation, w1, w2, and w3 represent the weight coefficients that quantify the contribution of each term within the fitness function.

$$J_1 = \frac{PL_{-IDVR}}{PL_{-base}}, J_2 = \frac{VD_{-IDVR}}{VD_{-base}}, J_3 = \frac{OC_{-IDVR}}{OC_{-base}} \tag{15}$$

In this context, PL_{-IDVR} and PL_{-base} represent the real power losses associated with the integration and non-integration of the FACTS controller into the power system. Similarly, VD_{-IDVR} and VD_{-base} denote the voltage deviations experienced with and without the installation of FACTS controllers. Furthermore, OC_{-IDVR} and OC_{-base} indicate the system operating costs incurred with and without the installation of FACTS controllers.

Constraints

The constraints described below are applicable to the optimization problems under consideration.

$$P_{G_i} - P_{D_i} - \sum_{j=1}^{N} V_i V_j [G_{ij} \cos(\delta_{ij}) + B_{ij} \sin(\delta_{ij})] = 0 \tag{16}$$

$$Q_{G_i} - Q_{D_i} - \sum_{j=1}^{N} V_i V_j [G_{ij} \sin(\delta_{ij}) + B_{ij} \cos(\delta_{ij})] = 0 \tag{17}$$

$$V_{j\_min} \le V_j \le V_{j\_max} \tag{18}$$

$$S_{ij} \le S_{ij\_max} \tag{19}$$

In this context, P_{Gi} and PDi denote the active power generated and demanded at bus i, while QGi and QDi signify the reactive power generated and demanded at bus i. The variable N represents the total number. In the context of buses, Sij denotes the apparent power flow along the line connecting nodes i and j. The parameter Sij_max indicates the thermal limit of the line between nodes i and j. Gij and Bij represent the transfer conductance and inductance between bus i and bus j, respectively.

Basic Overview Of Optimisation Methods

The suggested technique is contrasted with the classic PSO algorithm, as well as the GWO, IGWO, and CSO algorithms, which are briefly in the subsequent subsections.

Particle Swarm Optimisation Technique

Particle Swarm Optimisation (PSO) is a metaheuristic optimization technique initially proposed by Kennedy and Eberhart. A swarm of particles adjusts their relative locations from one iteration to the next, enhancing the performance of the PSO algorithm in the search process. To get the optimal solution, each particle navigates towards its previous personal best position P_{best} and the global best position g_{best} inside the swarm (Zang Y *et al*., 2014). In the context of a minimization problem, one has

$$P^t_{best_i} = x^*_i \left| f\left(x^*_i = \min_{k=1,2,\ldots k} \left(\left\{ f\left(x^k_i \right) \right\} \right) \right) \right| \tag{20}$$

Where i $\in \{1, 2, \ldots\ldots, N\}$ *and*

$$g^t_{best_i} = x^t_* \mid f\left(x^t_*\right) = \min_{\substack{i=1,2,\ldots\ldots N \\ k=1,2,\ldots t}} \left(\left\{ f\left(x^t_i \right) \right\} \right) \tag{21}$$

In this context, (i) represents the index of a particle, (t) signifies the current iteration number, (f) defines the objective function to be optimized (minimized), (x) refers to the position vector (or a potential solution), and (N) Indicates the total number of particles in the swarm. The subsequent equations update at each iteration $(t+1)$, the velocity (v) and location (x) of each particle i as follows:

$$v^{t+1}_i = \omega v^t_i + c_1 r_1 \left(p^t_{best_i} - x^t_i \right) + c_2 r_2 \left(g^t_{best} - x^t_i \right) \tag{22}$$

$$x^{t+1}_i = x^t_i + v^{t+1}_i \tag{23}$$

where (v) is the velocity vector, and (ω) is the inertia weight employed to equilibrate local exploitation and global exploration. r_1 and r_2 are random vectors uniformly distributed within the interval $[0,1]^D$, (D) where represents the dimensionality of the search space or the size of the issue. The constants. c_1 and c_2, referred known as "acceleration coefficients," are positive values. An upper limit is often established for the velocity vector. The "velocity clamping" strategy was employed to prevent particles from reducing the search space and to ensure they take an appropriate step size to explore the whole search domain (Shahzad F *et al.*, 2014). The "constriction coefficient" concept, introduced by Clerc and Kennedy (Clerc M *et al.*, 2002), involves constricting velocities through theoretical observation and analysis of swarm dynamics. Upon examining Eq. (3), it is evident that the first segment referred to as the "inertia component," signifies the preceding velocity, which endows the particles with the requisite momentum to traverse the search space (Yue Y *et al.*, 2019). The second half, the "cognitive component," refers to the inherent positivity associated with each particle. It encourages the particles to advance toward their previously identified optimal places in subsequent rounds. The third component, termed the "social component," signifies the collective influence of the particles in achieving the global optimal solution (Xu G *et al.*, 2019).

Grey Wolf Optimization Technique (GWO)

The GWO algorithm is a heuristic method inspired by the hunting habit of grey wolves. Grey wolves are recognized for their social organization and collaborative hunting techniques. The GWO algorithm simulates social behavior to address optimization challenges (Zhou Z *et al.*, 2007). The GWO method relies on mathematically simple equations, facilitating implementation and comprehension. It is readily adaptable to various optimization challenges, enhancing its applicability across many domains. GWO can typically get the global answer without being ensnared in local optima (H. Faris *et al.*, 2018). GWO necessitates a few parameters for optimization, rendering it more user-friendly. The algorithm consistently yields uniform results across several executions and iterations.

The GWO algorithm is founded on the hierarchical organization of grey wolves. Wolves are categorized into many categories according to their hierarchy and functions within the pack. The alpha group comprises the dominant wolves, tasked with making critical choices on hunting targets, picking sleeping locations, and defining wake-up times. The beta group comprises wolves that aid the alpha wolves in decision-making and various activities. The delta and omega groupings signify subordinate wolves within the hierarchy (Lu *et al.*, 2016). The hunting habit of grey wolves is a multifaceted process comprising multiple stages. The steps of the GWO algorithm are abstracted and integrated into the optimization process. The method starts by initializing a population of possible solutions denoted by the placements of wolves. The ranks of the wolves in the alpha, beta, delta, and omega categories represent the optimal, suboptimal, tertiary, and least favorable potential solutions, respectively.

The GWO algorithm simulates the three primary steps of the hunting process: surrounding the prey, hunting, and attacking the prey. In the encircling phase, the wolves synchronize their actions to encircle the prey, reflecting the exploration and exploitation of the search space inside the algorithm (Celtek *et al.*, 2020). During the hunting phase, the wolves aggregate around the prey, symbolizing the convergence of solutions toward the best outcome. Ultimately, during the offensive phase, the wolves modify their locations to seize the prey, illustrating the enhancement and sophistication of the solutions. The grey wolf can unpredictably alter its location throughout its hunt using Equations (24) and (25). The surrounding prey can be articulated as follows:

$$\mathrm{D} = \left|\mathrm{C.X_p}(\mathrm{t}) - \mathrm{X}(\mathrm{t})\right| \tag{24}$$

$$X(t+1) = \left|X_P(t) - A.D\right| \tag{25}$$

In this context, t denotes the iteration value, A and C signify the coefficients, $\mathrm{X_p}$ the position of the hunt, and X indicates the position of a wolf. The A and C are calculated using Equations (26) and (27):

$$A = \left|2a.r_1 - a\right| \tag{26}$$

$$\mathrm{C}{=}\left|2a.r_2\right| \tag{27}$$

The parameter progressively falls from 2 to 0 over t iterations, whereas r_1 and r_2 are random vectors within the range of [0, 1]. The alpha, beta, and delta subspecies of grey wolves possess exceptional hunting skills. They are aware of the present whereabouts of their target. Consequently, the top three solution choices are documented, and the remaining wolves can adjust their placements in relation to the optimal search agents utilizing Equations (28)–(30).

$$D_\alpha = \left|C_1.X_\alpha - X\right|, D_\beta = \left|C_1.X_\beta - X\right|, D_\delta = \left|C_1.X_\delta - X\right| \tag{28}$$

$$X_1 = \left|X_\alpha - A_1.D_\alpha\right|, X_2 = \left|X_\beta - A_2.D_\beta\right|, X_3 = \left|X_\delta - A_3.D_\delta\right| \tag{29}$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{30}$$

During the exploitation phase, the value diminishes, thereby narrowing the range of variation of A. When A assumes random values within the range of [–1, 1], the search agent's subsequent position will be located anywhere between its present position and the target. Comprehensive information on GWO is available in (Mirjalili *et al.* 2014).

Improved grey wolf optimization (IGWO) Algorithm

IGWO aims to reduce the disparity between exploration and exploitation inside the GWO algorithm (Kamboj *et al.*, 2016). The IGWO method is derived from the behavior of wolves and the dimension-learning-based hunting (DLBH) seen in nature. Wolves (N: number of wolves) are first scattered randomly inside the search region defined by the limits $[l_i, u_j]$, as indicated in equation (31).

$$X_{ij} = I_j + rand_j[0,1]x(u_j - l_j), i_g[1,N], jg[1,D] \tag{31}$$

$X_i(t) = \{X_{i1}, X_{i2}, \ldots\ldots\ldots X_{iD}\}$ denotes i^{th} position in the point inside iteration (D = dimension). The population is represented in a matrix with N rows and D columns. During the moving phase, the IGWO calculates the subsequent position of the wolf $X_i(t)$. In this calculation, IGWO utilizes the various neighbors of the wolf alongside a randomly chosen wolf from the matrix $R_i(t)$. The radius between the present position $X_j(t)$ and the candidate's position $X_{j-GWO}(t+1).R_i(t)$ is calculated using equation (32).

$$R_i(t) = X_j(t) - X_{j-GWO}(t+1) \tag{32}$$

$$N_i(t) = \{X_j(t) \mid D_i(X_j(t), X_j(t)) \le R_i(t), X_j(t) gMatrix\} \tag{33}$$

The $N_i(t)$ is the neighbor of $X_j(t)$. It is calculated by equation (33). Here D_i is the Euclidean distance between $X_j(t)$ and $X_i(t)$ as shown in equation (33).

$$X_{iDLH,d}(t) = (X_{i,d}(t) + rand[0,1]x(X_{n,d}(t) - X_{r,d}(t))) \tag{34}$$

$X_{iDLH,d}(t+1)$ is the new position of the DLH-based model, calculated using equation (35). Here, n is the number of wolves and d denotes the dimension

$$X_i(t+1) = \begin{Bmatrix} X_{iGWO}(t+1), if\ f(X_{iGWO}(t+1) < f(X_{iDLH,d}(t+1)) \\ X_{iDLH,d}(t+1) \quad otherwise \end{Bmatrix} \tag{35}$$

Cuckoo Search Optimisation

Cuckoo Search optimization is a widely utilized meta-heuristic approach that simulates the breeding parasitism behavior of cuckoos(Shehab *et al*., 2017), (Alkhateed *et al.,* 2019). During the iterative process, the innovative candidate solution is generated via Levy flight as described in equation (36).

$$Y_i = Y_i - \gamma ë |Y_i - Y_g| + levy(\ ) = Y_i + \frac{0.01\mu}{v^{1/ë}}(Y_i - Y_g) \tag{36}$$

In the above equation (no) ë represents the levy flight exponent, Y_i represents i^{th} solution + represents entry-wise multiplications, Y_g represents global optimal solution, $\gamma > 0$ represents step scaling size, u and v denote arbitrary numbers, and they are satisfied by normal distribution means

$$u\hat{N}(0, \sigma_u^2), v\hat{N}(0, \sigma_u^2) \tag{37}$$

$$\sigma_u = \left[\frac{\sin\frac{\lambda\pi}{2}.\tau(1+\lambda)}{2^{(\lambda-1)/2}\lambda.\tau\left(\frac{1+\lambda}{2}\right)} \right] \tag{38}$$

In equation (no) $\tau(\cdot)$ represents Gamma function

In addition, Cuckoo search exploits detection operators to put find nests through probability P_a in equation no (39)

$$Y_i = \begin{Bmatrix} Y_i + m.(Y_j - Y_k), if\ p > p_a \\ Y_i, \quad else \end{Bmatrix} \tag{39}$$

In equation no P $\in [0,1]$ describes a random number Y_j *and* Y_k represents the candidate solutions from the population, accordingly.

Hybrid IGWO-CSO Optimisation

The hybrid approach alternates the stages from both IGWO and CSO. The optimal solutions from IGWO can impact the subsequent generation in CSO, improving the exploration phase. Following specific iterations in IGWO, the algorithm transitions to CSO for the exploration of novel regions. The optimal position of the alpha wolf may direct the newly established nests in CSO. Developing a hybrid method that integrates improved grey wolf optimization (IGWO) with cuckoo search optimization (CSO) may yield a more efficient solution for complex optimization challenges. The combination of IGWO and CSO improves the advantages of both methods to improve optimization efficiency. IGWO Inspired by the social hunting dynamics of grey wolves, IGWO emulates its leadership structure (alpha, beta, and delta wolves) to identify optimal solutions. The alpha wolf directs the group, while beta and delta wolves provide support. This hierarchy affects the wolves' progression toward the optimal solution. IGWO (Ting T *et al.* 2015) equilibrates exploration (investigating new territories) and exploitation (enhancing familiar advantageous locations) by constantly adjusting coefficients. The enhancement of conventional GWO (P.Hu *et al.* 2020; Guptha S *et al.*, 2019) may incorporate approaches such as adaptive parameters or hybrid procedures that augment solution variety. Cuckoo Search Optimization (CSO), inspired by the brood parasitism of some cuckoo species, entails depositing eggs in the nests of other avian species and improving these nests according to fitness criteria. The use of CSO facilitates a more comprehensive exploration of the search space, which is essential for circumventing local optima. The systematic methodology of IGWO facilitates enhanced solution refining. The integration of two algorithms yields a more resilient optimization approach, adept at addressing complex and multimodal challenges efficiently.

Mathematical Model of IGWO-CSO Hybrid Optimisation method

Fitness function

Define a Function $f(x)$ that quantifies the quality of solutions, where x describes potential solutions

Positional update for IGWO-CSO Method

$$X_i^{new} = X_i^{old} + A.\left|C.X_{best} - X_i^{old}\right| \tag{40}$$

Where

X_i^{new} = New Position of the i –th wolf.

X_i^{old} = Current position of the i –th wolf

X_{best} = position of the best wolf (alpha).

A and C are mentioned as Coefficient vectors controlling exploration and exploitations

A= $2a.r_1 - a$, where a decreases linearly from 2 to 0

C= $2.r_2$ where r_1 and r_2 describes random numbers in the range [0,1]

The update for a nest's location is provided by:

$$X_{new} = X_{best} + \alpha.Levy() \tag{41}$$

Where

X_{new} mentions New Position of the nest

X_{best} describes position of the best nest found so far.

α Represents scaling factor

$Levy()$ descibes Levy Flight behaviour

The hybrid model proficiently integrates the exploitation capabilities of IGWO with the exploration capabilities of CSO.

- Wolves Update: Employ the leadership structure to enhance solutions according to prevailing best estimates.
- Nests Update: Employ Lévy flights to investigate the search space utilizing the optimal solutions identified by IGWO.
- Dynamic Switching: Adaptively alternate between the two methodologies to sustain variety and enhance convergence.

The conventional cuckoo search optimization is formulating the static nest upgrade problem as articulated in several types of publications. Hybrid IGWO and CSO algorithm employs an averaging-based method for nest upgrading. The output of CS comprises optimal values derived from equations.

$$x_i^{t1+1} = x_i^{t1} + \alpha \oplus levy(\lambda) \tag{42}$$

$$levy(\lambda) = t1^{-\lambda} \tag{43}$$

whereas the community hierarchy selection is determined by fitness.wherever $X_\alpha = 1$ st hunt agent, $X_\beta =$ 2nd hunt agent and $X_\delta = 3$rd hunt agent. Figure 2 illustrates the flow chart of the hybrid IGWO and CSO algorithm.

In the hybrid model, the procedures from both IGWO and CSO are interchanged. The optimal solutions from IGWO can impact the subsequent generation in CSO, improving the exploration phase. After certain iterations in IGWO, the algorithm transitions to CSO for the exploration of novel regions. The optimal position of the alpha wolf may direct the new nests established in the CSO. The hybrid IGWO-CSO method, by integrating these mathematical models, can proficiently balance exploration and exploitation, resulting in enhanced performance in intricate optimization challenges. This method allows adaptive search techniques that utilize the advantages of both algorithms.

Simulation Results

In order to assess the efficiency and flexibility of the IGWO-CSO approach, the IEEE 30 bus system(Kanaan *et al.* 2020) has been studied to determine the optimal siting and capacity of the IDVR. The effectiveness of the proposed IGWO-CSO method is evaluated with PSO, GWO, IGWO, IGWO-CSO, and CSO algorithms in order to determine its performance in the optimal allocation of IDVR. The optimization problem is formulated in two cases: (1) mono-objective optimization and (2) multi-objective optimization. The optimization issues are implemented as follows.

IEEE 30 bus system

The tested IEEE 30 bus system has six generators and 41 transmission lines. The overall active and reactive load demands of the system are 250.16 MW and 160.54 MVAR, respectively.

Mono-objective optimization

Each objective function is indicated in Eqs. (8)–(13) performs independently on the IEEE 30-bus system with IDVR.

Installation of IDVR.

The IDVR device's optimal parameters for minimizing the active power losses and voltage division of the IEEE 30 bus system are illustrated in Table no 1, which is based on various proposed techniques. In the event that the sole

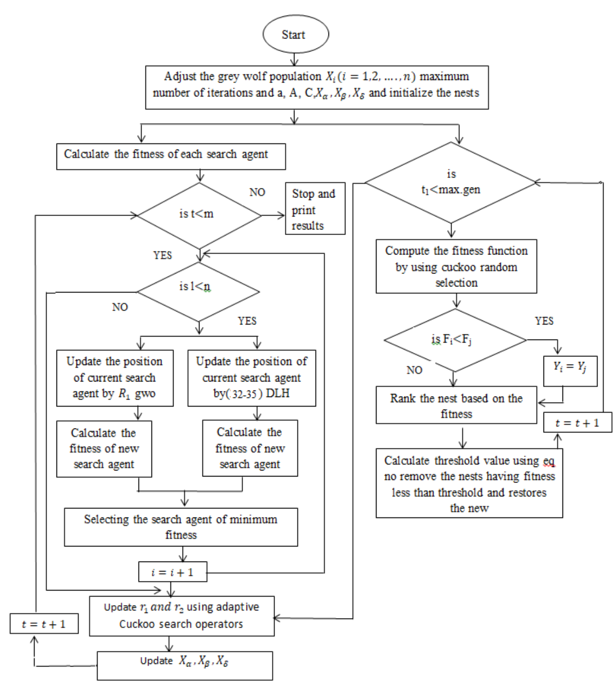

Figure 2: Flow chart of IGWO - CSO

objective function is to minimize total active power losses, the installation of the IDVR resulted in a reduction of the total real power losses from 7.48 to 6.85 MW, with high capacities values, as compared to the IGWO-CSO technique (Table 1).

The IDVR is proposed to be located at bus 8 and line 12, with a capacity of -77.114 MVAR and -0.653 of the reactance of the connected line. Table 1 illustrates that the objective values are subpar due to the non-optimal location of IDVR. In contrast, the objective values are higher for the non-optimal IDVR location and dimensions than for the optimized location. The PL value is 6.657, 6.642, and 6.341 MW, respectively, as determined by the GWO, PSO, and IGWO algorithms. In contrast, the optimal location for the IGWO-CSO and IGWO generates 6.442 and 6.442 MW, respectively.

Additionally, Table 1 illustrates that the installation of the IDVR based on the IGWO-CSO is effective in minimizing the voltage deviation of the system as the individual objective function. The greatest results are achieved by the IGWO and CSO algorithms, which reduce the voltage deviation from 0.0342 to 0.0120 p.u. in comparison to the GWO and PSO algorithms. The IDVR's most suitable location is at bus 7 and line 14, which is connected to buses 7 and line 14 and has a reactance of -0.7 and a magnitude of -89.565 MVAR. Conversely, the PSO algorithm recommended that the UPFC be situated at bus 5 and line 39, which is connected between buses 5 and 30, with a magnitude of -89.56 MVAR and -0.7 of the reactance of the connected line. This location yielded the highest voltage deviation value (0.0124 p.u.). The optimal solution of all algorithms to minimize the OC based on the location of the IDVR is illustrated in Table no. The OC is reduced to $4.567*10^6$ $ by installing the IDVR using the IGWO-CSO, IGWO, and CSO algorithms. Conversely, the IDVR's optimal location and size, as determined by the PSO and GWO techniques, yielded the highest OC values of $4.628*10^6$ and $4.651*10^6$ $, respectively. As demonstrated in Figures 3,4 and 5, the IGWO-CSO technique shows the best results throughout the optimization process. The IGWO-CSO algorithm identifies global optima with a reduced number of iterations when compared to alternative algorithms. Figure 3 indicates that the IGWO algorithm was nearly confined to a local optimum. The PSO and GWO algorithms encountered a local optimum and failed to reach the optimal global minimum values for PL, VD, and OC, as illustrated in Figures 3-6, respectively.

Table 1: The optimal solution of all algorithms for active power losses and voltage deviation at the installation of IDVR

Items			*PL is the only objective function*				*VD is the only objective function*				
Without IDVR			*7.48MW*				*0.0342 p.u*				
IDVR	ALGORITHMS	LOC.	Size		PL(MW)	VD(pu)	LOC	Size		VD(pu)	PL(MW)
	PSO	bus	6	-65.145	6.6427	0.0160	bus	8	-89.565	0.0124	6.8212
		line	30	0.0162			line	31	0.3		
	GWO	bus	11	-79.124	6.6571	0.0150	bus	7	-90	0.0123	6.8130
		line	12	-0.7			line	7	0.3		
	IGWO	bus	8	-79.225	6.6421	0.0140	bus	7	-89.565	0.0120	6.5620
		line	12	-0.634			line	14	-0.7		
	CSO	bus	11	-61.632	6.4423	0.0170	bus	7	-89.565	0.0120	6.5619
		line	10	-0.7			line	14	-0.7		
	IGWO-CSO	bus	8	-77.114	6.6421	0.0140	bus	7	-89.565	0.0120	6.5620
		line	12	-0.653			line	14	-0.7		

Table 2: The optimal solution of all algorithms for minimization of OC at installation of IDVR only

Operational Cost (OC) is the only objective function							
	Without IDVR $4.7861*10^6$ $						
IDVR	ALGORITHMS	LOC.		Size	OC($)	PL(MW)	VD(pu)
	PSO	bus	11	-15.0724	$4.6281*10^6$	6.0368	0.0161
		line	20	-0.1536			
	GWO	bus	10	-26.5421	$4.6121*10^6$	6.0368	0.0161
		line	16	0.3254			
	IGWO	bus	8	-19.2126	$4.5561*10^6$	6.0368	0.0161
		line	10	-0.7			
	CSO	bus	8	-19.2126	$4.5561*10^6$	5.9012	0.0153
		line	10	-0.7			
	IGWO-CSO	bus	8	-19.2126	$4.5561*10^6$	6.1652	0.0184
		line	10	-0.7			

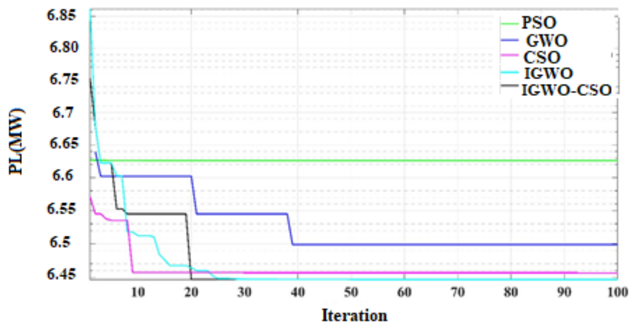

Figure 3: Convergence curves of all algorithm for the IDVR only in the system for minimization of real power losses

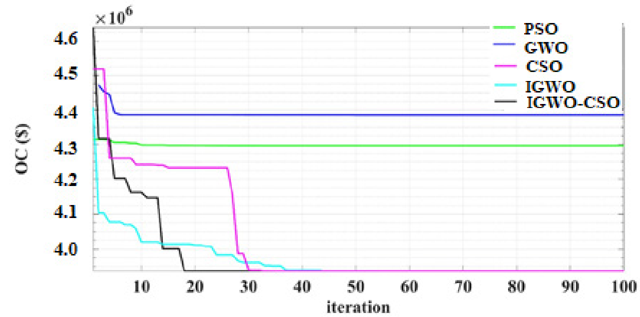

Figure 5: Convergence curves of all algorithms for the installation of IDVR in the system for the minimization of OC.

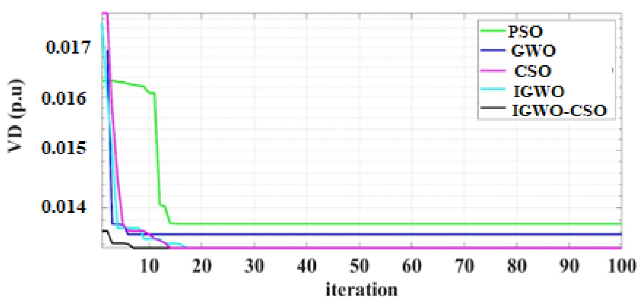

Figure 4: Convergence curves of all algorithms for the IDVR only in the system for minimization of voltage deviation

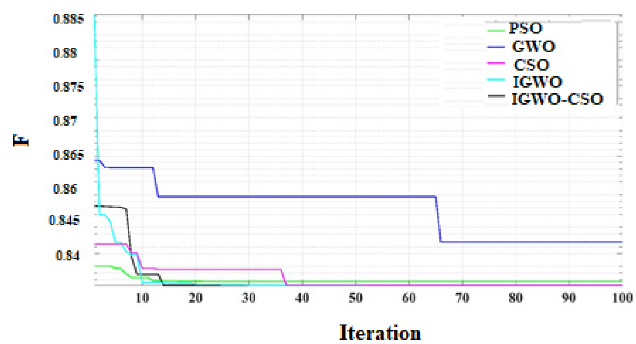

Figure 6: Convergence curves for minimization of the multi-objective optimization problem for IDVR alone installation

Table 3: The optimal Solution of all optimization techniques for minimizing the multi-objective optimization problem during the installation of IDVR only

PL, VD and OC Values								
	*Without IDVR 7.48MW&0.0342p.u&4.7662*10⁶$*							
	ALGORITHMS	LOC.		Size	OC($)	PL(MW)	VD(pu)	F
IDVR	PSO	bus	7	-22.864				
		line	30	-0.7	$4.6721*10^6$	5.7264	0.0132	0.8432
	GWO	bus	7	-27.228				
		line	30	-0.7	$4.6610*10^6$	5.7319	0.0132	0.8519
	IGWO	bus	5	-28.322				
		line	12	-0.7	$4.7042*10^6$	5.7310	0.0132	0.8431
	CSO	bus	5	-28.4255				
		line	12	-0.7	$4.6612*10^6$	5.7321	0.0124	0.8431
	IGWO-CSO	bus	8	-28.5332				
		line	11	-0.7	$4.7042*10^6$	5.7310	0.0166	0.8431

Multi-objective Optimization

This article presents the implementation of multi-objective functions through the proposed techniques aimed at minimising active power losses, voltage deviation, and system operating costs concurrently in IDVR installations. The multi-objective function is crucial for the performance of the optimization technique process, as it ensures the identification of the global minimum. The resolution of this issue is contingent upon the optimal evaluation of the proposed fitness function. Consequently, the IGWO-CSO algorithm has been implemented through a multi-objective function (F) as defined in Eq. (14) to assess the optimal capacity and placement of the IDVR in this case study. These values ensure a balance between PL, VD, and OC values while minimizing the capacity of the IDVR device installation, in contrast to all cases presented in Table 3. This section details the installation of the IDVR within the IEEE 30-bus system, aimed at minimizing the specified multi-objective function. Table no 3 presents the minimum value of the PL, which is 5.7310 MW. The resolution of this issue involves the installation of the IDVR within the system utilizing the IGWO and IGWO-CSO algorithms. The IGWO-CSO technique attained optimal global solutions in comparison to alternative algorithms by implementing IDVR at bus 5 and line 12, with a capacity of -28.5332 MVAR and a connected line reactance of -0.7. The optimal IDVR setting, determined using the IGWO-CSO algorithm, resulted in a reduction of the system's bus voltage deviation to 0.0132 pu and operating costs to 4.7042×10^6 $.

The GWO and PSO algorithms encountered a local optimum for the function F, with the GWO attaining the maximum OC value and the PSO algorithm reaching the maximum PL value. A visual demonstration of the optimal placement of IDVR within the system, utilizing the IGWO-CSO technique, is presented in Tables 1, 2, and 3.

Conclusion

Meta-heuristic algorithms have been widely applied for the allocation of interline dynamic voltage restorers (IDVR). The GWO algorithm is widely recognized for its straightforward implementation, minimal variable adjustments required, and rapid convergence to the optimal solution. Despite these advantages, it experiences a reduction in diversity, which leads to entrapment in local optima. This paper presents a novel hybrid algorithm, referred to as the IGWO-CSO algorithm, designed to resolve the limitations associated with the standard GWO algorithm. The proposed method employed an improved version of the CSO technique to enhance both the accuracy and efficiency of the traditional GWO algorithm. The IGWO-CSO algorithm has been utilized on the IEEE 30 bus power systems to ascertain the optimal location and size of the IDVR. The FACTS are distributed to reduce active power loss, minimize voltage deviation, and lower the operating costs of the power system. The objectives have been optimized in both single and multi-objective formats. The simulation results demonstrated the effectiveness of the new approach, specifically the IGWO-CSO technique, in optimizing both single and multi-objective functions. The locations of FACTS devices and their ratings have been determined concurrently. The findings indicate that the optimal allocation of the FACTS device, specifically the IDVR, results in a reduction of power loss and voltage deviation, in addition to lowering the system operating cost. Furthermore, the non-optimized location results in suboptimal objective values for both single and multi-objective optimization. The PSO, GWO, CSO, and IGWO algorithms were employed to validate the proposed method. The numerical results and conversion curves demonstrated that the IGWO-CSO technique outperformed the other comparable algorithms. The simulation clearly demonstrates that the IGWO-CSO approach exhibits a markedly superior convergence profile compared to all other algorithms. The proposed algorithm efficiently identifies the optimal global value while avoiding the issue of local optimum trapping.

Acknowledgment

The authors gratefully acknowledge the authorities of Annamalai University for the facilities offered to carry out this work.

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