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REACTIVE POWER MANAGEMENT USING HGWO UNDER DIVERSE LOAD SCENARIOS

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Abstract: Reactive power optimization is essential for ensuring the efficiency, stability, and reliability of power systems. It plays a critical role in maintaining voltage stability and minimizing transmission losses. Poor reactive power management can result in voltage instability, increased losses, and even large-scale blackouts. This study introduces two optimization techniques—Grey Wolf Optimization (GWO) and its hybrid variant, HGWO—for effective reactive power management (RPM). These methods utilize shunt capacitors and transformer tap settings to optimize voltage profiles and minimize active power losses. The IEEE 30-bus system is used as a benchmark to evaluate their performance under various constrained and unconstrained scenarios with diverse load conditions. Results show that HGWO significantly outperforms GWO, achieving faster convergence, reduced power losses, and improved voltage profiles. By addressing these challenges effectively, HGWO offers a practical solution for real-world power systems, ensuring secure and sustainable operations under dynamic conditions.

***IndexTerms* - Reactive power planning, shunt capacitance, transformer tap settings, Grey Wolf Optimization (GWO), HGWO, power loss minimization, voltage profile improvement.**

I. INTRODUCTION

The optimization of reactive power is crucial for the economic, stable, and secure operation of modern power systems. Although reactive power does not perform actual work, it plays an essential role in maintaining voltage stability, which is key to ensuring the reliable operation of power systems. Reactive power directly influences voltage profiles, transmission losses, and system reliability [1]. Its improper management can lead to significant operational challenges, such as voltage instability, system inefficiencies, and even widespread blackouts [2]. This highlights the importance of reactive power optimization (RPO) as a critical task for power system operators. Effective RPM is fundamental to maintaining the stability of the power grid. An adequate supply of reactive power supports active power transfer and ensures voltage levels stay within acceptable limits. Imbalances in reactive power—whether inadequate or excessive—can cause voltage fluctuations, leading to operational inefficiencies and equipment malfunctions. In extreme cases, these imbalances can result in cascading failures and large-scale blackouts, as evidenced by the massive blackout in northern USA in 2003 [3], which was partly attributed to poor reactive power management.

One of the primary goals of RPO is to improve the voltage profile across the power network while minimizing active power losses. This can be achieved by optimizing controllable parameters such as generator voltages, transformer tap settings, and shunt capacitors or inductors. Through these adjustments, power systems can operate more efficiently, reducing the cost of energy delivery while ensuring reliability. However, the problem of reactive power optimization is inherently complex. Power systems are non-linear and multi-modal, characterized by a mix of continuous and discrete variables, numerous constraints, and interdependencies among system components. For instance, generator voltages are continuous variables, while transformer tap settings and shunt capacitors/inductors are discrete variables. These mixed-variable characteristics, along with the presence of multiple local optima, make RPO a challenging optimization problem. Furthermore, power systems are subject to operational constraints, including limits on voltage magnitudes, reactive power generation, and line loading capacities. The optimization process must satisfy these constraints while minimizing active power losses and ensuring voltage stability.

Additionally, the dynamic nature of power systems—driven by load variations and renewable energy integration—requires robust optimization techniques that can manage uncertainty and variability. Over time, various traditional methods for RPO have been developed, such as classical coordination equations [4], which work well for small-scale systems but are inefficient for larger, non-linear systems. Techniques like interior-point programming and quadratic programming simplify the problem [5], but often struggle with non-convexities and suboptimal solutions. Non-linear programming [6], though useful, faces convergence issues and computational inefficiencies, particularly for large-scale systems. These traditional methods often fall short in handling the complex, non-linear, and mixed-variable characteristics of RPO, and are sensitive to initial conditions, making it challenging to guarantee global optimality.

The emergence of artificial intelligence (AI)-based techniques has revolutionized RPO by addressing the limitations of traditional methods. Inspired by natural processes, these techniques offer distinct advantages, such as a global search capability that allows them to explore the entire solution space, reducing the likelihood of getting trapped in local optima. Their flexibility enables them to handle complex, non-linear, and mixed-variable problems efficiently, while their robustness ensures they are less sensitive to initial conditions and can adapt to dynamic changes within the system. Additionally, AI-based methods can generate multiple near-optimal solutions, providing operators with a range of choices to suit specific requirements. Among the most widely used AI-based optimization techniques for RPO are Particle Swarm Optimization (PSO) [7], Genetic Algorithms (GA) [8], Evolutionary Programming, Ant Colony Optimization [9], Whale Optimization Algorithm (WOA) [10] and GWO [11]. Each of these approaches comes with unique strengths and limitations, making them suitable for addressing various RPO challenges effectively. Out of this GWO has gained popularity in power system optimization due to its simplicity, flexibility, and ability to handle non-linear and multi-modal problems effectively. GWO has been successfully applied to various power system optimization problems, including RPO. Its ability to balance exploration and exploitation makes it particularly effective for solving complex, high-dimensional problems. Although GWO is a powerful optimization method, its performance can be significantly enhanced by incorporating additional strategies or combining it with other optimization techniques. HGWO is an advanced version of GWO that integrates elements from Genetic Algorithms (GA) to improve its convergence speed and solution quality [11]. By utilizing the strengths of multiple optimization strategies, HGWO addresses some of the limitations of traditional GWO.

In the context of reactive power optimization (RPO), HGWO offers several advantages over standard GWO:

- Faster Convergence: HGWO achieves optimal solutions more rapidly by utilizing diverse optimization approaches.
- Improved Solution Quality: The hybrid approach enhances exploration and exploitation of the solution space, leading to better optimization results.
- Adaptability: HGWO is more robust in handling dynamic system conditions and solving complex optimization problems.

This paper presents HGWO as advanced methods for RPM in power systems. The study emphasizes optimizing key controllable parameters such as generator voltages, transformer tap settings, and shunt capacitors/inductors to reduce active power losses and improve voltage profiles. To thoroughly evaluate the proposed optimization algorithms, comprehensive case studies were conducted on the IEEE 30-bus system, testing the algorithms' ability to address diverse objective functions in both constrained and unconstrained environments. The credibility of the proposed algorithm is tested under varying loading conditions. These objective functions and operating conditions allow for a detailed assessment of the algorithm's adaptability and performance in optimizing reactive power, minimizing transmission losses, and maintaining voltage stability across diverse scenarios. The results of these case studies provide valuable insights into the optimal cost of reactive power, which is further analyzed in subsequent chapters. This detailed evaluation underscores the importance of reactive power optimization in dynamic environments, ensuring system reliability and cost-effectiveness even under challenging loading conditions. The performance of HGWO is compared with GWO, and the results reveal that HGWO outperforms GWO in minimizing active power losses and enhancing voltage stability. By adopting a hybrid approach, HGWO not only achieves faster convergence but also provides higher-quality solutions, making it an effective and practical tool for real-world power system management.

This paper presents a comprehensive approach to RPO in power systems, focusing on the development and evaluation of an advanced hybrid optimization technique, HGWO, for improving RPM. The key contributions of this paper are as follows:

- The paper introduces HGWO, an enhanced version of GWO, which combines the strengths of GA and GWO to improve the speed of convergence and solution quality in solving complex RPO problems.
- Extensive case studies on the IEEE 30-bus system are conducted to assess the performance of HGWO in both constrained and unconstrained scenarios. The study evaluates the ability of HGWO to optimize controllable parameters such as generator voltages, transformer tap settings, and shunt capacitors/inductors, with the objective of reducing active power losses and improving voltage profiles under varying loading conditions.
- A detailed comparison between HGWO and traditional GWO is provided, highlighting the superior performance of HGWO in terms of faster convergence, better exploration and exploitation of the solution space, and enhanced solution quality.
- The paper underscores the practical implications of reactive power optimization in ensuring the stability, efficiency, and reliability of power systems, particularly in dynamic environments with fluctuating loads and renewable energy integration.

The remainder of the paper is organized as follows: Section 2 outlines the mathematical formulation of RPO. Section 3 details the proposed HGWO approach. In Section 4, the process flow diagram for the proposed solution is provided. Section 5 presents and discusses the simulation results. The paper concludes in Section 6, summarizing the key findings.

II. Formulation of RPM Optimization Problem

The primary objective of RPO is to minimize active power losses and enhance voltage stability across the network. This is represented by the following objective function:

$$F_p = \sum_{i=1}^{N} P_{loss}^{i} \quad (2.1)$$

$$= \sum_{i=1}^{N} G^{i}\left[2|V_j||V_k|\cos(\delta_j - \delta_k) - |V_j|^2 - |V_k|^2\right] \quad (2.2)$$

Where P^{i}_{loss} is the real power loss in i^{th} transmission line between j^{th} and k^{th} buses; N is the count of the all transmission lines; G^{i} is the conductance of i^{th} transmission lines; V_j and V_k are voltages of the busses in per unit and δ_j, δ_k are phase angles in radians at the end buses i.e j^{th} and k^{th} of the i^{th} transmission line, respectively.

The voltage stability term, which aims to minimize the deviation of the voltage profile, can be expressed as:

$$F_v = \sum_{j=1}^{N_{bus}} |V_j - V_{spec}| \quad (2.3)$$

Where N_{bus} represents the total number of buses, and V_{spec} is the specified bus voltage, typically set to 1.0.
The problem formulations described above require optimization, ensuring that the load flow balances and satisfies all equality constraints as outlined in equation (2.4) and equation (2.5) below:

2.1 Satisfaction of equality constraints

Equality constraints are constraints that must be satisfied exactly. For example, the total reactive power injection at each bus must equal the total reactive power demand at that bus. The load flow equation for equality constraints are illustrated as follows:

$$P_{Gj} - P_{Dk} - V_j \sum_{n=1}^{N_{bus}} V_k \left[G_{jk}\cos(\delta_{jk}) + B_{jk}\sin(\delta_{jk})\right] = 0, \; n=1, 2, 3\ldots, N_{bus} \quad (2.4)$$

$$Q_{Gj} - Q_{Dk} - V_j \sum_{n=1}^{N_{bus}} V_k \left[G_{jk}\cos(\delta_{jk}) + B_{jk}\sin(\delta_{jk})\right] = 0, \; n=1, 2, 3\ldots, N_{bus} \quad (2.5)$$

Where,
N_{bus} = number of buses,
P_{Gj}= Active power generation at the j^{th} bus,
Q_{Gj} = Reactive power generation at the j^{th} bus,
P_{Dk} = Active power demand at the k^{th} bus,
Q_{Dk}= Reactive power demand at the k^{th} bus,
G_{jk} = Transfer conductance between j^{th} bus and k^{th} bus,
B_{jk}= Transfer susceptance between j^{th} bus and k^{th} bus, respectively.

2.2 Satisfaction of inequality constraints

Inequality constraints are conditions that must generally be satisfied but may allow for some level of violation. These constraints include the generator voltage magnitude, reactive power output from generator buses, shunt capacitors, and transformer tap positions. Inequality constraints define the boundary limits of the system and must be adhered to.

It is important to note that the proposed work is based on a split objective function, which must satisfy all equality constraints outlined in equations (2.4) and (2.5), as well as the inequality constraints in equation (2.6). Additionally, the magnitude of the load bus voltage must remain within the permissible limits.

$$\left.\begin{array}{l} V_{gm}^{min} \le V_g \le V_{gm}^{max} \\ P_{Gj}^{min} \le P_G \le P_{Gj}^{max} \\ Q_{Gj}^{min} \le Q_G \le Q_{Gj}^{max} \\ Q_{Cj}^{min} \le Q_C \le Q_{Cj}^{max} \\ T_{m}^{min} \le T_j \le T_{m}^{max} \end{array}\right\} \quad (2.6)$$

III. Optimization Techniques

3.1 GWO

GWO is a metaheuristic algorithm inspired by the hierarchical hunting behavior of grey wolves. The mathematical modeling of GWO revolves around three key phases: encircling the prey, hunting, and attacking the prey. These phases are represented using specific equations to guide the search process. Here's a detailed explanation with respect to the governing equations:

Encircling the Prey: Grey wolves encircle their prey during the hunting process. This behavior is mathematically modeled as:

$$\vec{F} = \left|\vec{E} \cdot Y_p(t) - Y(t)\right| \quad (3.1)$$

$$Y(t+1) = Y_p(t) - \vec{D} \cdot \left(\vec{F}\right) \quad (3.2)$$

where t denotes current iteration, $\vec{D}$ and $\vec{E}$ are coefficient vectors, Y_p is the position vector of the prey and X is the position of wolf. Vectors $\vec{D}$ and $\vec{E}$ are equal to:

$$\vec{D} = 2d.\vec{r}_1 - \vec{d}_1 \quad (3.3)$$

$$\vec{E} = 2.\vec{r}_2 \quad (3.4)$$

where components of $\vec{d}_1$ are linearly decreased from 2 to 0 through iterations and $\vec{r}_{1,}\vec{r}_2$ are random vectors with values from [0 1], calculated for each wolf at each iteration. Vector $\vec{D}$ controls the trade-off between exploration and exploitation while $\vec{E}$ always adds some degree of randomness. This is necessary because our agents can get stuck in the local optima and most of the metaheuristics have a way of avoiding it.

Hunting: The hunting process is guided by the three best wolves in the hierarchy: alpha ($\vec{Y}_\alpha$), beta ($\vec{Y}_\beta$), and delta ($\vec{Y}_\delta$). The positions of other wolves are updated based on the positions of these leaders as follows:

$$\vec{F}_\alpha = \left|\vec{E}_1 \cdot \vec{Y}_\alpha - Y\right|,\ Y_1 = Y_\alpha - \vec{D}_1 \quad (3.5)$$

$$\vec{F}_\beta = \left|\vec{E}_1 \cdot \vec{Y}_\beta - Y\right|,\ Y_2 = Y_\beta - \vec{D}_2 \quad (3.6)$$

$$\vec{F}_\delta = \left|\vec{E}_1 \cdot \vec{Y}_\delta - Y\right|,\ \vec{Y}_3 = Y_\delta - \vec{D}_3 \quad (3.7)$$

Finally, the updated position of the wolf is calculated as the average of these three positions:

$$Y(t+1) = \frac{Y_1+Y_2+Y_3}{3} \quad (3.4)$$

This mechanism ensures that all wolves are influenced by the best solutions found so far, guiding the population toward optimal regions in the search space.

Attacking the Prey (Exploitation Phase): As the wolves get closer to the prey, the parameter $\vec{\alpha}$ decreases linearly, which in turn reduces the value of $\vec{D}$. When $|\vec{D}|<1$, the wolves focus more on exploitation by converging toward the best solutions. This can be interpreted as "attacking" the prey.

Exploration (Diverging to Discover New Areas): When $|\vec{D}|>1$, the wolves are encouraged to explore the search space further by moving away from the prey. This ensures diversity in the search process and helps the algorithm avoid getting trapped in local optima.

Despite its effectiveness in balancing exploration and exploitation, the GWO has certain limitations. One key drawback is its tendency to stagnate in local optima, as the algorithm heavily relies on the alpha, beta, and delta wolves, which can lead to premature convergence in complex, multimodal problems. Additionally, while the surrounding mechanism provides some exploratory capability, GWO often lacks sufficient diversity to thoroughly explore the entire search space. To overcome these challenges, enhancements such as hybridization with other algorithms or the incorporation of adaptive mechanisms have been introduced. These modifications improve GWO's performance by accelerating convergence, maintaining diversity, and reducing the likelihood of stagnation in suboptimal solutions.

3.2 HGWO

The Grey Wolf Optimizer (GWO) is a flexible and effective optimization algorithm that has demonstrated strong performance on benchmark functions and various optimization problems. However, like many optimization tools, GWO has room for improvement, particularly in addressing issues like stagnation in local optima and limited diversity during the search process.

To enhance its performance, hybridization strategies—such as incorporating evolutionary operators like mutation and crossover—have been introduced into the basic GWO framework. The key enhancements in HGWO are as follows:

i. **Opposition-Based Learning for Initial Population:** The original GWO initializes the population randomly, which may cluster wolves within a limited region of the search space, reducing efficiency. HGWO employs opposition-based learning (OBL) to generate an evenly distributed initial population, improving global search capability by ensuring a better exploration of the solution space.

ii. **Optimal Maintenance Strategy:** HGWO retains the best individuals from the parent population during each iteration. This guarantees that the newly generated population builds on the most optimal solutions, thereby guiding the search in a desirable direction.

iii. **Crossover Operator:** Borrowed from Genetic Algorithms, the crossover operator enhances the global search ability by allowing wolves (solutions) to exchange information. This helps maintain a balance between exploration and exploitation, prevents premature convergence, and improves the diversity of the population. Crossover is applied probabilistically, with a crossover probability (P_C) determining how much of the population undergoes crossover. The process involves selecting pairs of wolves, randomly identifying crossover points, and swapping elements between them.

iv. **Mutation Operator:** The mutation operator introduces random changes in the population, increasing diversity and avoiding stagnation in local optima. A mutation probability (P_m)—set at 1% in this framework—determines the frequency of mutation. Mutation alters specific elements in the population matrix, ensuring that the algorithm continues exploring new areas in the solution space, particularly in later iterations.

The original GWO primarily emphasizes exploitation by relying on the alpha, beta, and delta wolves, which can result in a loss of diversity and premature convergence, particularly in multimodal optimization problems. To address these limitations, the HGWO incorporates genetic operators such as crossover and mutation. These enhancements promote greater diversity throughout the search process, enabling a more thorough exploration of the solution space. Additionally, the inclusion of these operators allows wolves to exchange information beyond the top three solutions, significantly improving global search capabilities. By maintaining diversity and facilitating information sharing, HGWO effectively prevents the population from stagnating in local optima, making it more robust for solving complex optimization problems.

IV. Results and Discussions

The performance of the proposed HGWO-based ORPD approach was evaluated using the IEEE 30-bus standard power system. This system consists of 41 transmission lines, six generator buses, and 24 load buses. Of these, five buses (Bus 2, Bus 5, Bus 8, Bus 11, and Bus 13) are PV buses, while Bus 1 serves as the slack bus. The remaining buses are classified as PQ buses. Additionally, four transmission lines, namely 6-9, 6-10, 4-12, and 27-28, are equipped with load tap setting transformers. Reactive power sources, such as capacitor and inductor banks, are installed at Bus 3, Bus 10, and Bus 24. Simulations were performed using MATLAB.

4.1. Objective Function Analysis Under Different Operating Conditions

The optimal values of control parameters and objective functions, particularly the total real power transmission line losses, were calculated using the HGWO algorithm and compared with GWO and other approaches. These results, summarized in Table 1 and table 2, demonstrate that HGWO achieves the lowest transmission line losses, confirming its ability to effectively identify global or near-global optimal solutions for reactive power dispatch.

Table 1 Comparison of optimal values of control parameters

Control variables	HGWO	GWO
V1	1.0266	1.069297
V2	1.0059	1.060347
V5	0.9833	1.035578
V8	0.9871	1.027609
V11	1.0283	1.00703
V13	1.004	1.014764
TC6-9	0.9918	1.092684
TC6-10	1.0391	0.966694
TC4-12	0.9999	0.964725
TC27-28	0.9	0.955906

Q10(MVAR)	9.1098	17.07352
Q24(MVAR)	14.65	6.992714

The optimal reactive power dispatch values obtained for the generators, presented in Table 3, highlight the superior performance of HGWO compared to GWO. Additionally. The results indicate that HGWO consistently outperforms GWO in terms of statistical performance metrics.

Table 2 Comparison of objective functions of IEEE-30 bus systems

Objective Functions	HGWO	GWO
Losses (MW)	4.8126	4.9717

Table 3 Reactive power dispatch value of each generator obtained using HGWO and GWO in IEEE 30 bus system.

Bus no	Dispatch of Reactive power at each generator with HGWO (MVAr)	Dispatch of Reactive power at each generator with GWO (MVAr)
1	6.215537	6.335581
2	23.33853	32.21293
5	8.444262	27.76506
8	33.21169	32.80172
11	6.714723	11.16305
13	8.602718	0.222903
Total	**86.52746**	**110.5013**

4.2 Objective Function Analysis Under Different Operating Conditions

The proposed algorithm's performance was further tested under varying objective functions and operational conditions, including both constrained and unconstrained environments. These case studies on the IEEE 30-bus system included:
Case 1A: Minimization of transmission active power losses under constrained conditions.
Case 1B: Minimization of transmission active power losses under unconstrained conditions.
Case 2A: Minimization of bus voltage deviation under constrained conditions.
Case 2B: Minimization of bus voltage deviation under unconstrained conditions.

The robustness of the HGWO algorithm was evaluated under three distinct loading conditions:

i. Base loading condition.
ii. A 5% increase in active and reactive power loads at each bus.
iii. A 10% increase in active and reactive power loads at each bus.

These loading conditions were designed to assess the algorithm's adaptability and effectiveness in diverse operational scenarios.

Case 1A and Case 1B Results: The results of loss minimization under constrained (Case 1A) and unconstrained (Case 1B) conditions are presented in Table 4. It was observed that as system loading increased, the total active power losses also increased. Furthermore, the loss minimization results for unconstrained conditions were lower than those under constrained conditions. This can be attributed to the larger search space available in the unconstrained scenario, enabling better solutions.

Case 2A and Case 2B Results: Table 5 presents the results for bus voltage deviation minimization under constrained (Case 2A) and unconstrained (Case 2B) conditions. The findings reveal that as system loading increases, the bus voltage deviation also increases. However, the deviation values for the unconstrained case were lower than those for the constrained case. This outcome is again due to the wider search space available in unconstrained problems, facilitating improved solutions.

Table 4 Loss minimization with constraints and without constraints

Percentage of load variation	case1A : with constraints (MW)	case1B : without constraints (MW)
5% increase active and reactive load	5.949	5.5114
10% increase active and reactive load	7.1151	6.5292

Table 5 Bus Voltage deviation minimization with constraints and without constraints

Percentage of load variation	case1A : with constraints	case1B : without constraints
5% increase active and reactive load	0.2349	0.2337
10% increase active and reactive load	0.2397	0.2339

The HGWO algorithm demonstrated superior performance across all tested scenarios, including diverse loading conditions and objective functions, proving its robustness and adaptability for optimized reactive power management.

CONCLUSION

The results of this study highlight the effectiveness and superior performance of the HGWO algorithm in optimizing RPM for the IEEE 30-bus system. The HGWO-based approach outperformed the standard GWO method, as demonstrated by the lower transmission line losses and better voltage profiles, even under varying operational conditions. The objective function analysis revealed that HGWO significantly minimized active power losses and improved voltage stability, as reflected in the comparison of control parameters, reactive power dispatch values, and transmission losses between the two methods. Furthermore, the robustness of the HGWO algorithm was validated through various case studies, including both constrained and unconstrained environments. The algorithm proved adaptable and efficient under different loading conditions, showing better performance in loss minimization and bus voltage deviation control, particularly in unconstrained scenarios. This adaptability highlights the algorithm’s potential for real-world applications in reactive power management. The HGWO approach is a promising optimization tool for power system operators seeking to enhance the stability, efficiency, and reliability of modern power grids. Its ability to achieve optimal reactive power dispatch under diverse conditions makes it an effective solution for managing the dynamic nature of power systems and addressing the challenges of modern grid operations.

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