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Comparative Performance Analysis of GWO and SHO Algorithms for Optimal Reactive Power Dispatch on the IEEE 30-Bus System

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Abstract

This study presents a comparative analysis of two metaheuristic algorithm Grey Wolf Optimization (GWO) and Sea Horse Optimization (SHO for solving Optimal Reactive Power Dispatch (ORPD) problem in modern power systems. The ORPD problem aims to minimize active power losses and improve voltage profiles while satisfying operational and security constraints. A wind-integrated IEEE 30-bus test system including 27 control parameters is employed to assess the algorithms under a realistic scenario. While GWO, inspired by the social hierarchy and hunting behavior of grey wolves, was previously applied with successful outcomes, this paper evaluates the performance of the nature-inspired SHO algorithm, which mimics swaying and spatial memory behavior of sea horses. Simulation results show that SHO outperforms GWO in minimizing power losses and improving voltage stability in considered wind-integrated scenario. These findings highlight the effectiveness of SHO as a promising tool for solving complex nonlinear optimization problems in renewable-rich power systems.

Key words: Optimal reactive power dispatch (ORPD), Grey wolf optimization (GWO), Sea horse Optimization (SHO), Wind-integrated power systems

1. Introduction

The planning and operation of modern electrical power systems have become increasingly complex due to the proliferation of distributed generation (DG) sources, rising energy demands, and environmental constraints. In this context, the effective control of both active and reactive power flows is essential to ensure the secure, economical, and stable operation of power systems.

The Optimal Reactive Power Dispatch (ORPD) problem is a critical optimization task that addresses multiple objectives such as minimizing system losses, improving voltage profiles, and complying with operational constraints [1–3]. The ORPD problem involves the coordinated optimization of generator voltage magnitudes, transformer tap settings, shunt compensation devices, and other controllable parameters. Due to its nonlinear structure, which includes both continuous and discrete variables, traditional deterministic methods (e.g., gradient-based algorithms) often fall short, especially in large-scale systems, and may become trapped in local minima [4]. Consequently, recent years have witnessed a growing interest in metaheuristic algorithms. These algorithms are capable of approaching global optima without being strictly dependent on the mathematical structure of the problem, making them suitable for solving complex and multi-constrained problems such as ORPD [5,6].

The Grey Wolf Optimization (GWO) algorithm, inspired by the social hierarchy and hunting

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strategies of grey wolves in the process of exploring and exploiting potential solutions, has become a widely adopted method in power systems due to its structural simplicity and low number of control parameters [7]. GWO's fast convergence capability and balanced search behavior in high-dimensional problems make it an attractive choice for ORPD applications [8]. Studies employing GWO have reported significant reductions in total active power losses and improvements in voltage profiles [9].

In contrast, the Sea Horse Optimization (SHO) algorithm, which is a relatively recent development inspired by the movement and memory behaviors of seahorses, has been evaluated in only a limited number of power system studies to date [10]. A distinctive feature of SHO is its ability to store and utilize previous position data, enabling it to perform effective searches in both local and global regions of the solution space. This capability suggests that SHO holds promising potential in solving complex and high-dimensional optimization problems.

The objective of this study is to perform a comparative analysis of the GWO and SHO algorithms in solving a complex ORPD problem, taking into account the integration of renewable energy systems. To this end, a test scenario based on the IEEE 30-bus system was developed, incorporating a wind power plant and 27 control variables. Both algorithms were applied under the same scenario, and the results were analyzed and compared in terms of system losses and voltage stability. This study also serves as one of the preliminary investigations into the potential contributions of the SHO algorithm to the power systems optimization literature.

2. ORPD Problem Formulation

The Optimal Reactive Power Dispatch (ORPD) problem represents a specific formulation within the broader scope of the Optimal Power Flow (OPF) framework, wherein the objective is to minimize active power losses in transmission networks through the coordinated control of generator voltage magnitudes, transformer tap positions, and the reactive power contribution of switchable shunt capacitors [11]. ORPD plays a critical role in ensuring the secure and economical operation of power systems. Maintaining bus voltages within acceptable limits is essential for preserving power system quality and security [12]. Adjusting system variables between their upper and lower limits to minimize transmission losses can also impact overall generation costs.

2.1. Objective Functions

Objective function(*F1*)

$$P_L = \sum P_i = \sum P_{gi} - \sum P_{di} \quad , i = 1.,N_b \tag{1}$$

In this formulation, Nb denotes the total number of buses within the power system. Pgi represents the active power generated at bus i, while Pdi corresponds to the active power demand at the same bus. PL indicates the total active power losses in the system, and Pi refers to the net active power injection at bus i [13].

Objective function(*F2*)

$$V_D = \sum |V_i - V_i^{ref}| \quad , i = 1,.,N_{PQ} \tag{2}$$

The total voltage deviation of all load buses, denoted as VD, quantifies the cumulative deviation of bus voltage magnitudes from their nominal reference values. Here, $Viref$ represents the reference voltage magnitude at bus i, typically assumed to be 1.0 per unit, while Vi denotes the actual voltage magnitude at the ith load bus. The number of PQ or load buses in the system is indicated by the parameter NPQ. At each load bus in the power system, this equation measures the discrepancy between the desired and actual voltage magnitudes [13].

Fitness function is

$$\text{Min. F} = P_L + K_V \sum_{i=1}^{N_{PQ}} \left(V_i - V_i^{lim}\right)^2 + K_q \sum_{i=1}^{N_g} (Q_{gi} - Q_{gi}^{lim})^2 + K_f \sum_{l=1}^{N_l} (S_l - S_{li}^{lim})^2 \quad (3)$$

The penalty variables in this case are Kf, Kv and Kq which stand for line flow violation, bus voltage limit violation, and generator reactive power infringement, respectively. In this context, Ng denotes the total number of generator units, while Nl refers to the number of transmission lines in the system. Sl represents the loading level of the l^{th} transmission line, and Vi indicates the voltage magnitude at bus i. N_{PQ} corresponds to the number of PQ-type load buses, and Q_{gi} signifies the reactive power output of the generator connected to bus i [13].

2.2. Constrains of Power System's

The Optimal Reactive Power Dispatch problem seeks to optimize specific objective functions while ensuring the secure and stable operation of power systems by considering various constraints. These constraints represent the physical and operational limits of the system and are typically categorized into two main types: equality constraints and inequality constraints. Below, the fundamental constraints considered in the ORPD problem are elaborated upon.

a)- Voltage Magnitude Constraints:

$$V_{i-min} \leq V_i \leq V_{i-max} \quad (4)$$

In this formulation, V_i^{min} and V_i^{max} represent the lower and upper bounds, respectively, of the voltage magnitude Vi at bus i.

b)- Active Power Generation Constraints:

$$P_{gi-min} \leq P_{gi} \leq P_{gi-max} \quad (5)$$

The active power output of the i^{th} generator is denoted by P_{gi}, while P_{gi}^{max} P and P_{gi}^{min} represent its upper and lower operational limits, respectively [13]

c)- Constrains of Reactive Power Generation:

$$Q_{gi-min} \leq Q_{gi} \leq Q_{gi-max} \quad (6)$$

The reactive power of the ith generator is shown by Qgi. The ith generator's highest reactive power is Qgi-max, and its minimum reactive power is Qgi-min [13].

d)- Reactive Power Source Capacity Constraints:

$$q_{ci-min} \leq q_{ci} \leq q_{ci-max}, \; i \in N_c, \; q_{ci} = q_{ci-min} + N_{ci}\,\Delta q_{ci} \quad (7)$$

q_{ci} denotes the reactive power of the i^{th} shunt compensator, N_C is the total number of such devices, and q_{ci}^{min} and q_{ci}^{max} define its operational limits [13].

e)- Transformer Tap Position Constraints:

$$T_{i-min} \leq T_i \leq T_{i-max}, \; i \in N_T, \; T_i = T_{i-min} + N_{Ti}\Delta T_i \quad (8)$$

T_i is the transformer tap ratio, N_T is the number of tap setting transformers, T_{i-min} and T_{i-max} are the minimum and maximum limits of the transformer tap ratio [13].

3. Implementation of GWO-SHO Algorithm for Solving the ORPD Problem with Wind Placement

In the context of applying the Grey Wolf Optimization algorithm to solve the Optimal Reactive Power Dispatch problem with wind integration, suitable buses within the IEEE 30-Bus power system were identified for wind turbine placement. The performance outcomes of the GWO and Sea Horse Optimization techniques were then compared, adhering to the constraints inherent to the ORPD problem.

3.1. GWO-Based Control Strategy for Wind-Integrated IEEE 30-Bus System with 27 Parameters

The IEEE 30-bus power system was expanded in this work to include 27 control variables, making wind power integration easier. These factors include power control and generator voltage magnitude control. The following are the particular control variables taken into account [13].

- 7 variables affecting generator bus voltages with wind buses
- 7 wind power generation variables
- 4 transformer TAP setting variables.
- 9 factors pertaining to the VAR compensators' reactive power

Table 1 provides the upper and lower bounds for various control variables, including wind power output, generated power, voltage levels, transformer tap settings, and reactive power compensation devices. These specified limits establish the permissible operating ranges for each variable during the optimization process, ensuring that the solutions adhere to system constraints and contribute to enhanced overall performance.

Table 1. Limit Settings for control variables for IEEE 30-bus system [13]

Variables	***Upper Limit***	***Lower Limit***
Wind Power	0.10 p.u.	0.00 p.u.
Generated Power	2.00 p.u.	0.05 p.u.
Voltages	1.10 p.u.	1.00 p.u.
Tap Settings	1.10 p.u.	0.90 p.u.
Compensation Devices	5 MVAR	0 MVAR

Table 2 provides a detailed evaluation of the Grey Wolf Optimization (GWO) algorithm's effectiveness in the IEEE 30-bus test system, emphasizing performance indicators such as voltage deviation and total active power loss. The table outlines the lower and upper bounds defined for each control parameter, including generator outputs, voltage magnitudes, transformer tap positions, and reactive power compensation units. Additionally, it presents the optimal values obtained through the GWO algorithm within these constraints, demonstrating its capability to enhance system performance while maintaining compliance with operational limits [13].

Table 2. GWO-Based Optimization of Control Variables for ORPD in the IEEE 30-Bus System with Wind Integration [13]

Control Variables	**Limits**		***IEEE-30 Bus Test Case with GWO***
	Upper Limits	**Lower Limits**	
P_{wind}	0.10	0.00	0.0982
P_1	1.00	0.50	0.2351
P_2	0.80	0.20	0.4848
P_5	0.50	0.15	0.4700
P_8	0.50	0.10	0.4688
P_{11}	0.50	0.10	0.4693
P_{13}	0.50	0.12	0.4617
V_{wind}	1.10	1.00	1.0604
V_1	1.10	1.00	1.0531
V_2	1.10	1.00	1.0436
V_5	1.10	1.00	1.0500
V_8	1.10	1.00	1.0977
V_{11}	1.10	1.00	1.0473
V_{13}	1.10	1.00	0.9781
T_{11}	1.10	0.90	0.9500
T_{12}	1.10	0.90	1.0500
T_{15}	1.10	0.90	1.0343
T_{36}	1.10	0.90	0.9884
Q_{C10}	5.00	0.00	4.9322
Q_{C12}	5.00	0.00	4.3456

Q_{C15}	5.00	0.00	0.7096
Q_{C17}	5.00	0.00	2.2971
Q_{C20}	5.00	0.00	1.6113
Q_{C21}	5.00	0.00	3.0152
Q_{C23}	5.00	0.00	0.3921
Q_{C24}	5.00	0.00	2.2213
Q_{C29}	5.00	0.00	0.4657
Totally Loss (MW)			***1.8010***
Voltage-Deviation(p.u)			***1.0154***

Incorporating P_{wind} and V_{wind} within the set of control variables, the GWO algorithm operated efficiently within the given bounds. The inclusion of wind power (0-10 MW) and wind bus voltage control parameters in the GWO (proposed) algorithm to optimise the system with 25 control variables without the addition of the IEEE 30-bus wind farm without changing the generator power ratings resulted in 9.8 MW wind power control and 1.0604 p.u. wind bus voltage among the 27 optimised control variables. This proved that GWO successfully integrated the wind unit and control parameters, producing positive outcomes in the IEEE 30 test system scenario. The control variables of the IEEE 30-bus test system were successfully optimized, resulting in a voltage deviation of 1.0154 p.u. and a total active power loss of 1.8010 MW. As depicted in Figure 1 [13], the proposed GWO algorithm demonstrates effective convergence behavior under Scenario 3, utilizing different population sizes (20, 30, and 40 agents) in the power loss minimization process.

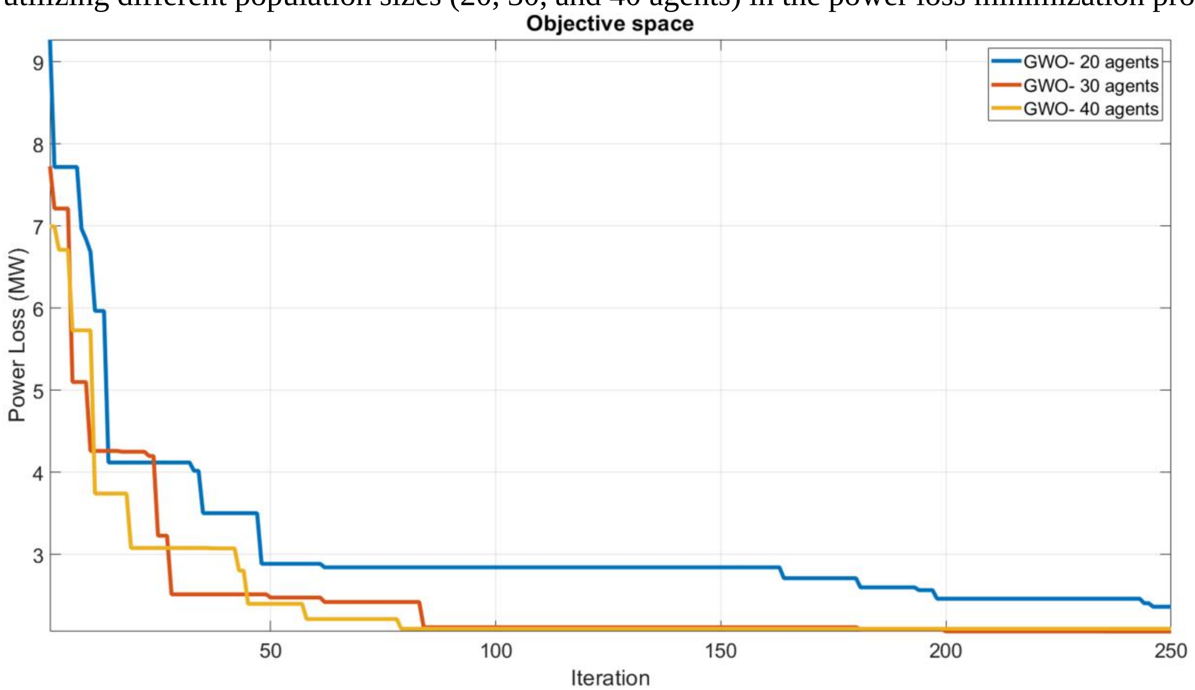

Figure 1. Convergence patterns for 27 variables IEEE 30-bus test system using GWO

Similarly, the IEEE 30-bus power system with 40 agents demonstrated exceptional performance, according to the voltage deviation convergence study of the GWO (proposed) algorithm. in achieving convergence for the system with 27 control variables and wind turbine integration, as shown in Figure 2[13].

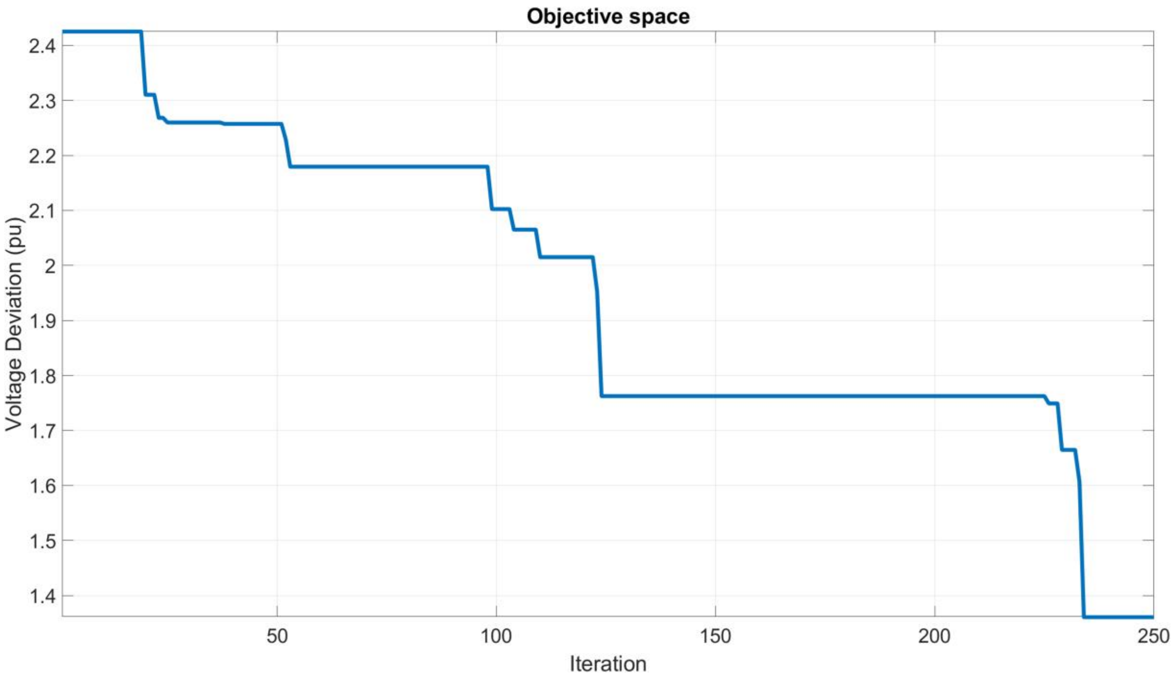

Figure 2. Voltage deviation convergence models for IEEE 30-bus system using 27 control variables

In the IEEE 30-bus transmission system, buses other than 1, 2, 5, 8, 11, and 13 were connected to wind energy as a renewable energy source. Values of power loss were noted for every bus. Figure 3 illustrates that, with a power loss of 1.801 MW, the wind connected to bus 21 results in the least amount of power loss [13].

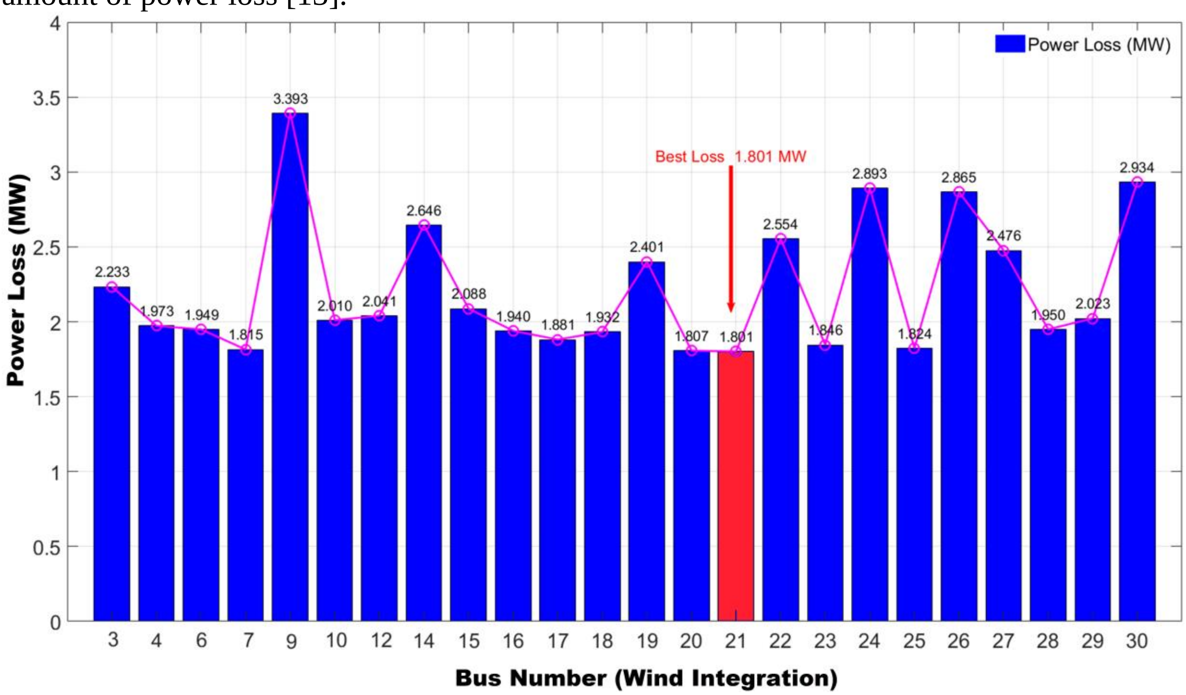

Figure 3. Power loss convergence patterns for IEEE 30-bus system with 27 control variables using GWO [13]

3.2. IEEE 30-bus Power System with 27 Control Variables Wind İntegration using SHO

In this study, the IEEE 30-bus system was utilized to evaluate the effectiveness of the Sea Horse Optimization (SHO) algorithm in addressing the Optimal Reactive Power Dispatch (ORPD) problem. For comparative purposes, it is noted that the IEEE 30-bus system comprises 5 PV buses, 21 load buses, 41 branches, 4 transformer tap changers, and 3 shunt capacitors. In contrast, the IEEE 118-bus system includes 54 PV buses, 99 loads, 186 branches, 9 tap changers, and 14 shunt VAR compensators. The detailed system parameters are provided in Table 1 [13]. Table 3 offers a comprehensive performance evaluation of the SHO algorithm applied to the IEEE 30-bus test system, with particular emphasis on voltage deviation and total active power loss. The table also outlines the predefined lower and upper operational limits for each control variable, including generator outputs, bus voltages, transformer tap positions, and shunt reactive power devices. It also details the optimized values obtained by the SHO algorithm within these specified constraints, and highlights its effectiveness in improving system performance while adhering to operational limits.

Table 3. Application of SHO to ORPD Control Variables in the IEEE 30-Bus Test System with Wind Integration

Control Variables	Limits		*SHO (caseIEEE-30)*
	Upper	Lower	
P_{wind}	**0.10**	**0.00**	**0.0953**
P_1	1.00	0.50	0.1625
P_2	0.80	0.20	0.4989
P_5	0.50	0.15	0.4697
P_8	0.50	0.10	0.4511
P_{11}	0.50	0.10	0.4700
P_{13}	0.50	0.12	0.4700
V_{wind}	**1.10**	**1.00**	**1.0038**
V_1	1.10	1.00	1.0531
V_2	1.10	1.00	1.0859
V_5	1.10	1.00	1.0500
V_8	1.10	1.00	1.0947
V_{11}	1.10	1.00	1.0571
V_{13}	1.10	1.00	0.9781
T_{11}	1.10	0.90	1.0473
T_{12}	1.10	0.90	0.9685
T_{15}	1.10	0.90	1.0392
T_{36}	1.10	0.90	1.0312
Q_{C10}	5.00	0.00	4.0804
Q_{C12}	5.00	0.00	0.9272
Q_{C15}	5.00	0.00	3.2867
Q_{C17}	5.00	0.00	1.1192
Q_{C20}	5.00	0.00	3.3433
Q_{C21}	5.00	0.00	1.0827
Q_{C23}	5.00	0.00	2.6595
Q_{C24}	5.00	0.00	3.4334
Q_{C29}	5.00	0.00	0.2785
Total Loss (MW)			***1.7708***
Voltage Deviation (pu)			***1.0174***

As seen in Table 3, the effect of the SHO algorithm on the ORPD problem has been investigated and the voltage deviation and total loss values have been written. In the system analysis with 27 control variables, a 0-10 MW wind turbine has been integrated into the IEEE 30-bus power system.

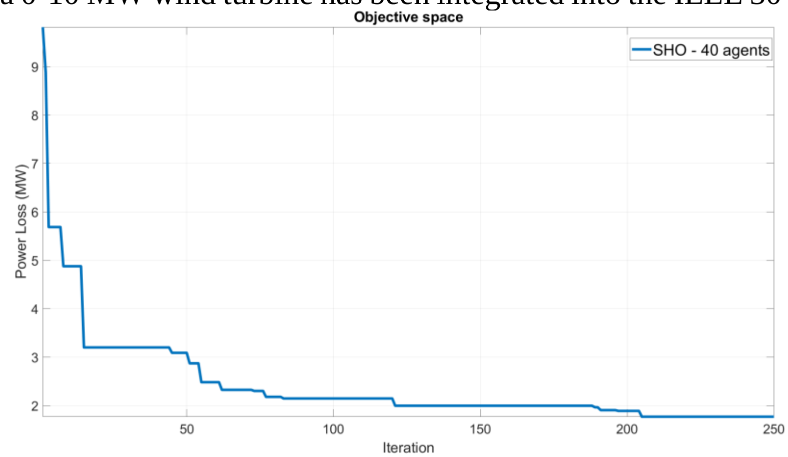

Figure 4. Power Loss Convergence Characteristics Using SHO in the IEEE 30-Bus Test System with 27 Control Variable

As illustrated in Figure 4, the power loss convergence analysis for the wind-integrated IEEE 30-bus system with 27 control variables highlights the effectiveness of the proposed SHO algorithm when applied with a population size of 40 agents.

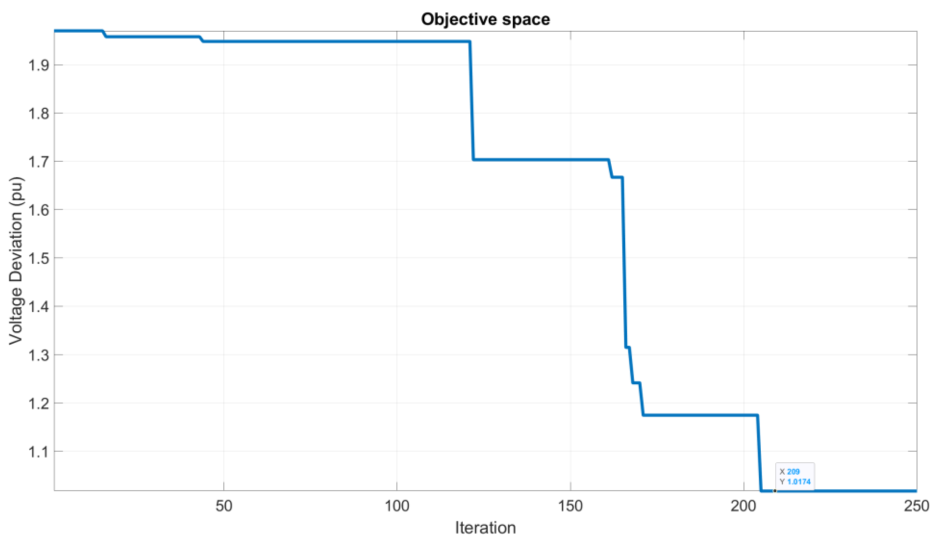

Figure 5. Voltage deviation convergence profiles for IEEE 30-bus system with 27 control variables using SHO

The voltage deviation convergence analysis for wind integrates 27 control variables of the IEEE 30-bus power system demonstrates the robust convergence capability of the proposed SHO algorithm when utilizing a population of 40 agents, as illustrated in Figure 5.

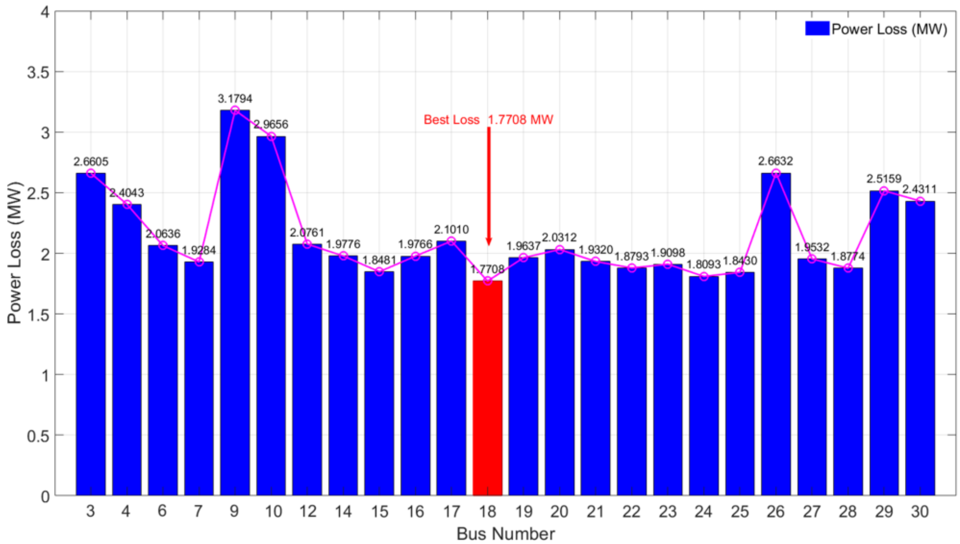

Figure 6. Power loss convergence patterns for IEEE 30-bus system with 27 control variables using SHO

Wind-powered distributed generation units (DGUs) were deployed across multiple buses in the IEEE 30-bus transmission system, excluding buses 1, 2, 5, 8, 11, and 13 from integration. A comprehensive analysis of power loss values was conducted for each bus within the system. The findings revealed that the DGU incorporated to bus 18 achieved the lowest power loss, measuring 1.7708 MW [13].

4. Discussion

In this study, the performance of the Grey Wolf Optimization (GWO) and Sea Horse Optimization (SHO) algorithms was comparatively evaluated within the scope of an Optimal Reactive Power Dispatch (ORPD) scenario involving 27 control variables and wind power integration. Both algorithms were tested on the IEEE 30-bus system, with a focus on key performance indicators such as active power loss, voltage deviation, and the identification of optimal generation locations. In the GWO-based implementation, the integration of a wind turbine at Bus 21 resulted in the lowest recorded power loss of 1.801 MW. Conversely, the highest power loss of 3.393 MW occurred when the wind unit was placed at Bus 9. This corresponds to an approximate difference of 88.34%, clearly demonstrating the impact of wind unit placement on system performance. Additionally, the GWO algorithm not only achieved a reduction in power losses but also improved the voltage profile.

These outcomes highlight the algorithm's effective global search capability and its ability to manage system constraints efficiently. In comparison, the SHO algorithm yielded a minimum power loss of 1.7708 MW when the distributed generation unit (DGU) was placed at Bus 18. The maximum power loss, again observed at Bus 9, was 3.1794 MW. The corresponding difference of approximately 79.55% indicates the SHO algorithm's high precision in optimal placement and reactive power control.

The Sea Horse Optimizer (SHO) exhibited notable performance in integrating variable renewable energy sources particularly wind power due to its memory-guided search capability and adaptive exploitation-exploration balance. Overall, although both algorithms effectively addressed the

ORPD problem, SHO yielded more favorable outcomes by attaining lower active power losses and enhanced voltage stability across the network. The nature-inspired, intelligent structure of the SHO algorithm contributes to a more efficient generation-load balance across the network. These findings emphasize the importance of utilizing advanced metaheuristic algorithms like SHO for the effective integration of renewable energy into modern power systems.

References:

Reference to a journal publication:

[1] Lopes, J. P., Hatziargyriou, N., Mutale, J., Djapic, P., & Jenkins, N. (2007). Integrating distributed generation into electric power systems: A review of drivers, challenges and opportunities. Electric power systems research, 77(9), 1189-1203.

[2] Viral, R., & Khatod, D. K. (2012). Optimal planning of distributed generation systems in distribution system: A review. Renewable and sustainable energy Reviews, 16(7), 5146-5165.

[3] Das, P., Dawn, S., Gope, S., Das, D., & Salata, F. (2024). Optimal Reactive Power Dispatch and Demand Response in Electricity Market Using Multi-Objective Grasshopper Optimization Algorithm. Processes, 12(9), 2049.

[4] Carpentier, J. (1979). Optimal power flows. International Journal of Electrical Power & Energy Systems, 1(1), 3-15.

[5] Abido, M. A. (2002). Optimal power flow using particle swarm optimization. International Journal of Electrical Power & Energy Systems, 24(7), 563-571.

[6] Tomar, V., Bansal, M., & Singh, P. (2024). Metaheuristic algorithms for optimization: A brief review. Engineering Proceedings, 59(1), 238.

[7] Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey wolf optimizer. Advances in engineering software, 69, 46-61.

[8] Sarhan, S., Shaheen, A., El-Sehiemy, R., & Gafar, M. (2023). An augmented social network search algorithm for optimal reactive power dispatch problem. Mathematics, 11(5), 1236.

[9] Zhang, J., Wang, X., & Ma, L. (2019). An optimal power allocation scheme of microgrid using grey wolf optimizer. IEEE Access, 7, 137608-137619.

[10] Zhao, S., Zhang, T., Ma, S., & Wang, M. (2023). Sea-horse optimizer: a novel nature-inspired meta-heuristic for global optimization problems. Applied Intelligence, 53(10), 11833-11860.

[11] Khanmiri, D. T., Nasiri, N., & Abedinzadeh, T. (2012). Optimal reactive power dispatch using an improved genetic algorithm. International Journal of Computer and Electrical Engineering, 4(4), 463.

[12] El-Samahy, I., Canizares, C. A., Bhattacharya, K., & Pan, J. (2007, June). An optimal reactive power dispatch model for deregulated electricity markets. In 2007 IEEE Power Engineering Society General Meeting (pp. 1-7). IEEE.

[13] Varan, M., Erduman, A., & Menevşeoğlu, F. (2023). A grey wolf optimization algorithm-based optimal reactive power dispatch with wind-integrated power systems. Energies, 16(13), 5021.