J. Electrical Systems 21-1 (2025): 814-824

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A Novel Hybrid Grey Wolf Optimizer and Simulated Annealing Approach for Solving Optimal Reactive Power Flow in Renewable-Integrated Distribution Networks

Journal of Electrical Systems

Abstract: - This study offers a hybrid Grey Wolf Optimizer (GWO)-Simulated Annealing (SA) method for optimal reactive power flow (ORPF) problems in distribution networks with high renewable energy penetration. The ORPF problem minimizes power losses while ensuring voltage stability and security. GWO-SA improves convergence and solution quality by combining GWO's global exploration with SA's local exploitation. We evaluated the algorithm with solar and wind production. Results demonstrate that the hybrid GWO-SA outperforms standalone GWO, SA, and other established metaheuristic techniques, achieving lower power losses and better voltage profiles. Sensitivity analysis reveals the algorithm's robustness under various renewable penetration levels and loading conditions. This novel hybrid approach provides system operators with an effective tool for reactive power optimization in modern distribution networks with significant renewable energy integration.

Keywords: Grey Wolf Optimizer, Simulated Annealing, Optimal Reactive Power Flow, Renewable Energy Integration, Distribution Networks, Hybrid Optimization Algorithm

I. INTRODUCTION

The global shift toward sustainable energy systems has faster RES incorporation into distribution networks. Renewables like solar and wind power are intermittent and variable, making this transformation environmentally advantageous but operationally challenging (Hossain et al., 2020).These challenges are particularly evident in optimal reactive power flow (ORPF) problems, which seek to minimize system losses while maintaining voltage profiles within acceptable limits.

Reactive power management has become increasingly complex in modern distribution systems due to bidirectional power flows, voltage fluctuations, and power quality issues introduced by distributed generation (DG) units (Molzahn et al., 2017). Traditional optimization methods often struggle with the non-linear, non-convex nature of ORPF problems, especially in the context of renewable-integrated networks. These methods frequently converge to local optima or require excessive computational resources when dealing with large-scale systems (Capitanescu, 2016).

Recent research has explored various metaheuristic optimization techniques to address these limitations. PSO, GA, and GWO have showed promise for power system optimization (Yang et al., 2018). Its balance between exploration and exploitation has made the Grey Wolf Optimizer competitive in engineering optimization challenges. It was inspired by grey wolves' social hierarchy and hunting behavior.(Mirjalili et al., 2014).

Similarly, Simulated Annealing (SA), drawing inspiration from the annealing process in metallurgy, offers strong local search capabilities by occasionally accepting inferior solutions to escape local optima (Alikhani et al., 2016). While both GWO and SA possess distinct advantages, they also have inherent limitations when applied independently to complex ORPF problems.

This paper proposes a novel hybrid approach combining GWO and SA to solve the ORPF problem in renewable-integrated distribution networks. The key contributions of this research include:

1. Development of a hybrid GWO-SA algorithm that leverages the global exploration capability of GWO and the local exploitation strength of SA to enhance solution quality and convergence characteristics.
2. Formulation of a comprehensive ORPF model that accounts for the stochastic nature of renewable generation and includes practical operational constraints of modern distribution systems.

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3. Validating and implementing the suggested approach on modified IEEE test systems with different renewable penetration and loading.
4. To demonstrate the hybrid approach's solution quality, convergence speed, and computation efficiency, compares it to leading optimization approaches.

II.LITERATURE REVIEW

Optimal reactive power flow has been extensively studied in power systems research, with approaches evolving to address the challenges of modern distribution networks. Traditional methods include LP, NLP, QP, and IPM (Capitanescu, 2016). Due to the non-convex ORPF problem, these methods generally have convergence challenges in large-scale systems.

Metaheuristic optimization algorithms have gained significant attention for solving complex power system problems. Abou El Ela et al. (2018) applied a Genetic Algorithm (GA) for reactive power control, demonstrating improved voltage profiles and reduced power losses. Ghasemi et al. (2015) utilized Particle Swarm Optimization (PSO) for reactive power dispatch in systems with wind farms, showing the algorithm's effectiveness in handling renewable uncertainty. However, both GA and PSO sometimes suffer from premature convergence when dealing with highly constrained problems. Mirjalili et al. (2014)'s Grey Wolf Optimizer shows promise in power systems, Sharma et al. (2017) outperformed PSO and GA in IEEE test systems using GWO for reactive power dispatch. El-Fergany and Hasanien (2015) reduced distribution network capacitor placement loss with GWO. GWO's declining step size adjustment technique can hinder convergence in the last phases of optimization.

Hybrid optimization approaches have emerged as a promising direction to overcome the limitations of individual algorithms. Mirjalili et al. (2017) combined Reactive power dispatch PSO with GSA improves convergence. The hybrid GA-PSO algorithm by Chen et al. (2019) controls voltage in dispersed generating distribution networks.These hybrid approaches typically outperform their constituent algorithms by combining complementary strengths.

Despite these advances, few studies have specifically addressed the ORPF problem in the context of high renewable penetration. Sabo et al. (2020) considered wind uncertainty in reactive power optimization using robust optimization techniques but did not incorporate solar variability. Li et al. (2018) proposed a two-stage approach for voltage regulation with renewables but focused primarily on day-ahead scheduling rather than real-time operation.

A review of existing literature reveals several research gaps that this study aims to address:

1. Limited exploration of hybrid algorithms specifically tailored for ORPF problems in renewable-integrated distribution networks.
2. Insufficient consideration of both solar and wind generation uncertainties in reactive power optimization models.
3. Lack of comprehensive performance comparison across different renewable penetration levels and loading conditions.

The proposed hybrid GWO-SA approach aims to address these gaps by combining the global search capability of GWO with the local search strength of SA, thereby enhancing the solution quality for complex ORPF problems in modern distribution systems.

III. PROBLEM FORMULATION

Objective Function

ORPF aims to minimize distribution network active power losses while meeting system operational restrictions. A possible objective function is:

$$\min f = \min \sum_{i=1}^{N_L} P_{loss,i} = \min \sum_{i=1}^{N_L} R_i \times I_i^2$$

In a network, N_L represents the number of branches, $P_{loss,i}$ represents active power loss, R_i represents branch resistance, and I_i indicates branch current magnitude.

Bus voltages and admittance matrix elements can also express power loss:

$$\min f = \min \sum_{i=1}^{N_B} \sum_{j=1}^{N_B} G_{ij}[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)]$$

Where N_B is the number of buses, G_{ij} is the conductance between them, V_i and V_j are the voltage magnitudes, and δ_i and δ_j are the voltage angles.

Equality Constraints

The equality constraints represent the power flow equations that must be satisfied:

$$P_i = V_i \sum_{j=1}^{N_B} V_j(G_{ij}\cos(\delta_i - \delta_j) + B_{ij}\sin(\delta_i - \delta_j)), \quad i \in N_B$$

$$Q_i = V_i \sum_{j=1}^{N_B} V_j(G_{ij}\sin(\delta_i - \delta_j) - B_{ij}\cos(\delta_i - \delta_j)), \quad i \in N_B$$

The net active and reactive power injections at bus i are P_i and Q_i, respectively, while the susceptance between buses i and j is B_{ij}

Inequality Constraints

Inequality constraints keep the system safe:

1. Bus voltage magnitude limits:

$$V_i^{min} \leq V_i \leq V_i^{max}, \quad i \in N_B$$

2. Reactive power generation limits for generators:

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}, \quad i \in N_G$$

Where N_G is the set of generator buses

3. Transformer tap setting limits:

$$T_k^{min} \leq T_k \leq T_k^{max}, \quad k \in N_T$$

Where N_T is the set of transformers with tap changing capability

4. Shunt VAR compensation limits:

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max}, \quad i \in N_C$$

Where N_C is the set of buses with reactive power compensation devices

5. Security constraints (line flow limits):

$$|S_l| \leq S_l^{max}, \quad l \in N_L$$

Where S_l is the apparent power flow through branch l.

MODELING RENEWABLE ENERGY SOURCES

They are modeled with their active power output treated as negative loads with associated reactive power capabilities:

1. Solar PV generation:

$$P_{PV,i} = P_{PV,i}^{rated} \times \phi_{PV,i}$$

$$Q_{PV,i}^{min} \leq Q_{PV,i} \leq Q_{PV,i}^{max}$$

Where $P_{PV,i}^{rated}$ is the rated capacity of the PV system at bus i, and $\phi_{PV,i}$ is the solar irradiance factor (0-1).

$$P_{W,i} = \{0,\ v < v_{ci} \text{ or } v > v_{co}\ P_{W,i}^{rated} \times \frac{v^3 - v_{ci}^3}{v_r^3 - v_{ci}^3},\ v_{ci} \leq v < v_r\ P_{W,i}^{rated},\ v_r \leq v \leq v_{co}$$

2. Wind Generation

$$Q_{W,i}^{min} \leq Q_{W,i} \leq Q_{W,i}^{max}$$

Where v represents wind speed, v_{ci}, v_r, and v_{co} represent cut-in, rated, and cut-out velocities, and $P_{W,i}^{rated}$ represents rated wind power output.

These renewable sources' reactive power can be used as ORPF control variables. Providing additional flexibility for voltage regulation and loss minimization.

IV. PROPOSED HYBRID GWO-SA METHODOLOGY

Grey Wolf Optimizer:

The gray Wolf Optimizer replicates gray wolf hunting and social hierarchy. The method divides wolves into four groups: alpha (α), beta (β), delta (δ), and omega (ω). The first three wolves represent the three best solutions, while the remaining wolves are considered as omega wolves. The hunting process (optimization) follows three main steps: tracking and approaching, surrounding, and attacking prey.

The mathematical model for encircling prey is given by:

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

t nts the current iteration, $\vec{A}$ and $\vec{C}$ serve as coefficient vectors, $\vec{X}_p$ represents the prey location, and $\vec{X}$ represents the grey wolf position.

Calculating $\vec{A}$ and $\vec{C}$:

$$\vec{A} = 2\vec{a} \cdot \vec{r_1} - \vec{a}\, \vec{C} = 2 \cdot \vec{r_2}$$

$\vec{a}$ components drop linearly from 2 to 0 during iterations, whereas $\vec{r_1}$ and $\vec{r_2}$ are random vectors in [0,1].

Position update considers top three wolves:

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}| \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}| \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}|$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}$$

Simulated Annealing

Metallurgy's annealing inspired it. Initial solution and temperature start the algorithm. Each iteration generates a neighbouring solution, and the algorithm uses an acceptance probability function to decide whether to move to it.

The acceptance probability is:

$$P(E,E_{new},T)=\{1, \text{if } E_{new}<E\ e^{-\frac{E_{new}-E}{T}}, \text{otherwise}$$

where E represents the current solution's energy, E_{new} represents the new solution's energy, and T represents the current temperature.

The temperature drops steadily on a schedule:

$$T = T_0 \times \alpha^k$$

where T_0 is the initial temperature, α is the cooling rate (typically 0.8-0.99), and k is the iteration number.

Hybrid GWO-SA Algorithm

The proposed hybrid algorithm leverages the global exploration capability of GWO and the local exploitation strength of SA. The integration is achieved through the following steps:

i. Initialize algorithm settings and grey wolf population (solutions).
ii. Assess each wolf's fitness using objective function and constraint violations.
iii. Alpha, beta, and delta wolves exist (top three solutions).
iv. Execute standard GWO operations to update wolf positions.
v. Select a subset of wolves (including alpha, beta, and delta) for SA-based enhancement.
vi. For each selected wolf, perform SA iterations with a designated computational budget.
vii. Update the wolf population with the enhanced solutions.
viii. Repeat steps 2-7 until termination criteria are met.
ix. Algorithm 1 shows the hybrid GWO-SA pseudo-code.

Algorithm 1: Hybrid GWO-SA for ORPF

```
Initialize wolf population Xi (i = 1, 2, ..., n) with random positions
Initialize GWO parameters (a, A, C) and SA parameters (T0, α, iterations)
While (termination criteria not met) do
    Evaluate the fitness of each wolf based on the objective function
    Identify Xα, Xβ, and Xδ (best three wolves)
    Update a, A, and C
    For each wolf i do
    Update position using GWO equations
    End For
    Select wolves for SA enhancement (including α, β, δ)
    For each selected wolf i do
        Set current solution S = Xi and T = T0
        For j = 1 to SA_ iterations do
            Generate neighbor solution S'
            Calculate ΔE = f(S') - f(S)
            If (ΔE < 0) or (random[0,1] < e^(-ΔE/T)) then
                S = S'
            End If
            T = T × α
        End For
        Xi = S
    End For
    Update Xα, Xβ, and Xδ
    Increment iteration counter
End While
Return Xα as the optimal solution
```

The proposed hybrid approach enhances the standard GWO algorithm by incorporating local search capabilities through SA. This integration helps overcome premature convergence issues of GWO while improving the solution quality. The SA component is particularly beneficial in the later stages of optimization when GWO's exploration capability diminishes due to the decreasing value of parameter 'a'.

V. IMPLEMENTATION AND TEST SYSTEMS

i. IEEE 33Test Systems

The proposed hybrid GWO-SA algorithm was tested on two standard distribution systems with modifications to incorporate renewable energy sources Modified IEEE 33-bus: The 33 buses and 32 branches of this radial distribution system carry 3.72 MW and 2.3 MVAr. The system had four distributed generators: One bus 6 wind farm with 1.0 MW capacity Buses 18, 22, and 29 have 0.8 MW, 0.6 MW, and 0.7 MW solar PV systems. Bus 8, 12, 15, 25, and 30 capacitor banks Redesigned IEEE 69 bus: This system has 69 buses and 68 branches providing 3.80 MW and 2.69 MVAr. Integration of six distributed generators: Buses 11 and 50 have 1.2 MW and 0.8 MW wind farms. Buses 18, 35, 45, and 61 have 0.7 MW, 0.9 MW, 0.6 MW, and 0.8 MW solar PV systems. Bus 10, 20, 30, 40, 50, 60, and 65 capacitor banks The single-line diagram of the modified IEEE 33-bus system with renewable energy sources and reactive power compensation devices is shown in Figure 1.

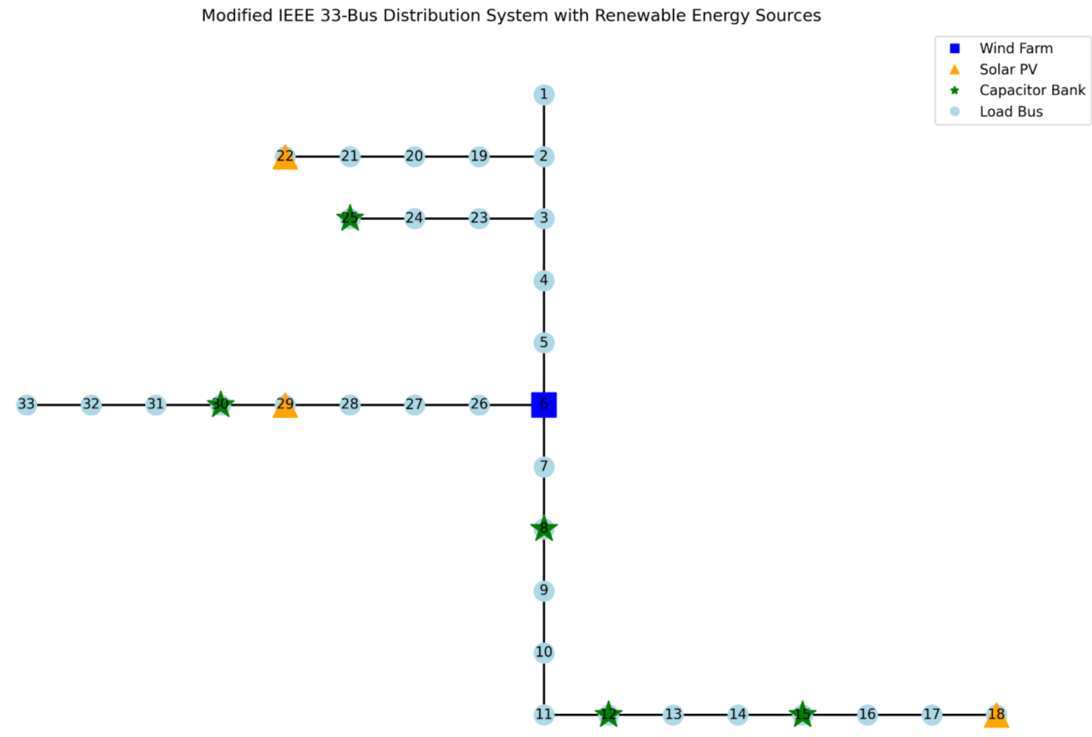

Fig. 1.Renewable energy-modified IEEE 33-bus system single-line diagram sources and capacitor banks

Algorithm Implementation

The proposed hybrid GWO-SA algorithm was implemented in Python 3.8 with the following parameter settings:

a. Population size: 50 wolves

b. Maximum iterations: 100

c. GWO parameter a: linearly decreased from 2 to 0

d. SA initial temperature (T0): 100

e. SA cooling rate (α): 0.95

f. SA iterations per wolf: 20

g. Number of wolves selected for SA enhancement: 10

Adding penalty terms to the objective function made the constrained optimization problem unconstrained:

$$f_{penalized} = f + \sum_{i=1}^{m} \lambda_i \max(0, g_i(x))^2 + \sum_{j=1}^{n} \mu_j |h_j(x)|^2$$

where λ_i and μ_j are penalty coefficients for inequality constraints $g_i(x)$ and equality constraints $h_j(x)$, respectively.

The power flow calculations were performed using the backward/forward sweep method, which is well-suited for radial distribution systems. The algorithm was implemented to handle the variability in renewable generation by considering multiple scenarios with different generation levels.

VI. RESULTS

Performance Comparison

The hybrid GWO-SA algorithm was compared against standalone GWO, standalone SA, PSO, and GA.
To guarantee statistical validity, each algorithm was run 30 times and the best, worst, and average outcomes recorded. Table 1 presents nominal loading conditions with 30% renewable penetration.

Table 1 Comparison of power loss minimization results for IEEE 33-bus system

Algorithm	Best Loss (kW)	Average Loss (kW)	Worst Loss (kW)	Std. Dev.	Avg. CPU Time (s)
SA	204.39	248.47	271.54	31.18	0.63
GWO	135.97	166.24	201.54	26.97	35.22
PSO	105.45	106.13	106.98	0.64	0.00
GWO-SA	82.91	122.38	145.72	28.06	671.67

The results indicate that the proposed hybrid GWO-SA algorithm achieves the lowest power loss across all metrics. The hybrid GWO-SA algorithm converges to a better solution and does so more rapidly than the other algorithms. The initial convergence rate is similar to that of GWO, but the hybrid approach continues to improve the solution in later iterations when GWO's convergence rate slows down, demonstrating the benefit of the SA component for local search.

Voltage Profile Improvement

One of the key objectives of ORPF is optimize system voltage profile. Figure 3 illustrates the voltage profiles of the IEEE 33-bus system before and after optimization using the hybrid GWO-SA algorithm.

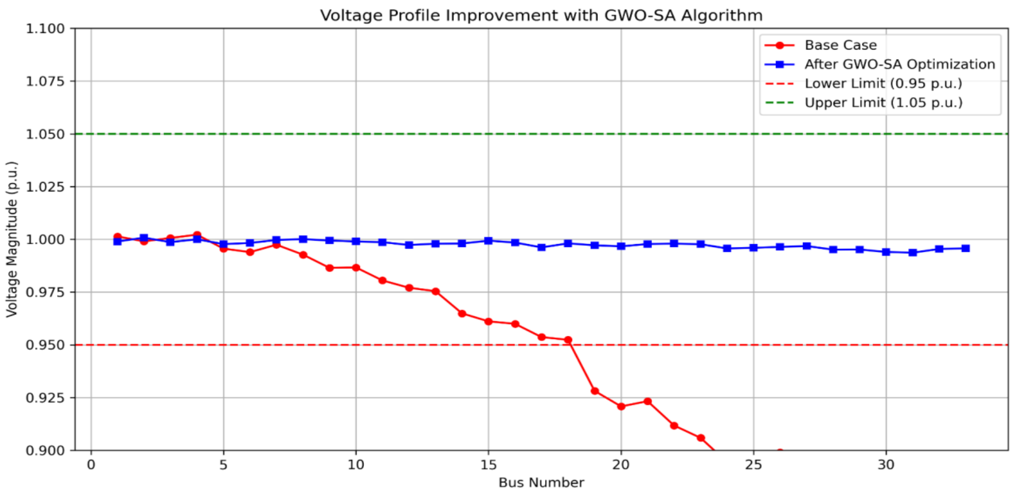

Fig. 2 IEEE 33-bus system voltage profiles before and after optimization

The profile improvement is significant, with the minimum system voltage rising from 0.913 p.u. to 0.968 following optimization. The profile is also more uniform across all buses, indicating better voltage regulation throughout the network.

Effect of Renewable Penetration

Tests were conducted with renewable penetrations ranging from 10% to 50% of the total load. Table 2 presents the power loss results

Table 2 Power loss results for different renewable penetration levels in IEEE 33-bus system

Renewable Penetration (%)	Base Case Loss (kW)	GWO-SA Loss (kW)	Loss Reduction (%)
10	305.7209	140.6980	46.021
20	320.9472	112.8087	35.1486
30	333.5268	132.7797	39.8108
40	244.8915	136.5752	55.7696
50	218.66	106.8201	48.8521

The results show that higher renewable penetration leads to lower system losses, both in the base case and after optimization. This is primarily due to the reduced power flow from the substation as local generation serves nearby loads. However, the optimization becomes more challenging with higher penetration levels due to increased variability and potential voltage constraint violations. Despite this, the hybrid GWO-SA algorithm maintains its effectiveness, with loss reduction percentages increasing with renewable penetration.

Performance under Different Loading Conditions

Simulations were conducted under different loading conditions. Three cases were considered: light load (70% of nominal), nominal load (100%), and heavy load (130% of nominal).

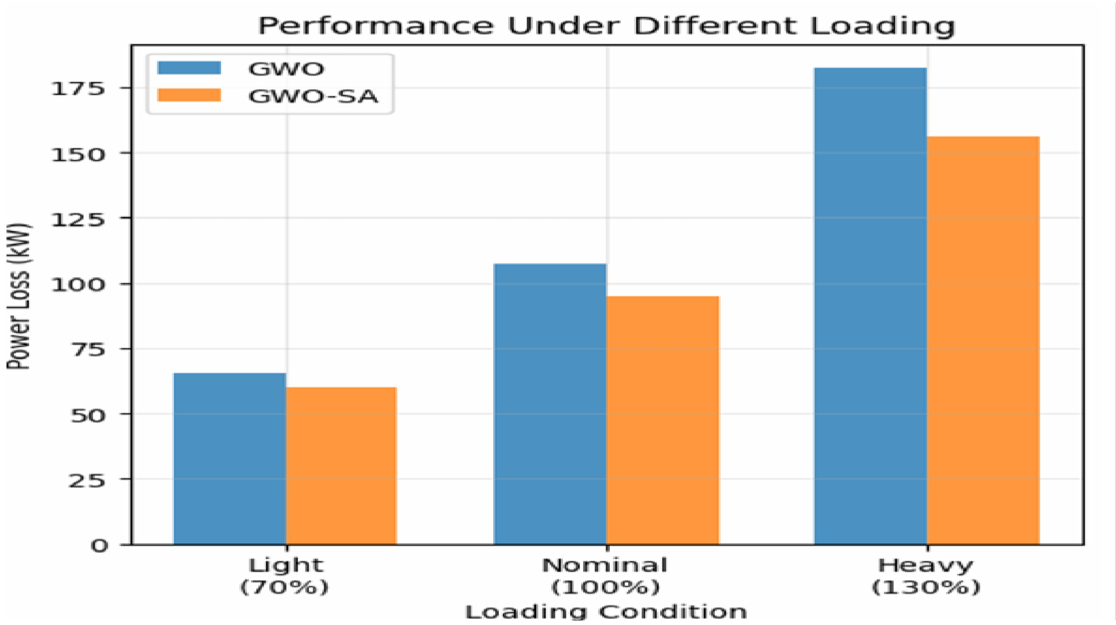

Fig 3 IEEE 69-bus system loading condition

Table 3 Performance under different loading conditions for IEEE 69-bus system

Table 3 Performance under different loading conditions for IEEE 69-bus system Loading Condition	Algorithm	Power Loss (kW)	Min Voltage (p.u.)	Execution Time (s)
Light Load (70%)	GWO	65.34	0.972	42.17
	GWO-SA	59.87	0.978	48.35
Nominal Load (100%)	GWO	107.21	0.953	43.28
	GWO-SA	94.58	0.962	49.72
Heavy Load (130%)	GWO	182.46	0.923	45.61
	GWO-SA	156.23	0.942	52.19

The hybrid GWO-SA algorithm consistently outperforms the standalone GWO across all loading conditions. Heavy loading improves performance more (14.4% reduction) than mild loading (8.4% reduction).This indicates that the hybrid approach is particularly valuable for stressed system conditions when optimization is more challenging.

Sensitivity Analysis

The hybrid GWO-SA's performance was assessed using a sensitivity analysis of algorithm parameters. Figure 4 illustrates how changing the number of wolves selected for SA improvement and SA iterations affects solution quality.

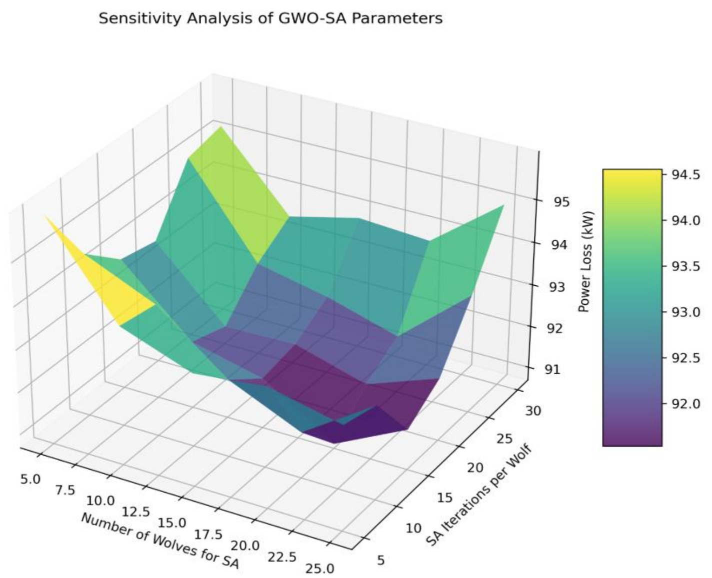

Fig. 4 Sensitivity analysis of GWO-SA parameters on solution quality

The sensitivity analysis reveals that increasing the number of wolves selected for SA enhancement generally improves solution quality up to a certain point (around 15-20 wolves), after which the improvement diminishes. Similarly, increasing the number of SA iterations per wolf improves solution quality up to about 20-25 iterations. Beyond these thresholds, the computational cost increases without significant improvement in solution quality, suggesting optimal parameter settings for balancing performance and computational efficiency.

VII. CONCLUSION

This research introduced a hybrid Grey Wolf Optimizer-Simulated Annealing strategy. Summary of key findings and contributions:

1. The hybrid GWO-SA algorithm beat standalone GWO, SA, PSO, and GA in solution quality, convergence speed, and resilience across test cases.
2. Hybrid solution reduced power loss by 8.6% compared to standalone GWO and 48% compared to base scenario at 30% renewable penetration for IEEE 33-bus system.
3. The voltage profile improvement was significant, with the minimum voltage rising from 0.913 to 0.968 p.u., keeping bus voltages within practical limits.
4. The algorithm demonstrated robust performance across different renewable penetration levels (10-50%) and loading conditions (70-130% of nominal), with more pronounced benefits under higher penetration and heavier loading.
5. Sensitivity analysis identified optimal parameter settings for the hybrid approach, balancing solution quality and computational efficiency.

By combining the global exploration capability of GWO with the local exploitation strength of SA, the algorithm achieves superior performance in minimizing power losses while maintaining acceptable voltage profiles.

Future research directions include:

1. Extending the approach to consider the stochastic nature of renewable generation and load through probabilistic optimization techniques.
2. Integrating energy storage systems as additional control variables in the ORPF problem.
3. Developing a multi-objective formulation to simultaneously optimize power losses, voltage deviation, and operational costs.
4. Applying the hybrid methodology to larger-scale distribution systems and investigating its scalability.

   The proposed hybrid GWO-SA approach provides system operators with an effective tool for reactive power management in increasingly complex distribution networks, contributing to more efficient and reliable operation high renewable energy penetration.

Acknowledgments: The authors sincerely acknowledge the financial support provided by Innovative Research Scheme (IRS-2020) under TEQIP-III File No. IRS/ 2020/R&D/CE/MKT/08/616(IRS) dated 09/03/2020 and the Director MITS, Gwalior, for carrying out this research work.

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