

Quantum-Inspired Evolutionary Algorithms for Solving Medium-Scale, Non-Convex Optimal Power Flow Problems in Complex Smart Grid Systems with Renewable Integration

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Received: 23.07.2026 Accepted: 24.08.2026

Abstract- The Optimal Power Flow (OPF) problem is critical to the safe and profitable operation of smart grids that employ renewable energy (RE) like solar and wind. Conventional metaheuristic optimization algorithms struggle to solve medium-scale, nonlinear, nonconvex, and high-dimensional OPF problems. This leads to problems like premature convergence, insufficient global search, high computational complexity, and unstable performance in the face of variable renewable conditions. This research proposes a Golden Sine-tuned Quantum-Inspired Bacterial Foraging Algorithm (GS-QIBFA) for solving renewable-integrated OPF problems in complex smart grid environments. While preserving dependable and stable grid operation, the suggested approach seeks to reduce generation cost, transmission power loss, voltage variation, and constraint violations. Because of its medium-scale architecture, various generator interactions, and suitability for assessing renewable-integrated OPF scenarios under dynamic operating conditions, the IEEE 39-bus system is chosen as the benchmark network. The GS-QIBFA integrates GS to enhance the exploration–exploitation balance and accelerate convergence. The QIBFA improves global search capability through quantum probability representation and evolutionary updating. Together, they improve solution refinement, diversity maintenance, and constraint handling for efficient OPF optimization. The proposed model is implemented in a MATLAB-based smart grid simulation environment with renewable uncertainty modelling and nonlinear OPF constraint analysis. According to experimental data, GS-QIBFA outperforms current OPF optimization techniques with a minimal power loss of 9.7 MW, fuel cost of 760.2 \$/h, emission rate of 0.189 ton/MWh, and voltage stability index of 0.170. All things considered, GS-QIBFA is a dependable and efficient technique for resolving renewable-integrated OPF issues in smart grid systems.

Keywords Transmission Loss Reduction; Voltage Stability; Smart Grid Optimization; Energy Management; Economic Dispatch; IEEE 39-Bus System.

1. Introduction

The OPF problem is crucial to the creation, administration, and operation of power networks in the field of electrical engineering, where economic operation is a key component of contemporary energy systems [1]. By appropriately adjusting the control variables, OPF identifies the optimal operating conditions of a power system while ensuring safe, efficient, and economically viable operation [2]. In addition to reducing objectives such as generation cost, transmission losses, emissions, and voltage deviations, the OPF solution must satisfy all operational constraints related to

system reliability, stability, and security [3]. OPF has become a complex optimization problem characterized by increasing scale, multiple constraints, and non-convexity, largely due to the growing integration of renewable sources such as solar and wind power [4]. The intermittency and uncertainty of RE sources complicate system modelling and affect stability in power networks. The OPF problem aims to optimize the control variables to achieve the desired operational objectives while keeping all variables within their permissible limits [5]. Fuel cost reduction is frequently the primary objective; other important objectives include maintaining system variables within operational limits, improving voltage stability and

voltage profiles, reducing active power losses, and lowering emission costs [6,7]. Transformer tap settings, generator bus voltage magnitudes, active power generation, and reactive power compensation are the core control variables of OPF [8]. OPF is a complicated optimization problem involving combining discrete as well as continuous choice variables, non-linearity, high dimensionality, and non-convexity. By introducing uncertainty and non-smooth characteristics, the integration of RE sources increases these difficulties and raises the level of uncertainty in the current power grid [9]. Because of their adaptability, reduced computing complexity, and capacity to handle nonlinear, non-convex, and high-dimensional search spaces, metaheuristic approaches have drawn a lot of interest for resolving OPF problems [10]. Metaheuristic optimization techniques are commonly used for solving OPF problems; they encounter issues like premature convergence, slow convergence speed, reduced population diversity, and vulnerability to local optima [11]. Nonlinear, non-convex OPF problems with high RE penetration face increased solution complexity due to uncertainty and fluctuating operating conditions [12]. As a result, there is an increasing need for more robust optimization approaches that can provide accurate and reliable solutions for modern smart grid systems by successfully balancing local exploitation and global exploration.

The primary objective of the research is to develop an effective optimization method for medium-scale, nonlinear, and nonconvex OPF problems in smart grid systems that integrate RE sources. While maintaining dependable and stable grid operation, the suggested strategy seeks to reduce generating costs, transmission losses, voltage variations, and constraint violations. Some of the key contributions are:

- The suggested GS-QIBFA is designed for precise power scheduling, lower transmission distortions, and enhanced voltage profile stability in smart grid systems to handle RE unpredictability and complicated OPF limitations.
- An integrated optimization model is created and tested on the IEEE 39-bus system to provide dependable OPF efficacy considering RE ambiguities.
- Quantum-inspired probability modelling is used to improve population variety and bolster global search capabilities to combat premature convergence and local optimum decline.

2. Related Works

An overview is provided on OPF optimization methods, renewable-integrated smart grid modelling, and metaheuristic algorithms for nonlinear constraint handling. A MWSO method was presented in research [13] to handle the OPF issue in the presence of load and RE uncertainty. This approach combined quasi-oppositional-oriented learning with Gaussian barebones approaches to improve the primary WSO's efficacy and performance. When applied to the revised IEEE 30-bus and 57-bus platforms with links to Weibull and lognormal distributions along with stochastic loading for wind and solar power, the results showed better performance than the original WSO and many rival techniques. Practical adaptation to

unforeseen uncertainty is limited by the dependence on specified probabilistic models. Reference [14] presents a variation of the original AHA that enhances search efficiency and convergence by incorporating opposition-based learning and a local escape operator. Its goal was to reduce power loss, voltage variation, and emission costs by minimizing system fuel costs within constraints. The experimental results on benchmark and test systems demonstrated good performance when compared to the performance of several meta-heuristic algorithms, but cannot be generalizable for testing on standard test cases.

A modified AHA (MAHA) was proposed in [15] to improve the original AHA for solving the OPF problem. This approach avoids immobility and local optima by including exploration techniques like Lévy flight and fitness-distance balancing, while simultaneously supporting exploitation through the addition of bandwidth-based local search. For a variety of objectives, such as fuel cost, losses, pollutants, and voltage variation, it employed several benchmark functions, such as CEC2020 and IEEE 30-, 57-, and 118-bus systems. When compared to several meta-heuristic techniques, the results demonstrated superior performance. Its real-world use is constrained because the validation is restricted to the benchmark and standard test systems. The OPF issue is fixed with reduced fuel expenses, power loss, emissions, voltage deviation, and enhanced voltage stability [16]. A new hybrid JS-MFO approach is presented that combines JS and MFO to improve the exploration-exploitation performance. Due to their enhanced optimization potential over previous methods, both the IEEE 30-bus and RIM 27-bus systems produce an optimization result. However, this can only be used with large-scale renewable integrated smart grids and is only validated with a medium-scale test system. Research [17] proposed a CCDE algorithm for solving the OPF problem, introducing two restrictions for heuristic algorithms: constraint handling and limitations of penalty function schemes. This method integrates feasibility rules and the ϵ -constraint method for an efficient feasible region search without requiring multiple penalty parameters. It does not consistently provide a global optimum or guarantee quick convergence across all cases.

For the MO-OPF problem in electrical power grids, an ESNST was presented [18]. By adding the aggressive exploitation strategy and an adaptive parameter, the method aims at increasing the convergence and enhancing the quality of the solutions, while improving the original SNST. The West Delta region showcasing its efficacy and capability to outperform competitive techniques. Apparently, the results of its evaluation on prefixed test systems and limited scenarios in the real grid limit the applicability of its evaluation to wide-spread dynamics in a grid. Research [19] proposed a hybrid AO-AOA for OPF problems that seeks to accomplish objectives like fuel cost, power loss, emissions, voltage deviation, and stability index. This approach balances exploration and exploitation with an energy-based value and uses a piecewise linear mapping technique to guarantee convergence. When evaluated on IEEE 30-bus and 118-bus networks, it outperformed more recent techniques in terms of convergence speed and solution quality. Its application is limited because it was only evaluated on traditional platforms.

An HCSGWO technique is used to optimize power flow factors to reduce emissions, generating costs, power losses, and improve voltage stability [20]. This approach, which is an expansion of the fundamental GWO, uses the CS to enhance local search capabilities and solution accuracy. In terms of minimization targets and solution quality, it fared better than GWO and other approaches when tested on the IEEE 57-bus system. Its usage in more complicated real-world power networks may be restricted because its validation is restricted to a particular conventional test system.

An adaptive differential evolution algorithm was presented [21] with an ε constraint for the OPF problem. The approach is an enhanced ε -constrained method with a constraint-violation based p-best selection strategy for improving constraint handling. In most cases, it outperformed many advanced techniques whenever deployed to the IEEE 30-bus challenge. It is only being tested on one test system and cannot be usable for larger networks. For solving the OPF problem CGSCE method is used [22]. The method is an improvement to the standard cross entropy algorithm by employing a chaotic operator, with its better exploration capability, and a parameter-free constraint-handling technique. It was validated using IEEE 30 and 57-buses system, and it was found to exhibit better convergence and performance than other previously developed convergent methods. It has been tested on standard systems and evaluation be restricted to these systems, limiting its applicability. Research [23] proposed a stable matching based multi-objective evolutionary algorithm to resolve conflicts among costs, power loss, and voltage stability in OPF problems. This algorithm integrates stable matching theory with the MOEA/D technique to enhance Pareto-optimal search accuracy and diversity. Evaluated against established algorithms, it demonstrated superior performance in approximating the Pareto front, diversity, and computational efficiency. Its application is limited to benchmark OPF scenarios, restricting its use in more complex real-world power systems.

In [24], the LSDO algorithm was introduced as a fix for the OPF issue. It uses a constraint-handling strategy that is enhanced by crossover and mutation techniques for practical solutions. LSDO performs better than conventional algorithms in experiments on standard functions and IEEE 30, 57, and 118-bus systems with DER production connected to renewable sources. Its usefulness in real-world circumstances may be limited because its validation is restricted to well-established test systems. To solve the single- and multi-objective OPF problem in a transmission system, an ESDO approach was put out [25]. It is based on the behaviour of stray dogs in Egypt and evaluated using the IEEE 30-bus system under different operating situations. It has demonstrated superior performance in OPF issues when compared to several metaheuristic algorithms. It can't be used to larger, more complicated real-world power systems because it has only been validated under the one standard test system that is offered. An ESDE-MC was suggested to solve the OPF problem to integrate wind power [26]. To combine wind power and overcome the OPF problem, an ESDE-MC was proposed [26]. It takes into consideration the reserve cost and penalty cost of wind generating and uses a reactive power-

voltage formulation based on WRIG. The generating cost was the quickest to calculate when compared to earlier methods on both IEEE 30- and 57-bus test systems, and the Kruskal-Walli's test statistically verified the computing time. Its evaluation, however, is restricted to tried-and-true test systems that aren't suitable for managing dynamic, large-scale power networks in the real world.

To address the OPF issue with FACTS devices and wind power integration, PNMCPA was introduced [27]. The method uses a gradient pyramid mechanism to further accelerate search and a Nelder-Mead simplex strategy to increase variety for faster convergence. In terms of cost and power losses, it fared better than the existing approaches when evaluated on an IEEE 30-bus system. However, it is only intended for a single test system, and its usefulness in practical applications may rely on parameter values that impose certain limitations. Fuel generation costs and can be minimized within system constraints by employing a hybrid approach of PSO and ANN to solve the OPF problem [28]. This method, which employs ANN, is an iterative optimization procedure that was suggested to help enhance the PSO's parameter selection and search accuracy when compared to regular PSO. It is more economical and power-efficient than the current methods, according to tests conducted on IEEE-bus systems. Its validation is linked to tiny standard test systems, which may make it less applicable in larger, more complex real-world test systems.

The challenge aims to minimize the cost of fuel needed to provide the required amount of electrical power while satisfying the operating constraints of electrical systems [29]. The comparative test results are displayed on the IEEE 30-bus test system using a modified PSO technique. The results show that the suggested approach has a minimal fuel cost of 786.03 \$/h, with a 4.358% difference from the MBO algorithm's results when compared to PSO and other optimization methodologies. The primary goal of the research, which is limited to the IEEE 30 bus system and only supported by MATLAB simulation results, is fuel cost minimization. On solving the MaO-OPF problem in a way that simultaneously lowers fuel costs, pollution, power loss, and voltage deviation while concurrently improving the system's voltage stability [30]. For the IEEE 30 bus system, the HHO methodology is integrated with dynamic exploration-exploitation techniques and self-adaptive constraint management. The results show that the categorization of the obtained results is better than that of MOEA/D-DRA and NSGA-III in terms of convergence, diversity preservation, and generating better Pareto-optimal resolutions. The research is limited to the IEEE 30-story test system; its applicability for more complex and larger power networks must be assessed.

2.1. Research Gap

Some limitations remain in existing OPF optimization studies, which, despite demonstrating better performance, are primarily tested on standard benchmark systems, making them less relevant in real-life applications [15]. Many methods converge too early, often failing to deliver global optimal solutions [17]. Furthermore, the majority of which primarily

concentrate on reducing fuel costs, have only been tested on small-scale systems, such the IEEE 30-bus system, and have not been validated in bigger, renewable-integrated power systems [21,29,30]. To meet these limitations, the proposed IEEE 39-bus renewable-integrated smart grid is improved by incorporating GS-QIBFA, which increases the exploration capability and the speed of convergence, decreases the generation cost, transmission losses, voltage deviation, constraint violation, and improves the solution quality.

3. Methodology

To minimize generating transmission losses, voltage deviation, and constraint violations while satisfying power balance and operational limits, research formulates the renewable integrated OPF problem as a constrained nonlinear

optimization problem. The IEEE 39-bus system with RE sources with different loads and generation is used to assess the performance. A new hybrid GS-QIBFA is suggested to address the complex non-convex OPF problem. The GS algorithm accelerates the overall speed of the exploratory search and convergence of the population, and the QIBFA introduces stochastic searching and evolutionary foraging behaviours to counteract and avoid premature convergence of the population and increase its diversity. The integrated approach is good at the coordination between exploration and exploitation, which follows the optimal scheduling of power, decreased loss, voltage stabilization and safe operation of the smart grid. The entire workflow of the proposed GS-QIBFA-based OPF optimization, including system modelling, optimization, and performance evaluation stages are highlighted in Figure 1.

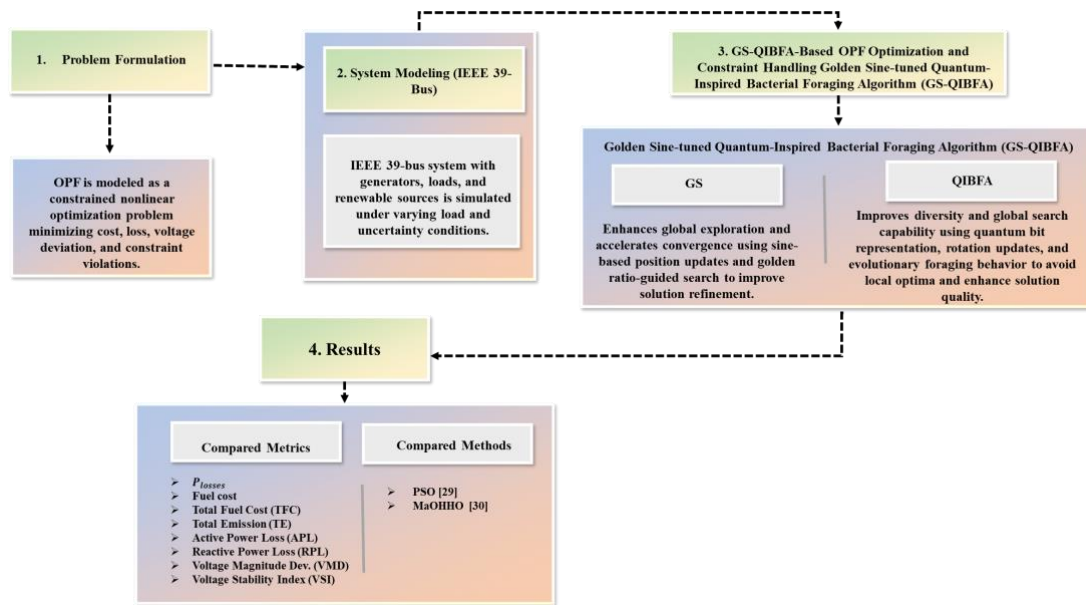


Fig. 1. Overall Flow of the Proposed GS-QIBFA for Renewable-Integrated OPF in IEEE 39-Bus Smart Grid System

3.1. Problem Formulation

To minimize cost of operation, transmitting losses, voltage variations, and constraint deviations, the renewable-integrated OPF issue is defined as a constrained nonlinear optimization challenge which finds the best operating conditions of generators, voltages, transformer taps, and RE sources.

➤ Objective Function

The renewable-integrated OPF problem aims to simultaneously minimize generation cost, transmission losses, voltage deviations, and operational constraint violations to achieve economical and reliable smart grid operation. Because the sub-objectives have different units and scales, the aggregated objective is formulated as a weighted sum:

$$\min F = w_1 F_{cost} + w_2 F_{loss} + w_3 F_{VD} + w_4 F_{penalty} \quad (1)$$

Where, w_1, w_2, w_3 , and w_4 are weighting coefficients. In this study, $w_1 = 1.0$, $w_2 = 50.0$, $w_3 = 200.0$, and $w_4 = 500.0$. These values were selected through preliminary

experiments so that the four terms have comparable influence during the search. The $\min F$ denotes the total objective function of OPF. F_{cost} specifies the generation fuel cost objective. F_{loss} is the transmission power loss objective. F_{VD} denotes the voltage deviation objective. $F_{penalty}$ mentions penalty function for constraint violations.

➤ Generation Cost Minimization

The objective, which is represented by a quadratic cost function and represents the total fuel cost F_{cost} incurred by all generating units, is expressed in equation (2).

$$F_{cost} = \sum_{i=1}^{N_G} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \quad (2)$$

Number of generating units is represented as N_G . a_i, b_i, c_i specifies the fuel cost coefficients of generator i . Active power result of generator i mentioned as P_{Gi} . Quadratic term representing fuel cost nonlinearity in generator cost function is given as P_{Gi}^2 .

➤ Transmission Power Loss Minimization

The transmission loss objective minimizes the active power dissipated in transmission lines, thereby improving system efficiency, and reducing operating expenses. The total transmission loss F_{loss} is calculated using equation (3).

$$F_{loss} = \sum_{i=1}^{N_B} \sum_{j=1}^{N_B} G_{ij} (V_i^2 + V_j^2 - 2V_i V_j \cos \delta_{ij}) \quad (3)$$

Where, N_B is the number of buses in the system. G_{ij} specifies the conductance between bus i and bus j . $V_i V_j$ are voltage magnitude at bus i and j . δ_{ij} is the voltage angle difference between bus i and j . $\cos$ defines the cosine function. $\sum$ denotes the summation operator. V_i^2 , V_j^2 are squares of voltage magnitudes at bus i and bus j .

➤ Voltage Deviation Minimization

To maintain voltage stability and improve power quality, the voltage deviation F_{VD} from the reference value is minimized according to equation (4).

$$F_{VD} = \sum_{i=1}^{N_L} |V_i - V_i^{ref}| \quad (4)$$

Number of load buses is indicated by N_L . Voltage magnitude at bus i is denoted as V_i . Reference (nominal) voltage at bus i is specified as V_i^{ref} .

➤ Equality Constraints

These constraints ensure power balance throughout the network by satisfying both active and reactive power flow requirements.

Active Power Balance Constraint: This is caused by conventional and renewable sources must satisfy the active load demand and network power flow conditions, as formulated in equation (5).

$$P_{Gi} + P_{Ri} - P_{Di} = V_i \sum_{j=1}^{N_B} V_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \quad (5)$$

Where, P_{Gi} denotes the active power from conventional generator. P_{Ri} is the active power from renewable source (solar/wind). P_{Di} defines active load demand at bus i . G_{ij} , B_{ij} are conductance and susceptance of transmission line. V_i , V_j , δ_{ij} represents the bus voltage magnitudes and angle difference. $\cos$ and $\sin$ indicates sine and cosine functions. N_B is the number of buses in the system.

Reactive Power Balance Constraint: It is generated within the system must satisfy reactive load demand while maintaining voltage support, as represented in equation (6).

$$Q_{Gi} + Q_{Ri} - Q_{Di} = V_i \sum_{j=1}^{N_B} V_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) \quad (6)$$

Reactive power from conventional generator is presented as Q_{Gi} . Reactive power from renewable sources is mentioned as Q_{Ri} . Reactive power demand at bus i is specified as Q_{Di} . Susceptance and Conductance between bus i and j are denoted

as B_{ij} , G_{ij} . V_i , V_j , δ_{ij} represents the bus voltage magnitudes and angle difference.

➤ Operational Inequality Constraints

Equation (7) illustrates the inequality function $h(X)$, which jointly represents the operational limits of generators, voltages, transformer tap settings, transmission line flows, and renewable generating outputs. Within allowable operating bounds, these limitations guarantee the renewable-integrated power system's safe and dependable operation.

$$h(X) \leq 0 \quad (7)$$

Where, $h(X)$ transmission line flow restrictions, bus voltage limitations, transformer tap limits, generator active and reactive power limits, and renewable generation limits.

➤ Final Optimization Model

The constrained optimization model is used to formulate the full renewable-integrated OPF problem. Equation (8) minimizes the objective function while meeting the equality constraints in equation (9) and the inequality restrictions in equation (10).

$$\min_X [w_1 F_{cost} + w_2 F_{loss} + w_3 F_{VD} + w_4 F_{penalty}] \quad (8)$$

$$g(X) = 0 \quad (9)$$

$$h(X) \leq 0 \quad (10)$$

Where $\min_X$ is decision/control variable vector optimized by GS-QIBFA. $g(X)$ denotes the power-flow equality constraints and $h(X)$ represents the operational inequality constraints. F_{cost} specifies the total fuel cost. F_{loss} is the transmission power loss objective. F_{VD} denotes the voltage deviation objective. $F_{penalty}$ mentions penalty function for constraint violations. The proposed GS-QIBFA algorithm determines the optimal control vector X that minimizes the objective function while ensuring secure, economical, and reliable operation smart grid.

➤ Emission Rate

The total emission from thermal generators is expressed as:

$$F_{emission} = \sum_{i=1}^{N_G} (\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) \quad (11)$$

Where, α_i , β_i and γ_i are the emission coefficients of generator i in ton/h. To report an emission indicator on a scale consistent with the other performance metrics, the emission rate is defined as:

$$TE = \frac{F_{emission}}{\sum_{i=1}^{N_G} P_{Gi}} \quad (12)$$

The TE values reported in Tables 3 and 4 correspond to this emission rate.

➤ Reactive Power Loss

The reactive power loss is computed as:

$$F_{RPL} = \sum_{i=1}^{N_B} \sum_{j=1}^{N_B} B_{ij} (V_i^2 + V_j^2 - 2V_i V_j \cos \delta_{ij}) \quad (13)$$

Where, B_{ij} is the line susceptance and V_i, V_j are bus voltage magnitudes. F_{RPL} is expressed in MVar. This term is evaluated after optimization and is not included in the weighted objective.

➤ Voltage Stability Index

For load bus j , the L-index is:

$$L_j = \left| 1 - \sum_{i \in G} F_{ji} \frac{V_i}{V_j} \right| \quad (14)$$

Where, G is the set of generator buses and F_{ji} are elements of the load-flow Jacobian. The overall voltage stability index is defined as:

$$VSI = 1 - \max_{j \in L} L_j \quad (15)$$

Where, L denotes the set of load buses. VSI ranges between 0 and 1; a larger value indicates a greater stability margin. VSI is reported as a post-optimization indicator and is not included as an objective term.

➤ Penalty Function

The penalty term $F_{penalty}$ aggregates the violations of equality and inequality constraints:

$$F_{penalty} = \lambda_P \sum_{i=1}^{N_B} (\Delta P_i)^2 + \lambda_Q \sum_{i=1}^{N_B} (\Delta Q_i)^2 + \lambda_V \sum_{i=1}^{N_B} (\Delta V_i)^2 + \lambda_S \sum_{l=1}^{N_l} (\Delta S_l)^2 \quad (16)$$

Where, ΔP_i and ΔQ_i are the active and reactive power mismatches at bus i , ΔV_i is the bus voltage limit violation, ΔS_l is the line flow limit violation, and $\lambda_P = \lambda_Q = \lambda_V = \lambda_S = 1000$ are the penalty coefficients. N_l denotes the number of transmission lines. The mismatch terms are computed in p.u., so $F_{penalty}$ is dimensionless.

➤ Decision-Variable Vector

The decision-variable vector X comprises the active power outputs of all generators except the slack bus, the voltage magnitudes of all generator buses, the tap settings of all transformers, and the active power outputs of renewable generators:

$$X = [P_{G1}, \dots, P_{G, N_G-1}, V_{G1}, \dots, V_{G, N_G}, T_1, \dots, T_{N_T}, P_{R1}, \dots, P_{R, N_R}]^T \quad (17)$$

Where, N_T is the number of transformers and N_R is the number of renewable generators. Transformer tap settings are treated as discrete variables with a step size of 0.0125 p.u.; all other variables are continuous.

3.2. System Modeling (IEEE 39-Bus System Setup)

The IEEE 39-bus power system is used as a representative system to assess the proposed OPF design with GS-QIBFA.

The system is suitable as a workable medium-scale power system for examining renewable integration for OPF because it has 39 buses, 10 generators, 46 transmission branches, and 21 load buses. The system can produce 7,367 MW in total, with a peak load demand of about 6,254 MW. By connecting the RE generation units to the IEEE 39-bus network and doing the OPF analysis under various operating situations, the effects of adding RE to the system are examined. Limits of the generators, the bus voltage limits, the transmission line capacity limits, the tap settings on the transformers, and the limitations on renewable generation are all represented in the system model. The OPF model incorporates cost coefficients for traditional generators while ignoring the cost of renewable energy. The suggested GS-QIBFA's utility in dependable, stable, and cost-effective power grid operation is confirmed by using the IEEE renewable-integrated smart grid model. Table 1 displays the criteria for the IEEE 39-bus test system. The IEEE 39-bus power system used to evaluate the suggested GS-QIBFA's performance is shown in Figure 2.

To establish a complete stochastic OPF framework, the uncertainty of renewable generation and load demand is modeled explicitly. Two wind farms are connected at buses 8 and 20, with rated capacities of 220 MW and 180 MW, respectively. Two solar PV plants are connected at buses 25 and 39, each with a rated capacity of 150 MW. The total renewable capacity is therefore 700 MW, corresponding to a renewable penetration of approximately 11.2% of the 6,254 MW peak load and 9.5% of the 7,367 MW total generation capacity. Wind speed is modeled by a Weibull distribution with a shape parameter of 2.0 and a scale parameter of 9.0 m/s. Solar irradiance follows a Beta distribution with shape parameters 2.0 and 2.5. The time-varying load demand is represented by a normal distribution with a mean equal to the base load and a standard deviation of 5% of the mean. A Latin hypercube sampling method is used to generate 1,000 joint wind-solar-load scenarios. To reduce computational burden while preserving statistical diversity, the scenarios are clustered into 10 representative scenarios using the k-means algorithm; the probability of each representative scenario is assigned in proportion to the number of original scenarios in the corresponding cluster. Correlation between wind and solar outputs is not assumed; the two sources are treated as independent stochastic variables. Load demand varies from 60% to 100% of the peak value across the scenarios, reflecting different operating hours and demand levels.

Table 1. Summary of the IEEE 39-Bus System

Items	Quantity
Generators	10
Loads	21
Branches	46
Tie lines	6
Areas	3

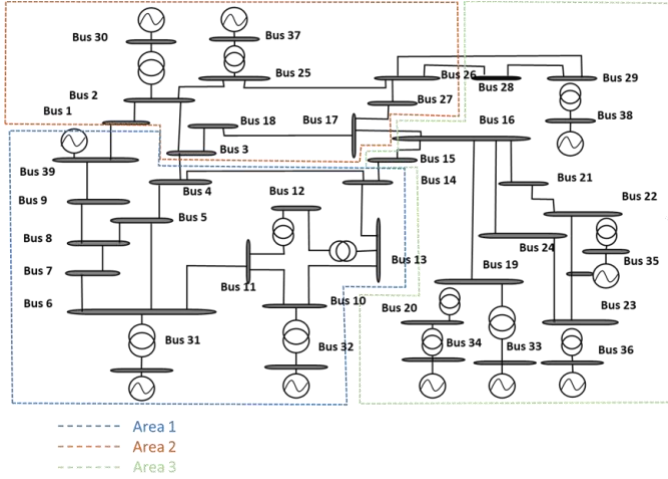


Fig. 2. IEEE 39-bus system

3.3. GS-QIBFA-Based OPF Optimization and Constraint Handling

The outputs, bus voltages, transformer tap settings, and renewable power dispatch can all be adjusted by GS-QIBFA. Unlike the standard Golden Sine and bacterial foraging algorithms, the proposed method combines the two mechanisms in a single search loop. The GS component accelerates local refinement and convergence, while the QIBFA component maintains population diversity and improves global exploration through quantum rotation and bacterial foraging. The novelty of the hybridization lies in the use of quantum probability amplitudes to encode candidate OPF solutions and the alternating application of GS and QIBFA updates, which is not present in the original component algorithms. To ensure the safe, reliable, economical, and secure operation of the smart grid, optimization processes must satisfy both equality and inequality requirements, such as power balance, generator constraints, voltage limits, transmission line capacity, and restrictions on renewable generation.

3.3.1 GS for enhancing global exploration and maintaining population diversity in medium-scale non-convex OPF problems

GS search mechanism is built in the proposed GS-QIBFA to enhance convergence speed and solution refinement, during the OPF optimization process. The algorithm works by generating candidate solutions and ensuring that those solutions get closer to a “good” solution by implementing the periodic search behavior enabled by the sine function in the candidate solution and the concept of the Golden Ratio, which shrinks the search set and helps to speed up the optimization without performing any unnecessary iterations. The position update equation of the GS mechanism is given in equation (18):

$$W_{j,i}(s+1) = W_{j,i}(s) \times |\sin(o_1)| - o_2 \times \sin(o_1) \times [c_1 \times W_{best,i}(s) - c_2 \times W_{j,i}(s)] \quad (18)$$

Where, $W_{j,i}(s)$ specifies the position of i -th candidate solution in j -th dimension at iteration s . $W_{j,i}(s+1)$ is the

updated position of candidate solution. $W_{best,i}(s)$ mentions the best solution in population at iteration s . o_1, o_2 are the random control parameters governing exploration behavior. $\sin$ represents the sine function. The coefficient factors c_1 and c_2 are computed as represented in equations (19) and (20):

$$c_1 = b \times \tau + a \times (1 - \tau) \quad (19)$$

$$c_2 = b \times (1 - \tau) + a \times \tau \quad (20)$$

Adaptive control parameters balancing exploration and exploitation are defined as c_1, c_2 . The constant boundary parameters defining search range is mentioned as a, b . Golden ratio-based scaling factor is represented as τ . Complementary weighting term is denoted as $1 - \tau$. The golden ratio is defined in equation (21):

$$\tau = \frac{\sqrt{5} - 1}{2} \quad (21)$$

The Golden ratio-based scaling factor is represented as τ . $\sqrt{5}$ is the square root of 5 used to compute the golden ratio. In the golden ratio formula, 2 is the scaling constant. To reduce generating costs, power loss in transmission networks, voltage deviation, and constraint violation in renewable aided OPF solvers, the suggested GS-QIBFA acquire the solution with a shorter convergence time and superior solution efficiency.

3.3.2 QIBFA for solving renewable-integrated OPF by avoiding local optima and improving optimization accuracy.

To achieve the goals and objectives of enhanced global search capacity and preserving population species diversity, the QIBFA is introduced to the proposed GS-QIBFA framework during the process of the optimization of renewable integrated OPF. The algorithm employed can exploit the qualitative factors of quantum probability representation and the bacterial foraging behavior to reduce the possibility of premature convergence and enhance the solution quality in medium-scale non-convex search spaces.

➤ Quantum Representation

Every bacterium is represented with a quantum bit (Q-bit) vector which probabilistically stores candidate OPF solutions shown in equation (22):

$$w_j(i, r, k) = [w_{j1}(i, r, k), w_{j2}(i, r, k), \dots, w_{jc}(i, r, k)] = [\alpha_{j1}(i, r, k), \alpha_{j2}(i, r, k), \dots, \alpha_{jc}(i, r, k)] [\beta_{j1}(i, r, k), \beta_{j2}(i, r, k), \dots, \beta_{jc}(i, r, k)] \quad (22)$$

Where, $w_j(i, r, k)$ is quantum representation of j -th bacterium (candidate OPF solution). C denotes the number of control variables. α_{jc}, β_{jc} mentions the probability amplitudes of quantum state in dimension c . i, r, k indicates iteration, reproduction, and elimination-dispersal indices. $w_{j1}, w_{j2}, \dots, w_{jc}$ specifies quantum probability amplitudes (or components) of the j -th bacterium's solution vector across C decision variables in the OPF problem. Equation (22) subject to equation (23):

$$|\alpha_{jc}(i, r, k)|^2 + |\beta_{jc}(i, r, k)|^2 = 1 \quad (23)$$

The probability amplitudes of quantum state in dimension c are specified as α_{jc}, β_{jc} .

For each candidate solution represented by a quantum bit vector, the quantum state is decoded into a real-valued OPF variable before fitness evaluation. For a continuous decision variable x_d with lower bound x_d^{min} and upper bound x_d^{max} , the decoded value is obtained as:

$$x_d = x_d^{min} + |\alpha_d|^2 (x_d^{max} - x_d^{min}) \quad (24)$$

Where, $|\alpha_d|^2$ is the probability of the quantum state collapsing to the "0" state. This decoding ensures that every generated solution lies within the feasible range of the corresponding OPF control variable. For discrete variables, the decoded value is rounded to the nearest allowable tap step or compensation setting after decoding.

Transformer tap settings are treated as discrete variables with a step size of 0.0125 p.u., as noted in the decision-variable definition. After the quantum decoding step, each transformer tap variable is rounded to the nearest multiple of the step size. Shunt compensation devices, if present, are handled in the same manner. This rounding step is applied before the AC power flow evaluation so that all candidate solutions satisfy the discrete nature of these control variables.

➤ Quantum Rotation Update

The quantum rotation angle be updated with both local and global best solutions represented in equation (25):

$$\theta_{id}(i+1, r, k) = f_1[a_{id}(i, r, k) - w_{id}(i, r, k)] + f_2[a_{gc}(i, r, k) - w_{id}(i, r, k)] \quad (25)$$

Where, θ_{id} is the quantum rotation angle. i, r, k indicates iteration, reproduction, and elimination–dispersal indices. f_1, f_2 are learning factors for local and global best guidance. a_{id} represents the current bacterium position. a_{gc} mentions global best solution. w_{id} is the current position of the quantum bacterium in the d^{th} search dimension. The updated quantum position is obtained as shown in equation (26):

$$u_{id}(i+1, r, k) = \begin{cases} u_{id}(i, r, k), & u_{id}(i, r, k) = 0 \\ \text{abs}[H(\theta_{id}(i+1, r, k))u_{id}(i, r, k)], & \text{otherwise} \end{cases} \quad (26)$$

Updated binary/quantum state of bacterium is indicated as u_{id} . $H(\cdot)$ is transformation function (probabilistic update rule). $\text{abs}(\cdot)$ denotes the absolute value function. i, r, k indicates iteration, reproduction, and elimination–dispersal indices.

➤ Fitness Evaluation

The objective function value given equation (27) is used for the assessment of the health (fitness) of each bacterium:

$$e_{health}^j(i, r, k) = e[a_j(i, r, k)] \quad (27)$$

Where, e_{health}^j is the fitness (health) of $j - th$ bacterium. $e[a_j]$ denotes objective function value of solution a_j . i, r, k indicates iteration, reproduction, and elimination–dispersal indices. The strongest bacteria breeds, the weaker vanish and

then spread out to enhance world-wide exploring and eliminate stagnation. Although guaranteeing steady and dependable smart grid operation, QIBFA allows precise reduction of generating cost, transmission power loss, voltage variation, and constraint violations. The proposed QIBFA optimization workflow for renewable-integrated OPF is shown in Figure 3.

The chemotaxis, reproduction, and elimination–dispersal operations of the QIBFA are applied after the quantum rotation update in each generation. The chemotaxis step perturbs the position of each bacterium within its local region, the reproduction step replaces the worst-performing half of the population with copies of the better half, and the elimination–dispersal step relocates a small fraction of bacteria to new random positions according to the probability P_{ed} . The Golden Sine mechanism is executed before the quantum rotation update in each iteration, so the search alternates between GS-guided exploitation and QIBFA-driven exploration. This alternation is the main novelty of the hybridization: GS provides a deterministic gradient-free refinement step, while the bacterial foraging operations maintain sufficient diversity to escape local optima.

The two algorithmic components of GS-QIBFA are the Golden Sine (GS) search and the Quantum-Inspired Bacterial Foraging Algorithm (QIBFA). The GS component refines candidate solutions and accelerates convergence through adaptive search steps based on the golden ratio. The QIBFA component improves global search capability and maintains population diversity through quantum probability representation and bacterial foraging behavior. The two components are integrated so that each GS position update is followed by a QIBFA quantum rotation and bacterial foraging operation. This combined structure is designed to avoid local optima and to handle the non-convex, constrained search space of the renewable-integrated OPF problem.

Hyperparameter Tuning: The intended balance between the global exploration and local exploitation aspects in the renewable integrated OPF optimization, the hyperparameters utilized in the suggested GS-QIBFA, displayed in Table 2, were empirically modified. The IEEE 39-bus system's voltage stability was improved, power losses and generation costs were reduced, and optimal convergence characteristics were attained with the chosen parameters.

Algorithm 1: GS-QIBFA for Renewable-Integrated OPF

Require: IEEE 39-bus system data D , population size N , maximum iterations $MaxIter$, golden ratio τ

Ensure: Optimal control vector X^*

- 1: Initialize quantum-encoded bacterial population of size N
 - 2: Decode each bacterium to real-valued OPF control variables
 - 3: // Discrete variables (e.g., transformer taps) are rounded to nearest step
 - 4: Run AC power flow for each candidate solution
-

5: Evaluate objective function:

$$F = w_1 F_{\text{cost}} + w_2 F_{\text{loss}} + w_3 F_{\text{VD}} + w_4 F_{\text{penalty}}$$

6: **for** $itre = 1$ **to** $MaxIter$ **do**

7: **// Golden Sine exploitation phase**

8: **for** each bacterium j in population **do**

9: Update position using Equation (18):

$$W_{j,i}(s+1) = W_{j,i}(s) \cdot |\sin(o_1)| - o_2 \cdot \sin(o_1) \cdot |c_1 W_{\text{best},i}(s) - c_2 W_{j,i}(s)|$$

10: **end for**

11: **// QIBFA exploration phase**

12: **for** each bacterium j in population **do**

13: Compute quantum rotation angle θ using Equation (25):

$$\theta_{id} = f_1(p_{id} - w_{id}) + f_2(p_{gc} - w_{id})$$

14: Apply quantum rotation gate using Equation (26):

$$\begin{bmatrix} \alpha'_d \\ \beta'_d \end{bmatrix} = \begin{bmatrix} \cos\theta_d & -\sin\theta_d \\ \sin\theta_d & \cos\theta_d \end{bmatrix} \begin{bmatrix} \alpha_d \\ \beta_d \end{bmatrix}$$

15: Decode updated quantum state to real variables

16: Apply chemotaxis local perturbation

17: **end for**

18: Evaluate fitness of all bacteria

19: Perform reproduction operation (replace worst half with best half)

20: Perform elimination–dispersal operation with probability $P_{ed} = 0.25$

21: Apply constraint penalty to infeasible solutions

22: Update global best solution X^*

23: **end for**

24: **return** X^*

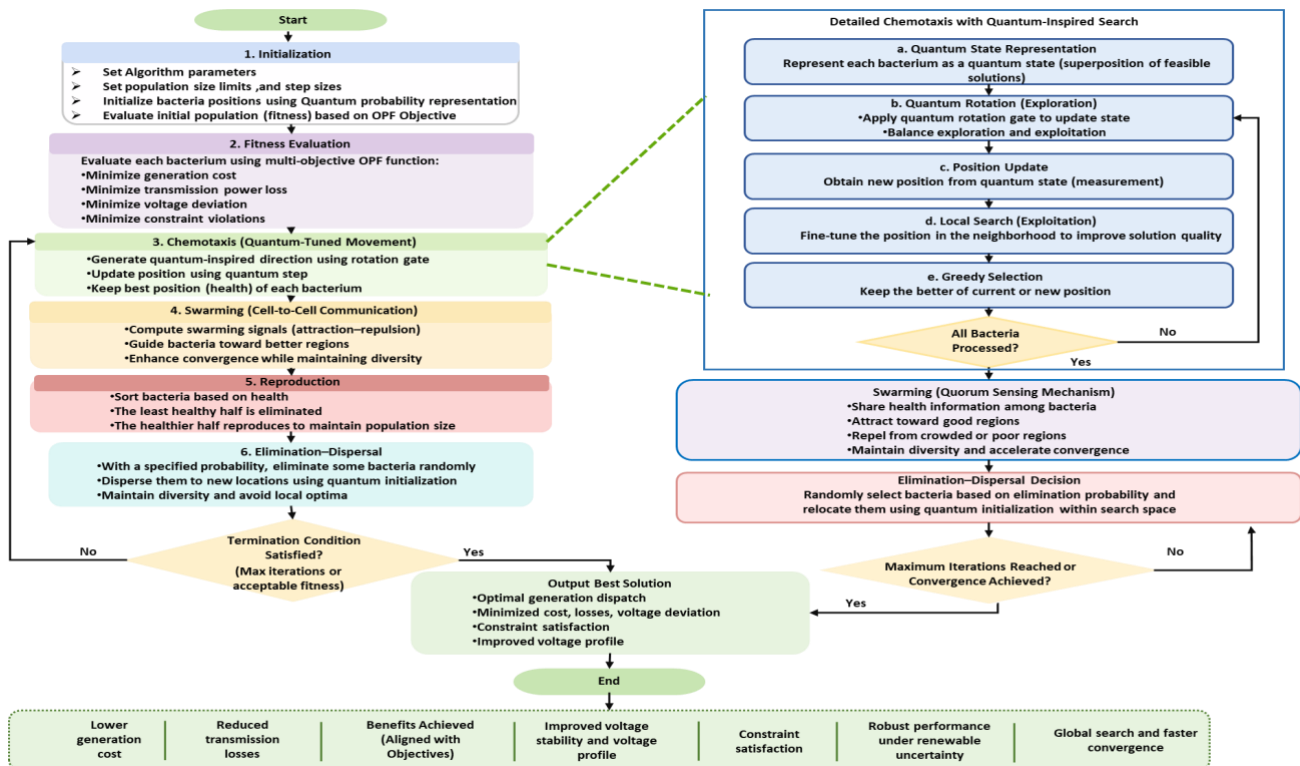


Fig. 3. Flowchart of the QIBFA Approach for Renewable-Integrated OPF Optimization

Table 2. Hyperparameter Settings of the Proposed GS-QIBFA Approach

Hyperparameter	Description	Range Tested	Optimal Value
Population Size (N)	Number of candidates OPF solutions	20 – 60	30
Maximum Iterations ($MaxIter$)	Maximum optimization iterations	50 – 200	100
Golden Ratio Coefficient (τ)	Golden Sine search scaling factor	0.50 – 0.80	0.618
Local Learning Factor (f_1)	Local best guidance coefficient	0.5 – 3.0	2.0

Global Learning Factor (f_2)	Global best guidance coefficient	0.5 – 3.0	2.0
Chemotactic Steps (N_c)	Number of bacterial foraging movements	10 – 30	20
Reproduction Steps (N_r)	Number of reproduction cycles	2 – 10	4
Elimination-Dispersal Events (N_{ed})	Number of eliminations–dispersal operations	1 – 5	2
Elimination-Dispersal Probability (P_{ed})	Probability of bacterium relocation	0.10 – 0.50	0.25
GS Random Parameter (σ_1)	Sine-based exploration parameter	0 – 2π	Random
GS Random Parameter (σ_2)	Search refinement parameter	0 – π	Random
Search Boundary Parameter (a)	Lower search boundary coefficient	$-\pi - 0$	$-\pi$
Search Boundary Parameter (b)	Upper search boundary coefficient	0 – π	π
Quantum Amplitude (α, β)	Initial Q-bit probability amplitudes	0 – 1	$1/\sqrt{2}$
Simulation Platform	Implementation environment	MATLAB	MATLAB
Objective Weight (w_1)	Fuel cost weight	0.5 – 2.0	1.0
Objective Weight (w_2)	Transmission loss weight	10 – 100	50.0
Objective Weight (w_3)	Voltage deviation weight	50 – 500	200.0
Objective Weight (w_4)	Penalty weight	100 – 1000	500.0
Penalty Coefficient λ	Constraint violation penalty	500 – 2000	1000

4. Result

By lowering P_{losses} , fuel costs, TFC, TE, APL, RPL, and VMD while increasing VSI, the suggested GS-QIBFA produced better OPF efficacy on the IEEE 39-bus system. When compared to current approaches, the MATLAB simulation results show improved convergence, improved optimization accuracy, and more dependable smart grid operation.

4.1. Metrics Explanation

The performances of the proposed GS-QIBFA are evaluated using system's variables such as Fuel Cost, TFC, TE, APL, RPL, VMD and VSI. P_{losses} , APL, and RPL are network loss measures, Fuel Cost and TFC are measures of the economic operation, TE measures the negative impacts on the environment, VMD is a measure of voltage regulation and VSI measures system voltage stability. These metrics together attest a good effectiveness, reliability, and stability of the proposed OPF framework.

- P_{losses} : determines the transmission network's overall active power loss; reduced values signify greater system performance.
- Fuel cost (\$/h): calculates the running costs of using traditional generators to produce power. Reducing fuel costs enhances the power system's economic efficiency.
- TFC: shows the total generating cost that all the network's generators must afford. It is a crucial goal for attaining cost-effective OPF functioning.

- TE: calculates the total amount of pollution that thermal generating units release while producing electricity. Grid functioning that is ecologically friendly is facilitated by reduced emission levels.
- APL: indicates the actual power lost in transmission lines because of network resistance. System functionality and power transmission efficiency are enhanced by lowering APL.
- RPL: determines how much reactive power is wasted in the transmission network. Reduced RPL improves system dependability and supports preserving voltage stability.
- VMD: assesses how much bus voltages deviate from the intended reference values. Increased power quality and voltage management are indicated by a decreased VMD.
- VSI: evaluates the power system's voltage stability in various operational conditions. Stronger voltage security and steady grid functioning are indicated by better VSI values.

4.2. Experimental Validation and Comparative Assessment on IEEE 39-Bus

For a consistent experimental comparison, the PSO and MaOHHO algorithms were rerun in the same MATLAB simulation environment as the proposed GS-QIBFA, using the identical IEEE 39-bus network data, renewable generation scenarios, objective functions, operational limits, equality and inequality constraints, population size, and stopping criterion. Table 3 reports the resulting OPF metrics. The proposed GS-QIBFA achieved the best performance with a power loss of

9.7 MW, fuel cost of 760.2 \$/h, TE of 0.189 ton/MWh, APL of 3.885 MW, RPL of 6.952, and VMD of 0.354. Figure 4(a) shows that GS-QIBFA reduces power loss and fuel cost compared with PSO, while Figure 4(b) shows that GS-QIBFA improves voltage regulation, lowers emissions, and enhances voltage stability. The proposed method also obtained the highest VSI of 0.170, indicating superior voltage security under renewable-integrated OPF conditions.

The effectiveness of the proposed GS-QIBFA remains consistent when parameter values are varied, as shown in Table 4. The best results were obtained for a population size of 30, maximum iterations of 100, quantum attraction coefficients of 2.0, and Golden Sine coefficient of 0.6, yielding a fuel cost of 760.20 \$/h, APL of 3.885 MW, VMD of 0.354, and VSI of 0.170. At the optimal solution, all equality constraints were satisfied with a maximum active power mismatch of 5×10^{-4} p.u. and a maximum reactive power mismatch of 1×10^{-3} p.u.; no bus voltage or line-flow limit violations were observed.

Table 3. Comparative Analysis of Existing and Proposed OPF Optimization Methods

Metrics	PSO [29]	MaOHHO [30]	GS-QIBFA [Proposed]
P_{losses} (MW)	10.5	10.3	9.7
Fuel cost (\$/h)	770.89	764.3	760.2
TE	0.204	0.198	0.189
APL	3.962	3.932	3.885
RPL	7.245	7.112	6.952
VMD	0.397	0.372	0.354
VSI	0.156	0.162	0.170

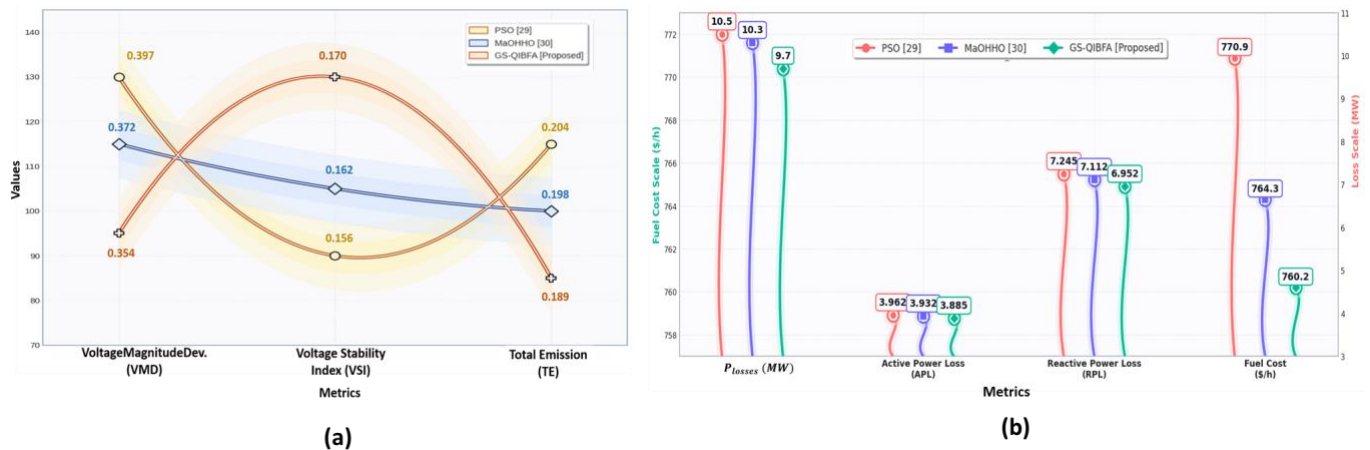


Fig. 4. Comparison Representation of (a) VMD, VSI, TE (b) P_{losses} , APL, RPL, Fuel Cost Among Optimization Methods.

The effectiveness of the proposed GS-QIBFA remains consistent when parameter values are varied, as shown in Table 4. The best results were obtained for a population size of 30, maximum iterations of 100, quantum attraction coefficients of 2.0, and Golden Sine coefficient of 0.6, yielding a fuel cost of 760.20 \$/h, APL of 3.885 MW, VMD of 0.354, and VSI of 0.170.

Table 4. Sensitivity Analysis of the Proposed GS-QIBFA Framework

Parameter Varied	Value Tested	Fuel Cost (\$/h)	APL (MW)	VMD	VSI
Population Size	20	768.84	3.921	0.371	0.163
	30 (Optimal)	760.20	3.885	0.354	0.170
	40	762.14	3.892	0.358	0.168
	50	763.26	3.898	0.361	0.167
Maximum Iterations	50	766.52	3.915	0.368	0.164
	100 (Optimal)	760.20	3.885	0.354	0.170
	150	760.43	3.887	0.355	0.169
Quantum Attraction Coefficient ((e_1, e_2))	1.0	764.35	3.905	0.362	0.166
	2.0 (Optimal)	760.20	3.885	0.354	0.170
	3.0	761.92	3.891	0.357	0.168

Golden Sine Coefficient	0.4	763.18	3.899	0.360	0.167
	0.6 (Optimal)	760.20	3.885	0.354	0.170
	0.8	761.47	3.889	0.356	0.168

4.3. Discussion

The proposed GS-QIBFA demonstrates potential superiority over current renewables-integrated OPF optimization techniques. It effectively balances exploration and exploitation by integrating Golden Sine adaptive search with QIBFA methods, leading to faster convergence, improved solution quality, and robustness. Comparative results indicate that GS-QIBFA achieves lower generation costs and power losses, while meeting operational criteria to minimize voltage deviation and enhance voltage stability. Existing studies have often focused on the IEEE 30-bus system and fuel cost minimization, with validation based mainly on MATLAB simulations [29,30]. In contrast, the present work validates GS-QIBFA on the IEEE 39-bus system, which provides a more realistic multi-generator scenario for evaluating OPF performance under renewable uncertainty. The comparison in Table 3 indicates that GS-QIBFA outperforms PSO and MaOHHO under identical IEEE 39-bus conditions. In overall, the suggested GS-QIBFA proves to be an effective optimization strategy for medium-scale non-convex OPF problems. By avoiding local optimum locations and accelerating convergence, the suggested approach increases search diversity, removes the drawbacks of earlier approaches, and guarantees dependable, cost-effective, and stable functioning in a smart grid.

5. Conclusion

An efficient and reliable optimization approach for resolving the OPF issue in renewable-integrated smart grid systems is presented by the GS-QIBFA. The findings show that the suggested strategy continuously enhances performance in terms of cheaper fuel costs, lower pollutants, lower power loss, higher voltage profiles, and better voltage stability. GS-QIBFA achieves optimal results among all critical performance metrics with the lowest power loss of 9.7 MW, fuel cost of 760.2 \$/h, and the highest VSI of 0.170, indicating its effectiveness in handling the nonlinear, nonconvex, and constrained characteristics of OPF issues under RE ambiguity. Golden sine optimization, bacterial foraging search, and quantum-inspired representation work together to balance exploration and exploitation, maximize convergence behavior, and avoid local optima stagnation. It has computational complexity problems for large-scale real-time power systems. Future research focus on developing lightweight implementations, parallel computing strategies, and real-time adaptive versions to further improve scalability and realistic implementation in smart grid situations.

Acknowledgements

N/A

Author Contributions

Yongchuan Zhou was responsible for the conceptualization, methodology, software development, validation, formal analysis, investigation, resources, data curation, original draft preparation, review and editing, visualization, supervision, project administration, and funding acquisition. The author has read and agreed to the published version of the manuscript.

Conflict of Interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Appendix Table

OPF	Optimal Power Flow
RE	Renewable Energy
MWSO	Modified White Shark Optimization
AHA	Artificial Hummingbird Algorithm
MAHA	Modified Artificial Hummingbird Algorithm
CCDE	Constrained Composite Differential Evolution
ESNST	Enhanced Social Network Search Technique
MO-OPF	Multi-Objective Optimal Power Flow
AO-AOA	Aquila Optimizer- Arithmetic Optimization Algorithm

HCSGWO	Hybrid Cuckoo Search and Grey Wolf Optimization
GWO	Grey Wolf Optimization
CGSCE	Cross-Entropy Method with Chaotic Operator
JS	Jellyfish Search
MFO	Moth Flame Optimizer
MOEA/D	Multi-Objective Evolutionary Algorithm based on Decomposition
STM-MOEA/D	Stable Matching-Based Multi-Objective Evolutionary Algorithm based on Decomposition
LSDO	Leader Supply-Demand-based Optimization
ESDO	Egyptian Stray Dog Optimization
ESDE-MC	Enhanced Self-adaptive Differential Evolution method with Mixed Crossover
WRIG	Wound Rotor Induction Generator
FACTS	Flexible AC Transmission System
PNMCPA	Pyramid Mechanism and the Nelder-Mead Simplex Colony Predation Algorithm
PSO	Particle Swarm Optimization
ANN	Artificial Neural Network
MaO-OPF	Multi-Objective Optimal Power Flow
HHO	Harris Hawks Optimization
MOEA/D-DRA	Multi-Objective Evolutionary Algorithm based on Decomposition with Dynamic Resource Allocation
NSGA-III	Non-dominated Sorting Genetic Algorithm III
TFC	Total Fuel Cost
APL	Active Power Loss
RPL	Reactive Power Loss
VMD	Voltage Magnitude Deviation
VSI	Voltage Stability Index