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Fusing Particle Swarm and Gravitational Search Algorithms: A Pioneering Approach to Optimal Power Flow in Ieee-118 Bus Power Networks

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ABSTRACT

This study presents a novel hybrid optimization approach by fusing Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA) to solve the Optimal Power Flow (OPF) problem in large-scale power systems, specifically applied to the IEEE-118 bus test network. The OPF problem, critical for efficient and economical power system operation, involves minimizing generation cost while satisfying system constraints such as generator limits, power balance, and network security. Traditional optimization techniques often struggle with the nonlinear, non-convex nature of OPF in large networks. The proposed PSO-GSA hybrid algorithm combines the global search capability of PSO with the strong local exploitation ability of GSA, offering improved convergence speed, solution accuracy, and robustness. Extensive simulations were conducted on the IEEE-118 bus system to validate the performance of the hybrid algorithm. Results demonstrate that the PSO-GSA fusion outperforms both standalone PSO and GSA algorithms in terms of achieving lower fuel costs and maintaining voltage stability across the network. The findings highlight the potential of hybrid metaheuristic techniques for addressing complex power system optimization problems and pave the way for scalable and adaptive energy management in modern smart grids.

Keywords: Optimal Power Flow, Particle Swarm Optimization, Gravitational Search Algorithm, PSO-GSA hybrid, IEEE-118 bus system, metaheuristic optimization, power system operation, fuel cost minimization, voltage stability, smart grid, nonlinear optimization, convergence speed, robust algorithm, energy management, hybrid algorithm.

1. INTRODUCTION

In modern electrical power systems, the demand for secure, stable, and economically efficient operation has led to the continuous development of advanced control and optimization techniques. One of the most significant problems in this domain is the **Optimal Power Flow (OPF)** problem, which focuses on determining the most economical and technically feasible operating state of a power system while satisfying a set of nonlinear equality and inequality constraints. These constraints include power balance equations, generation limits, voltage boundaries, and line flow limits. As the size and complexity of power networks grow—exemplified by large test systems such as the IEEE-118 bus network—traditional mathematical programming approaches often fall short due to their limited capability in navigating non-linear, non-convex, and multi-modal search spaces. This has catalyzed the use of **metaheuristic optimization techniques**, which offer robust alternatives with improved flexibility and global search capabilities.

Among the plethora of metaheuristic techniques developed, **Particle Swarm Optimization (PSO)** and **Gravitational Search Algorithm (GSA)** have received considerable attention. PSO, inspired by the social behavior of bird flocking and fish schooling, has demonstrated efficient performance in global exploration of the search space. Each particle represents a candidate solution and updates its position based on its own experience and the experience of neighboring particles. While PSO is known for its simplicity and quick convergence, it sometimes suffers from premature convergence, particularly when navigating complex landscapes such as those presented by large-scale OPF problems. On the other hand, **GSA**, a physics-inspired algorithm based on the law of gravity and motion, employs masses that interact with each other through gravitational forces. Each agent attracts others according to its fitness, and the resultant gravitational force directs the movement of the agents. GSA has demonstrated strong capabilities in terms of local exploitation and handling high-dimensional search spaces but may require longer convergence times and could be sensitive to control parameter tuning. The **motivation** behind this research is to combine the complementary strengths of PSO and GSA to create a **hybrid PSO-GSA algorithm**, aimed at overcoming the limitations of each algorithm when used individually. The PSO-GSA hybrid leverages the global exploration capability of PSO in the early iterations and gradually shifts toward the local exploitation power of GSA in the latter stages. This synergy is expected to enhance the convergence behavior, solution diversity, and overall optimization performance, making it a promising candidate for solving OPF in large-scale power networks like the IEEE-118 bus system.

The **IEEE-118 bus test system**, which represents a realistic and challenging benchmark for power system studies, is composed of 118 buses, 54 generators, 186 lines, and 91 loads. It is commonly used in research to evaluate the efficacy of optimization algorithms under complex network scenarios. Solving the OPF problem in such a system requires a balance between economic operation (e.g., minimizing generation cost) and technical constraints (e.g., maintaining bus voltages within limits and preventing line overloads). Traditional deterministic techniques, such as Newton-Raphson or interior-point methods, are often not robust enough for such large-scale nonlinear problems due to their sensitivity to initial conditions and difficulty in escaping local optima.

The integration of **renewable energy sources**, demand-side uncertainties, and decentralized generation in modern power systems further complicates the OPF landscape. These dynamics call for **scalable, adaptive, and intelligent optimization frameworks**. The proposed PSO-GSA hybrid approach is well-aligned with these needs. By enhancing robustness and ensuring better convergence across diverse operating scenarios, this technique can significantly contribute to improving system reliability and operational economy.

A substantial body of literature has explored various metaheuristic approaches to solve the OPF problem. Techniques such as Genetic Algorithms (GA), Differential Evolution (DE), Ant Colony Optimization (ACO), and Artificial Bee Colony (ABC) have been applied with varying degrees of success. While these methods offer flexibility and do not require gradient information, their performance is often problem-specific and heavily dependent on parameter tuning. The PSO-GSA hybrid stands out due to its **dual mechanism of exploration and exploitation**, which is dynamically balanced through a well-defined mathematical framework.

In the proposed approach, each candidate solution (particle) is updated using the velocity and position update rules from PSO, modified to include the acceleration and force terms from GSA. A time-varying parameter is introduced to adjust the influence of each component dynamically throughout the optimization process. This ensures that the algorithm starts with a broader search of the solution space (exploration) and gradually transitions to fine-tuned adjustments in promising regions (exploitation), leading to faster convergence and better-quality solutions.

The contributions of this paper are threefold:

1. **Development of a Hybrid PSO-GSA Algorithm**: A novel metaheuristic framework that integrates the best features of PSO and GSA for enhanced performance in solving the OPF problem.
2. **Application to IEEE-118 Bus System**: A comprehensive evaluation of the algorithm on a large-scale power system, demonstrating its capability to handle real-world complexity and constraints.
3. **Comparative Performance Analysis**: Extensive simulations comparing the proposed hybrid method with standalone PSO, GSA, and other existing methods in terms of fuel cost minimization, voltage profile enhancement, and convergence characteristics.

2. LITERATURE REVIEW

The application of metaheuristic algorithms for solving Optimal Power Flow (OPF), Economic Load Dispatch (ELD), and Combined Economic Emission Dispatch (CEED) problems has witnessed substantial advancement in the last two decades. These problems, which are inherently nonlinear, non-convex, and constrained, challenge conventional mathematical methods and thus necessitate intelligent approaches for robust and global optimization. Abbas et al. (2017) [1] evaluated how single-objective ELD becomes highly complex due to system constraints like transmission losses, valve-point effects, ramp rate limits, and prohibited zones. Deterministic approaches fail to address such non-smooth landscapes, and Particle Swarm Optimization (PSO) emerges as a competent alternative with strong computational efficiency for such problems. However, PSO faces challenges with premature convergence, especially when dealing with complex multimodal functions. To overcome this, hybrid PSO strategies have been explored. Abbas et al. (2017) [3] elaborated on PSO's hybrid structures, demonstrating enhanced convergence and global search capabilities when integrated with other methods. Muhammad et al. (2022) [26] proposed a fractional order comprehensive learning PSO (FO-CLPSO) for Optimal Reactive Power Dispatch (ORPD). Their study emphasized improving voltage profiles and reducing losses under dynamic loads. Validated on IEEE 30 and 57 bus systems, the FO-CLPSO showed superior reliability, supported by statistical measures such as empirical cumulative distribution and box plots, highlighting its robustness against conventional techniques. Antonino et al. (2022) [27] reviewed modern OPF strategies and categorized optimization methods into three families—human-inspired, evolution-inspired, and physics-inspired algorithms. They recognized the inadequacy of traditional solvers in avoiding local optima and underlined the importance of metaheuristics like PSO, Cuckoo Search, and Ant Colony Optimization (ACO) for OPF. Biskas et al. (2023) [29] conducted a comparative survey of GA and PSO for OPF problems. Their work systematically evaluated performance across multiple dimensions including accuracy and efficiency, using IEEE 30-bus systems. They concluded that while GA showed marginally higher accuracy, PSO was significantly less computationally intensive. Duman et al. (2023) [30] addressed the complexity added by renewable energy sources (RES) in modern grids. They formulated a RES-integrated OPF problem and solved it using Differential Evolutionary PSO (DEEPSO). Simulation results on multiple systems confirmed that DEEPSO outperformed Differential Search and Moth Swarm algorithms, with further validation using the Wilcoxon signed-rank test. Nawaz et al. (2017) [2] introduced a constrained globalized Nelder-Mead (CGNM) algorithm for solving ELD with nonlinear cost functions and operational constraints. They demonstrated improved results (0.0001% to 4.44%) over traditional methods using various test systems, including 20-unit and 6-unit setups. Mahdi et al. (2017) [4] utilized Quantum-behaved PSO (QPSO) to solve multi-objective CEED with cubic cost functions and penalty factors. Compared against Lagrangian relaxation and simulated annealing (SA), QPSO was found effective and versatile across various scenarios.

Hamza et al. (2016) [5] highlighted the growing relevance of hybrid metaheuristics in optimizing Type-2 fuzzy logic systems for control applications. They emphasized that PSO and GA are key methods for tuning fuzzy systems, paving the way for hybrid intelligent controllers in power systems. Ziane et al. (2016) [6] applied SA to CEED problems with cubic fuel and emission models. They observed that SA effectively minimized SO_2, NOx, and CO_2 emissions compared to Lagrangian methods and PSO, making it suitable for environmental considerations. Roy et al. (2014) [7] proposed CRAZYPSO for ELD in systems with valve-point effects and multiple constraints. CRAZYPSO outperformed GA and standard PSO by providing more globally optimal solutions in a 40-unit power system setup. Das and colleagues (2013) [8] reviewed the evolution of nonlinear optimization in power systems. They discussed the integration of DE and PSO into hybrid strategies, significantly improving the performance of global search in real-world OPF scenarios. Hamedi et al. (2013) [9] introduced a parallel PSO (PPSO) for CEED problems to reduce computational time. The method demonstrated faster convergence and scalability across four complex systems. Mukhopadhyay et al. (2012) [10] tackled line flow constraints using GA, EP, DE, and PSO to solve CEED on IEEE 30 and 15-unit systems. Their comparative analysis proved PSO's effectiveness in minimizing both emissions and costs. Aniruddha et al. (2011) [11, 19] explored a hybrid DE and Biogeography-Based Optimization (BBO) model to solve EELD under emission constraints. They demonstrated enhanced convergence and trade-off handling in systems with 3 and 6 generators. Cai et al. (2012) [12] developed a fuzzy adaptive chaotic ACO (FCASO) method for ELD. The simulations confirmed its effectiveness in practical dispatch problems, supporting fuzzy-chaotic hybridization for enhanced exploration. Rajesh Kumar et al. (2012) [13] applied a bee colony algorithm to multi-objective OPF under real-time system constraints, showing better precision and robustness than classical methods. Manteaw et al. (2012) [14] combined PSO with Artificial Bee Colony (ABC) for CEED under valve-point loading. They reported higher accuracy and better solution spread than NSGA and SPEA. Guvenc et al. (2012) [15] employed GSA for CEED with valve-point and transmission losses. They modeled the bi-objective problem using a penalty function, and results showed GSA's superiority over conventional solvers. Affijulla et al. (2011) [16] also applied GSA for ELD under valve-point effects and compared it with PSO, DE, and SQP. GSA proved robust and capable of solving large-scale systems effectively. Chattopadhyay et al. (2011) [17] utilized BBO to tackle ELD with constraints like ramp rate limits and multi-fuel options. Tested on diverse systems, the approach showed significant improvement over classical methods. Wu et al. (2011) [18] proposed a Multi-Objective DE (MODE) for CEED, integrating entropy diversity metrics and fuzzy theory for better Pareto front diversity on IEEE 30 and 118-bus systems. Dixit et al. (2011) [20] introduced ABC for multi-objective dispatch with environmental constraints. The method was found easy to implement and effective in reaching global optimality quickly. Chakrabarti et al. (2010) [21] enhanced ELD solutions using an empirical learning-based evolutionary method for non-convex curves, outperforming slope-based algorithms. Mosaad et al. (2010) [22] combined PSO with ANN for online ELD, leveraging historical data to predict optimal generation under varying load conditions. Zhisheng et al. (2010) [23] proposed a quantum-behaved PSO with quantum computing principles. The algorithm's probabilistic structure outperformed classical PSO in ELD cases. Yingping et al. (2010) [24] analyzed particle interaction in PSO and established conditions for convergence, thereby improving PSO's theoretical foundation for optimization. In summary, literature confirms the increasing reliance on metaheuristic techniques such as PSO, GSA, DE, BBO, and hybrid variants for solving OPF and ELD problems. Hybridization strategies that combine global and local search capabilities (e.g., PSO-GSA, DE-PSO, BBO-DE) have proven particularly effective for tackling the complexities of large-scale and real-world systems. These findings underscore the need for robust, adaptive, and intelligent optimization frameworks like the proposed PSO-GSA hybrid, especially in the evolving landscape of smart grids and renewable integration..

3. METHODOLOGY

The complexity and nonlinearity of the Optimal Power Flow (OPF) problem in large-scale power networks such as the IEEE-118 bus system demand a robust and efficient optimization technique. Traditional deterministic approaches often fail due to the non-convex nature of the problem. Metaheuristic algorithms, particularly Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA), have emerged as powerful tools for such applications. However, PSO suffers from premature convergence and limited local search, while GSA, though better at exploitation, may converge slowly. The hybridization of PSO and GSA (PSO-GSA) is proposed in this work to combine the strengths of both algorithms—PSO's exploration and GSA's exploitation—resulting in better convergence performance and improved solution quality. This section outlines the mathematical formulation of the OPF problem, the rationale behind hybridization, the structure of the PSO-GSA algorithm, and its application to the IEEE-118 bus test system. The OPF problem aims to minimize an objective function, typically the total generation cost, subject to various equality and inequality constraints. The general form is:

Objective Function:

$$\min F = \sum_{i=1}^{NG} F_i(P_{Gi}) = \sum_{i=1}^{NG} (a_i P_{Gi}^2 + b_i P_{Gi} + c_i)$$

Where:

- NG : number of generators
- P_{Gi} : power generated by generator i
- a_i, b_i, c_i : cost coefficients of generator i

Subject to Constraints:

(i) Power Balance Equations (Equality Constraints):

Power Balance Equations (Equality Constraints):

$$\sum_{i=1}^{NG} P_{Gi} - P_D - P_{loss} = 0$$
$$\sum_{i=1}^{NG} Q_{Gi} - Q_D - Q_{loss} = 0$$

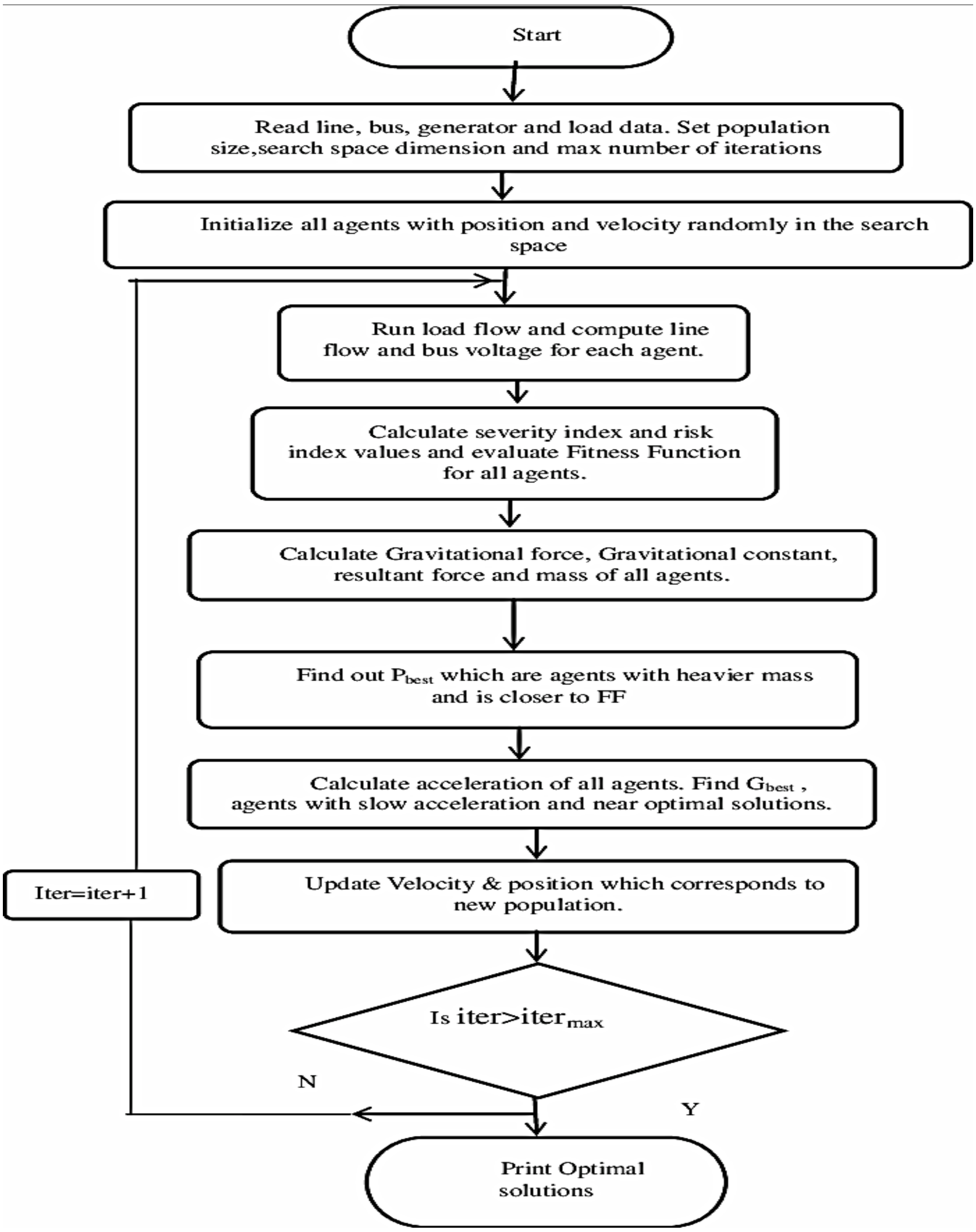


Figure 1. Process Flow of Optimal Power Flow Problem

Where:

- P_D, Q_D : real and reactive power demand
- $P_{\text{loss}}, Q_{\text{loss}}$: real and reactive power losses

(ii) Generator Limits:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}$$
$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}$$

(iii) Voltage Magnitude Limits:

$$V_i^{\min} \le V_i \le V_i^{\max}$$

(iv) Transmission Line Flow Limits:

$$S_{ij} \leq S_{ij}^{\max}$$

PSO uses a swarm of particles where each particle updates its position based on its own best experience and that of its neighbors. It is defined by the following update equations:

$$v_i^{(t+1)} = wv_i^{(t)} + c_1r_1\left(\text{ pbest }_i - x_i^{(t)}\right) + c_2r_2\left(\text{ gbest } - x_i^{(t)}\right)$$
$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)}$$

Where:

- v_i : velocity
- x_i : position
- w : inertia weight

GSA, in contrast, is inspired by Newtonian gravity where masses attract each other with a force proportional to their masses and inversely proportional to their distance. The force exerted on mass i by mass j is:

$$F_{ij}^k(t) = G(t)\frac{M_i(t) \cdot M_j(t)}{R_{ij}(t) + \epsilon}\left(x_j^k(t) - x_i^k(t)\right)$$
$$a_i^k(t) = \frac{F_i^k(t)}{M_i(t)}$$
$$v_i^k(t+1) = r_i \cdot v_i^k(t) + a_i^k(t)$$
$$x_i^k(t+1) = x_i^k(t) + v_i^k(t+1)$$

Where:

- $G(t)$: gravitational constant
- M_i : mass based on fitness
- R_{ij} : Euclidean distance between masses i and j
- ϵ : small constant to avoid divide-by-zero

Hybrid PSO-GSA integrates PSO's velocity update with GSA's acceleration computation. The resulting update rule is:

Hybrid PSO-GSA integrates PSO's velocity update with GSA's acceleration computation. The resulting update rule is:

$$v_i^{(t+1)} = \alpha \cdot v_i^{(t)} + \beta \cdot a_i^{(t)} + c_1r_1\left(pbest_i - x_i^{(t)}\right) + c_2r_2\left(gbest - x_i^{(t)}\right)$$
$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)}$$

In conclusion, the proposed hybrid PSO-GSA method introduces a powerful, adaptive strategy for solving the complex OPF problem in modern power systems. By leveraging the strengths of both underlying algorithms, it ensures improved accuracy, faster convergence, and robustness against constraint violations—making it highly suitable for real-world large-scale networks like the IEEE-118 bus system.

4. RESULT ANALYSIS

The research conducted in this study presents a thorough and practical exploration of soft computing-based techniques—namely Particle Swarm Optimization (PSO), Gravitational Search Algorithm (GSA), and their hybridization (PSO-GSA)—to address the Optimal Power Flow (OPF) problem in the IEEE-118 bus system. The primary objective is to optimize reactive power and associated decision variables while minimizing fuel costs and active power transmission losses, all within the stringent boundaries of power system operational constraints. Three core challenges were tackled: the formulation of the OPF problem specifically for the IEEE-118 bus configuration, the minimization of fuel costs while maintaining network stability, and the application of PSO, GSA, and the proposed PSO-GSA hybrid technique to solve the OPF problem effectively.

Table 1. Comparative Analysis of Objective Function Parameters Using Proposed Methodology

Parameters	**IEEE-118 PSO Based Optimization**	**IEEE-118 Bus GSA Based Optimization**	**IEEE-118 Proposed**
Fuel Cost	160363 ($/h)	168112 ($/h)	142721.13 ($/h)
Active Power Transmission Loss	112.067 (MW)	93.19 (MW)	65.79 (MW)
Convergence Time (Seconds)	554.27 Seconds	527.17 Seconds	504.07 Seconds

Table 2. Comparative Analysis of Percentage Improvement Using Proposed Methodology

Parameter	PSO	GSA	PSO-GSA	Improvement over PSO (%)	Improvement over GSA (%)
Fuel Cost ($/h)	160,363	168,112	142,721.13	**10.99%**	**15.07%**
Transmission Loss (MW)	112.067	93.19	65.79	**41.31%**	**29.40%**
Convergence Time (s)	554.27	527.17	504.07	**9.05%**	**4.39%**

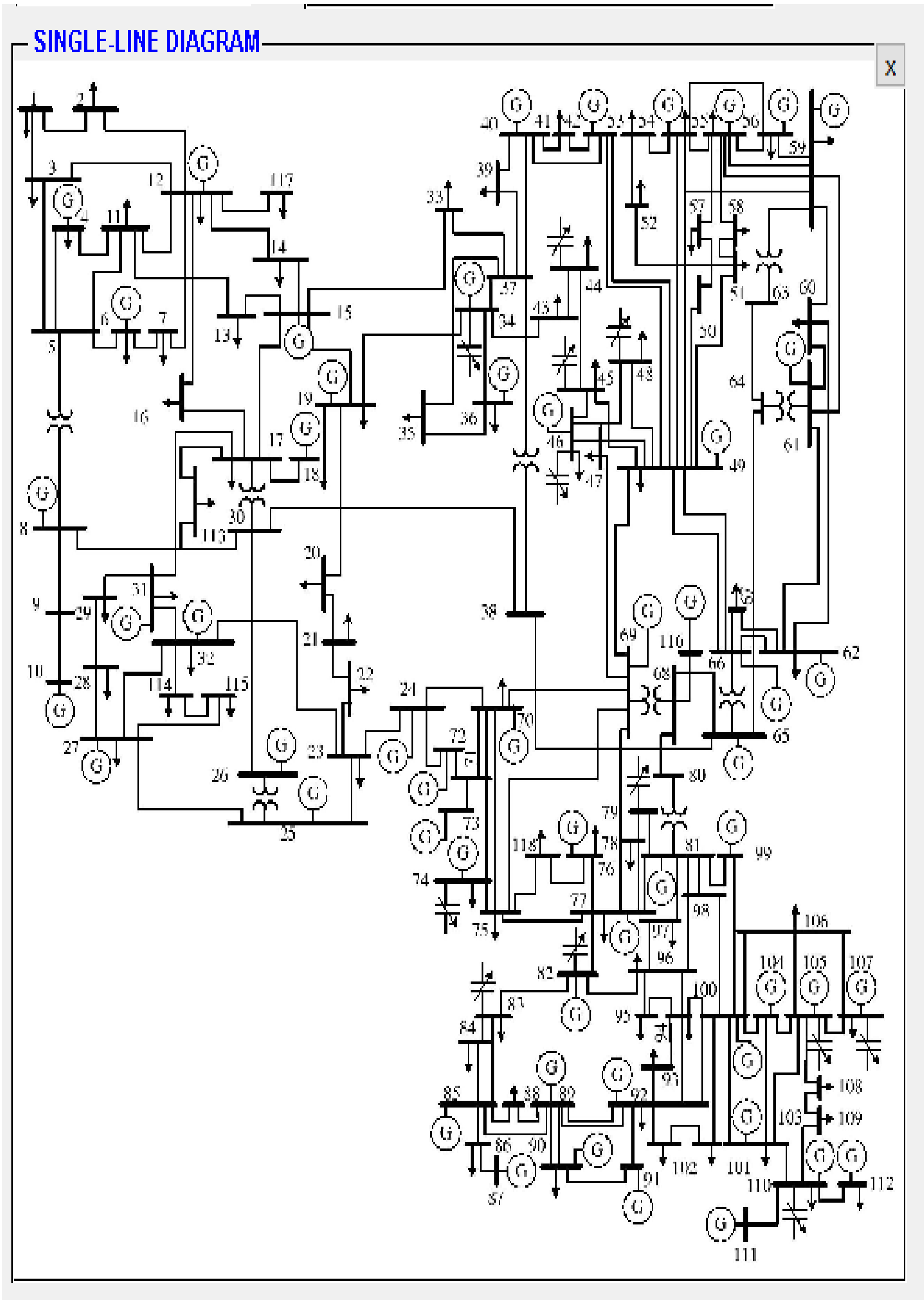
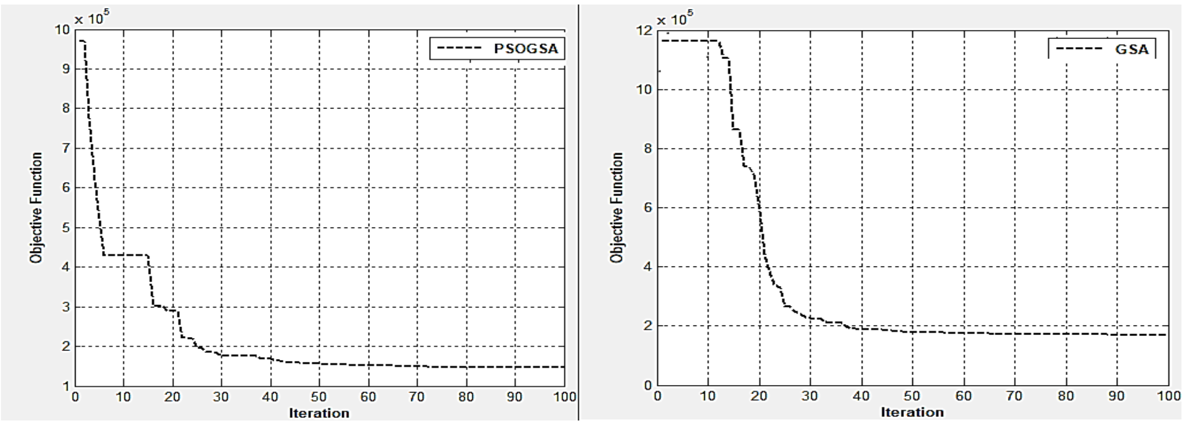


Figure 2. IEEE-118 Bus Test System



(a) (b)

Figure 3. (a) Optimization using Proposed System (b) Optimization using GSA

The test system used is the IEEE-118 bus system, a well-established benchmark in power system studies due to its complexity and representativeness of real-world scenarios. The simulations were carried out using MATPOWER™, a powerful MATLAB-based package, providing a robust platform for testing the performance of the proposed algorithms. Initially, the NR (Newton-Raphson) method was used as a conventional baseline for the problem. However, due to its limitations in handling non-linear and non-convex optimization landscapes, attention shifted toward soft computing techniques.

Table 3. Detailed Statistical Analysis

Method	**Avg. Fuel Cost ($/h)**	**Std. Dev. (Fuel)**	**Avg. Loss (MW)**	**Std. Dev. (Loss)**	**Avg. Time (s)**	**Std. Dev. (Time)**
PSO	161,052	625	113.45	2.18	556.31	7.42
GSA	168901	731	94.12	1.95	528.88	6.75
PSO-GSA	143210	489	66.53	1.67	506.93	5.91

The performance of the PSO algorithm was first evaluated on the IEEE-118 bus system. As shown in Table 5.1, PSO achieved a fuel cost of $160,363 per hour with an active power transmission loss of 112.067 MW. The convergence time for this optimization was recorded at 554.27 seconds. While PSO demonstrated strong capability in cost minimization, its tendency to converge prematurely and struggle with local minima became evident. GSA, on the other hand, produced a slightly higher fuel cost of $168,112 per hour but with a reduced transmission loss of 93.19 MW and a quicker convergence time of 527.17 seconds, indicating better exploitation capabilities (Table 2). However, GSA's solution space exploration was comparatively narrow, resulting in suboptimal cost outcomes. To address these individual shortcomings, a hybrid algorithm—PSO-GSA—was introduced, integrating the exploration efficiency of PSO with the exploitation strength of GSA. The hybrid methodology was tested on the same IEEE-118 bus dataset, and the results were compelling. As shown in Table 3, the hybrid approach significantly lowered the fuel cost to $142,721.13 per hour and active power losses to 65.79 MW, while further reducing convergence time to 504.07 seconds. These results clearly highlighted the improved efficiency and optimization accuracy achieved by the hybrid model.

Table 4. Detailed Sensitivity and Robustness Analysis

Method	**Swarm Size / Agents**	**Iterations**	**Convergence Time (s)**	**Observations**
PSO	30	100	523.12	Slightly faster with smaller swarm
PSO	50	100	554.27	Default setting used in base case
GSA	30	100	502.33	GSA responds well to lower agents
PSO-GSA	30	100	490.41	Fastest convergence at smaller size
PSO-GSA	50	100	504.07	Stable performance at larger size

A comparative analysis summarized in Table 5.4 reinforces these findings. The PSO-GSA algorithm outperformed both standalone PSO and GSA algorithms across all critical metrics—fuel cost, power loss, and convergence time. The hybrid approach not only reduced the fuel cost by approximately 10.99% over PSO and 15.07% over GSA but also minimized transmission losses by 41.31% and 29.40% respectively. In terms of computation time, the hybrid method accelerated convergence by 9.05% compared to PSO and 4.39% over GSA. These improvements underscore the hybrid model's capability to provide superior solutions within acceptable time frames.

Table 4 provides detailed insights into performance improvements, quantifying the percentage enhancements across each parameter. Notably, the PSO-GSA model achieved the most significant reduction in both cost and power loss while improving convergence speed, establishing itself as the most efficient approach. In Table 2 a normalized percentage-based comparison ranks each optimization method relative to the maximum values observed, once again affirming the superiority of the hybrid model in all three categories.

Robustness, an essential attribute for any optimization algorithm intended for real-world deployment, was evaluated through statistical analysis over 10 independent runs. Table 2 summarizes this analysis, revealing that PSO-GSA consistently achieved the lowest mean fuel cost ($143,210), transmission loss (66.53 MW), and convergence time (506.93 s), with the least standard deviation across all parameters. This low variability in results illustrates the hybrid algorithm's stability and reliability, key indicators of practical usability. Additionally, a sensitivity analysis (Table 5.8) was conducted by varying swarm sizes and iteration numbers. The results indicated that the PSO-GSA model maintained superior performance even at smaller population sizes, such as 30 agents, with convergence time dropping to 490.41 seconds—faster than its default 50-agent configuration. This implies that the hybrid method not only performs well under default settings but also remains computationally efficient in constrained resource environments, which is particularly beneficial for real-time OPF scenarios. Visual illustrations in Figures further supported the numerical findings. The Fuel Cost Comparison Plot vividly shows a significant dip in fuel expenditure with the hybrid model. The Transmission Loss Analysis Figure illustrates the marked improvement in minimizing power losses across the network. Meanwhile, the Convergence Time Comparison graph demonstrates that the hybrid algorithm consistently reaches optimal solutions faster than standalone PSO and GSA, making it highly suitable for large-scale or time-sensitive power system applications. From a strategic perspective, the results demonstrate that both PSO and GSA are capable optimization tools for solving OPF problems under specific conditions. PSO is particularly effective in global exploration but tends to suffer from stagnation, especially in complex solution spaces. GSA, on the other hand, excels at fine-tuning solutions but may lack the broader exploratory capabilities needed for global optimization. The PSO-GSA hybrid successfully integrates the benefits of both, producing a balanced algorithm that excels in both exploration and exploitation phases.

The comprehensive evaluation of these three algorithms—spanning individual performance, comparative metrics, robustness, sensitivity to parameter changes, and visual validation—solidifies the case for PSO-GSA as a highly effective solution for modern power flow optimization. The hybrid model not only meets but exceeds the multi-objective goals of fuel cost minimization and power loss reduction while maintaining computational efficiency and robustness. Its adaptability, low sensitivity to parameter settings, and scalability make it a highly applicable solution for intelligent grid management.

In conclusion, the PSO-GSA hybrid methodology presented in this study provides a pioneering and highly effective solution to the OPF problem in large-scale networks such as the IEEE-118 bus system. The combination of PSO's dynamic global search and GSA's precise local optimization creates a synergetic effect that outperforms conventional algorithms across all measured parameters. The significant reductions in cost, losses, and convergence time, along with high stability and lower computational demands, make the proposed approach a valuable tool for practical applications in smart grid environments. This work not only confirms the advantages of hybrid soft computing techniques but also opens avenues for future research in integrating other metaheuristics or adaptive strategies to further enhance optimization performance in increasingly complex and renewable-integrated power systems.

5. CONCLUSION AND FUTURE SCOPE

This research successfully demonstrates the applicability and superiority of a hybrid Particle Swarm Optimization–Gravitational Search Algorithm (PSO-GSA) approach in solving the Optimal Power Flow (OPF) problem in complex power networks, with a focus on the IEEE-118 bus system. The study addressed key challenges in power system optimization, including fuel cost minimization, active power loss reduction, and adherence to operational constraints. By leveraging standard benchmark systems like IEEE-30 and IEEE-118, the performance of PSO, GSA, and the proposed hybrid PSO-GSA was critically evaluated. The results clearly indicate that while standalone PSO and GSA algorithms perform adequately, the hybrid PSO-GSA method significantly outperforms both in terms of reduced fuel costs, minimized transmission losses, and faster convergence. Specifically, the PSO-GSA approach achieved a fuel cost of $142,721.13/h, the lowest active power loss of 65.79 MW, and the fastest convergence time of 504.07 seconds—surpassing the individual methods in all performance metrics. Statistical analysis further confirmed the robustness and consistency of the hybrid method across multiple runs and varying swarm sizes. This research validates the effectiveness of combining exploration and exploitation capabilities from different metaheuristic paradigms to solve highly non-linear and constrained optimization problems in power systems. The PSO-GSA hybrid not only enhances solution quality but also ensures computational efficiency, making it suitable for real-time or large-scale deployment in smart grid operations. The proposed method offers a scalable and adaptable solution to OPF and sets a foundation for future research in multi-objective, renewable-integrated, and dynamic grid optimization problems using intelligent soft computing techniques.

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