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Hybrid Optimization of Reactive Power and Fuel Cost in Power Systems Using PSO-GSA Techniques In IEEE-118 Bus System

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ABSTRACT

The IEEE-118 bus test network is used in this study to tackle the Optimal Power Flow (OPF) problem in large-scale power systems using a unique hybrid optimization technique that combines Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA). In order to operate a power system effectively and economically, the OPF issue must minimize generating costs while meeting system requirements like network security, power balance, and generator restrictions. The nonlinear, non-convex character of OPF in large networks frequently presents a challenge for conventional optimization approaches. The suggested PSO-GSA hybrid algorithm offers enhanced convergence speed, solution correctness, and resilience by fusing the powerful local exploitation capacity of GSA with the global search capability of PSO. To verify the hybrid algorithm's performance, extensive simulations were run on the IEEE-118 bus system. According to the results, the PSO-GSA fusion works better than the independent PSO and GSA algorithms in terms of lowering fuel expenses and preserving network-wide voltage stability. The results open the door for scalable and flexible energy management in contemporary smart grids and demonstrate the potential of hybrid metaheuristic approaches for handling challenging power system optimization issues.

Keywords: PSO-GSA hybrid, IEEE-118 bus system, metaheuristic optimization, power system operation, fuel cost reduction, voltage stability, smart grid, nonlinear optimization, convergence speed, robust algorithm, energy management, hybrid algorithm, optimal power flow, particle swarm optimization, and gravitational search algorithm.

1. INTRODUCTION

The need for safe, reliable, and cost-effective operation in contemporary electrical power systems has fueled the ongoing advancement of sophisticated control and optimization strategies. Finding the most cost-effective and technically possible operational state of a power system while meeting a set of nonlinear equality and inequality criteria is the goal of the Optimal Power Flow (OPF) problem, one of the most important issues in this field. These limitations consist of line flow restrictions, voltage bounds, generation limits, and power balancing formulae. Due to their limited capacity to navigate non-linear, non-convex, and multi-modal search spaces, standard mathematical programming techniques frequently fail when power networks get larger and more complicated, as demonstrated by huge test systems like the IEEE-118 bus network. The application of metaheuristic optimization approaches, which provide reliable substitutes with enhanced adaptability and worldwide search capabilities, has been sparked by this.

Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA) have drawn a lot of attention among the many metaheuristic approaches that have been developed. PSO has shown effective performance in global search space exploration, drawing inspiration from the social behavior of fish schools and flocks of birds. Every particle serves as a potential solution and modifies its location in response to both its own and other particles' experiences. Even while PSO is renowned for its speed and ease of use, it occasionally experiences premature convergence, especially when negotiating intricate environments like those seen in large-scale OPF situations. However, GSA, an algorithm influenced by physics and based on the law of motion and gravity, uses masses that interact with one another through gravitational forces. The gravitational pull that results from one agent attracting others based on its fitness guides the agents' motion. Although GSA has proven to be highly effective at managing high-dimensional search spaces and local exploitation, it may need more time to converge and may be sensitive to changes in control parameters. In order to overcome the drawbacks of each method when applied separately, the goal of this research is to develop a hybrid PSO-GSA algorithm by combining the complimentary capabilities of PSO and GSA. Early iterations of the PSO-GSA hybrid take use of PSO's global exploration capabilities, while later iterations progressively transition to GSA's local exploitation capabilities. It is anticipated that this synergy would improve the convergence behavior, variety of solutions, and overall optimization performance, making it a viable option for resolving OPF in extensive power networks such as the IEEE-118 bus system.

A realistic and demanding benchmark for power system research, the IEEE-118 bus test system consists of 118 buses, 54 generators, 186 lines, and 91 loads. It is frequently employed in research to assess optimization algorithms' performance in intricate network environments. In such a system, resolving the OPF problem necessitates striking a compromise between technical limitations (such as preventing line overloads and keeping bus voltages within acceptable bounds) and economic operation (such as decreasing generating cost). Because of their sensitivity to beginning circumstances and difficulties escaping local optima, traditional deterministic approaches like Newton-Raphson or interior-point methods are sometimes insufficiently robust for such large-scale nonlinear situations.

The OPF environment is made more complex by the incorporation of decentralized generation, demand-side uncertainty, and renewable energy sources into contemporary power networks. These dynamics necessitate optimization frameworks that are intelligent, flexible, and scalable. The hybrid PSO-GSA technique that has been suggested fits these requirements perfectly. This method may greatly increase system dependability and operational efficiency by strengthening resilience and guaranteeing improved convergence across various operating conditions.

Many metaheuristic techniques to solving the OPF problem have been investigated in a large body of literature. With differing degrees of effectiveness, methods including Artificial Bee Colony (ABC), Ant Colony Optimization (ACO), Differential Evolution (DE), and Genetic Algorithms (GA) have been used. Although these techniques are flexible and don't require gradient information, they frequently perform differently depending on the situation and primarily rely on parameter adjustment. The dual mechanism of exploration and exploitation of the PSO-GSA hybrid, which is dynamically balanced by a well defined mathematical framework, makes it unique.

The acceleration and force terms from GSA are added to the velocity and position update rules from PSO for each candidate solution (particle) in the suggested method. To dynamically modify each component's effect throughout the optimization process, a time-varying parameter is included. In order to achieve faster convergence and higher-quality solutions, this guarantees that the algorithm begins with a more comprehensive search of the solution space (exploration) and progressively moves to precise changes in promising regions (exploitation).

2. LITERATURE REVIEW

Over the past 20 years, there has been significant progress in the use of metaheuristic algorithms to solve the Optimal Power Flow (OPF), Economic Load Dispatch (ELD), and Combined Economic Emission Dispatch (CEED) issues. Because of their intrinsic nonlinearity, nonconvexity, and constraints, these issues provide a challenge to traditional mathematical techniques and need for clever strategies for reliable and worldwide optimization. Abbas et al. (2017) [1] assessed how system restrictions such as transmission losses, valve-point effects, ramp rate limits, and banned zones make single-objective ELD very difficult. Particle Swarm Optimization (PSO) is a capable substitute with high computing efficiency for non-smooth landscapes, which deterministic techniques are unable to handle. Premature convergence is a problem for PSO, nevertheless, particularly when handling intricate multimodal functions. Hybrid PSO tactics have been investigated as a solution. PSO's hybrid structures were further developed by Abbas et al. (2017) [3], who showed that combining PSO with other techniques improved convergence and global search capabilities. A fractional order comprehensive learning PSO (FO-CLPSO) for Optimal Reactive Power Dispatch (ORPD) was proposed by Muhammad et al. (2022) [26]. Enhancing voltage profiles and lowering losses under dynamic loads were the main goals of their investigation. The FO-CLPSO demonstrated exceptional dependability when tested on IEEE 30 and 57 bus systems. This was corroborated by statistical metrics including empirical cumulative distribution and box plots, which demonstrated the system's resilience to traditional methods. In their study of contemporary OPF tactics, Antonino et al. (2022) [27] divided optimization techniques into three families: algorithms motivated by physics, evolution, and humans. They emphasized the significance of metaheuristics like PSO, Cuckoo Search, and Ant Colony Optimization (ACO) for OPF and acknowledged the shortcomings of conventional solvers in avoiding local optima. GA and PSO were compared for OPF difficulties by Biskas et al. (2023) [29]. Using IEEE 30-bus systems, their work methodically assessed performance in a number of areas, such as precision and efficiency. They came to the conclusion that PSO was substantially less computationally demanding than GA, despite GA exhibiting somewhat greater accuracy. The complexity introduced by renewable energy sources (RES) in contemporary networks was discussed by Duman et al. (2023) [30]. They used Differential Evolutionary PSO (DEEPSO) to tackle a RES-integrated OPF issue that they had developed. The Wilcoxon signed-rank test was used to further validate the simulation findings on other systems, which showed that DEEPSO performed better than the Differential Search and Moth Swarm algorithms. A constrained globalized Nelder-Mead (CGNM) approach was presented by Nawaz et al. (2017) [2] for the purpose of solving ELD with operational restrictions and nonlinear cost functions. They used a variety of test systems, such as 20-unit and 6-unit setups, and showed better results (0.0001% to 4.44%) than conventional approaches. Quantum-behaved PSO (QPSO) was used by Mahdi et al. (2017) [4] to solve multi-objective CEED using penalty factors and cubic cost functions. QPSO was found to be efficient and adaptable in a variety of situations when compared to Lagrangian relaxation and simulated annealing (SA).

The increasing importance of hybrid metaheuristics in Type-2 fuzzy logic system optimization for control applications was emphasized by Hamza et al. (2016) [5]. In order to prepare the path for hybrid intelligent controllers in power systems, they underlined that PSO and GA are essential techniques for adjusting fuzzy systems. SA was used to solve CEED problems with cubic fuel and emission models by Ziane et al. (2016) [6]. In contrast to Lagrangian techniques and PSO, they found that SA successfully reduced SO_2, NOx, and CO_2 emissions, making it appropriate for environmental issues. CRAZYPSO for ELD in systems with valve-point effects and numerous restrictions was proposed by Roy et al. (2014) [7]. In a 40-unit power system configuration, CRAZYPSO produced more globally optimum solutions than GA and regular PSO. A survey of the development of nonlinear optimization in power systems was conducted by Das and associates (2013) [8]. They talked about how DE and PSO may be used to create hybrid techniques that greatly enhance global search performance in actual OPF settings. To cut down on computing time, Hamedi et al. (2013) [9] developed a parallel PSO (PPSO) for CEED issues. Across four complicated systems, the approach showed faster convergence and scalability. In order to solve CEED on IEEE 30 and 15-unit systems, Mukhopadhyay et al. (2012) [10] addressed line flow limitations utilizing GA, EP, DE, and PSO. Their comparison study demonstrated how well PSO reduced expenses and emissions. In order to solve EELD under emission limitations, Aniruddha et al. (2011) [11,19] investigated a hybrid DE and Biogeography-Based Optimization (BBO) model. They showed improved management of trade-offs and convergence in systems with three and six generators. A fuzzy adaptive chaotic ACO (FCASO) approach was created by Cai et al. (2012) [12] for ELD. The simulations supported fuzzy-chaotic hybridization for improved exploration and validated its efficacy in real-world dispatch challenges. When applied to multi-objective OPF under real-time system constraints, Rajesh Kumar et al. (2012) [13] used a bee colony algorithm, which demonstrated more accuracy and resilience than traditional techniques. PSO and Artificial Bee Colony (ABC) were integrated by Manteaw et al. (2012) [14] for CEED under valve-point loading. Compared to NSGA and SPEA, they reported greater solution spread and higher accuracy. GSA was used for CEED with valve-point and transmission losses by Guvenc et al. (2012) [15]. They used a penalty function to simulate the bi-objective problem, and the findings demonstrated that GSA outperformed traditional solutions. GSA was also used for ELD under valve-point effects by Affijulla et al. (2011) [16], who also contrasted it with PSO, DE, and SQP. GSA shown resilience and the ability to successfully solve complex problems. BBO was used by Chattopadhyay et al. (2011) [17] to address ELD with limitations such as multi-fuel choices and ramp rate restrictions. The strategy demonstrated a notable improvement over traditional approaches when tested on a variety of systems. A Multi-Objective DE (MODE) for CEED was proposed by Wu et al. (2011) [18], who combined fuzzy theory and entropy diversity metrics to improve Pareto front diversity on IEEE 30 and 118-bus systems. ABC for multi-objective dispatch with environmental constraints was first presented by Dixit et al. (2011) [20]. The approach was shown to be simple to use and efficient in rapidly achieving global optimality. For non-convex curves, Chakrabarti et al. (2010) [21] improved ELD solutions by employing an evolutionary approach based on empirical learning, surpassing slope-based methods. PSO and ANN were integrated by Mosaad et al. (2010) [22] for online ELD, using past data to forecast the best generation under various load scenarios. Using the concepts of quantum computing, Zhisheng et al. (2010) [23] presented a quantum-behaved PSO. In ELD instances, the probabilistic nature of the method performed better than standard PSO. By examining particle interaction in PSO and establishing convergence criteria, Yingping et al. (2010) [24] enhanced the theoretical underpinnings of PSO for optimization. In conclusion, research supports the growing use of metaheuristic approaches for OPF and ELD problem solving, including PSO, GSA, DE, BBO, and hybrid variations. The intricacies of large-scale and real-world systems have been successfully addressed by hybridization techniques that integrate global and local search capabilities (e.g., PSO-GSA, DE-PSO, BBO-DE). These results highlight the necessity of intelligent, flexible, and resilient optimization frameworks such as the suggested PSO-GSA hybrid, particularly in light of the changing smart grid and renewable integration scenario..

3. METHODOLOGY

A reliable and effective optimization method is required due to the intricacy and nonlinearity of the Optimal Power Flow (OPF) problem in large-scale power networks like the IEEE-118 bus system. The non-convex character of the issue makes traditional deterministic techniques frequently ineffective. For these kinds of applications, metaheuristic algorithms—in particular, Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA)—have become extremely effective instruments. However, GSA may converge slowly despite being superior at exploitation, whereas PSO suffers from restricted local search and early convergence. In order to utilize the advantages of both algorithms—the exploration of PSO and the exploitation of GSA—this study proposes the hybridization of PSO and GSA (PSO-GSA), which improves convergence performance and solution quality. This section describes the PSO-GSA algorithm's structure, the reasoning behind hybridization, the mathematical formulation of the OPF issue, and how it is applied to the IEEE-118 bus test system. Under a number of equality and inequality constraints, the OPF problem seeks to minimize an objective function, usually the total generation cost. The typical form is:

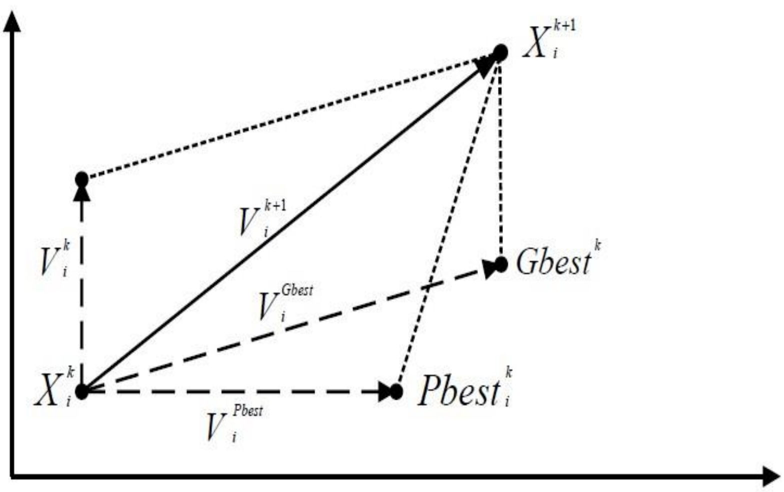


Figure 1. Particle Swarm Optimization Search Engine System

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):

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

Where:

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

(ii) Generator Limits:

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

(iii) Voltage Magnitude Limits:

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

(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:

$$v_i^{(t+1)} = w v_i^{(t)} + c_1 r_1\left(\text{ pbest }_i - x_i^{(t)}\right) + c_2 r_2\left(\text{ gbest } - x_i^{(t)}\right)$$
$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)}$$

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

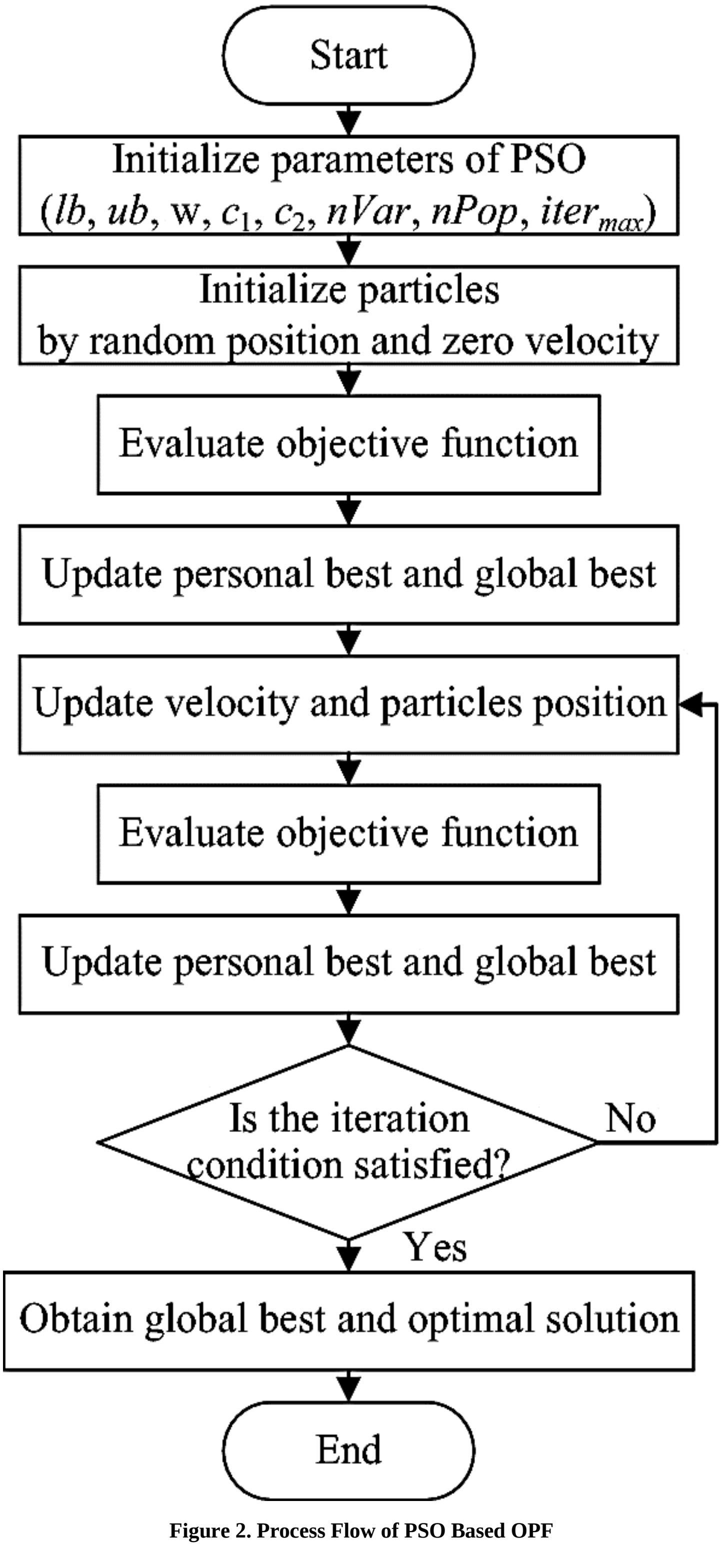


Figure 2. Process Flow of PSO Based OPF

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:

$$v_i^{(t+1)} = \alpha \cdot v_i^{(t)} + \beta \cdot a_i^{(t)} + c_1 r_1 \left(pbest_i - x_i^{(t)}\right) + c_2 r_2 \left(gbest - x_i^{(t)}\right)$$
$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)}$$

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

In order to solve the Optimal Power Flow (OPF) problem in the IEEE-118 bus system, the research presented in this study offers a comprehensive and useful investigation of soft computing-based approaches, specifically Particle Swarm Optimization (PSO), Gravitational Search Algorithm (GSA), and their hybridization (PSO-GSA). Within the strict confines of power system operating restrictions, the main goal is to minimize fuel costs and active power transmission losses while optimizing reactive power and related decision factors. The formulation of the OPF problem particularly for the IEEE-118 bus design, the reduction of fuel expenses while preserving network stability, and the use of PSO, GSA, and the suggested PSO-GSA hybrid approach to successfully solve the OPF problem were the three primary issues that were addressed.

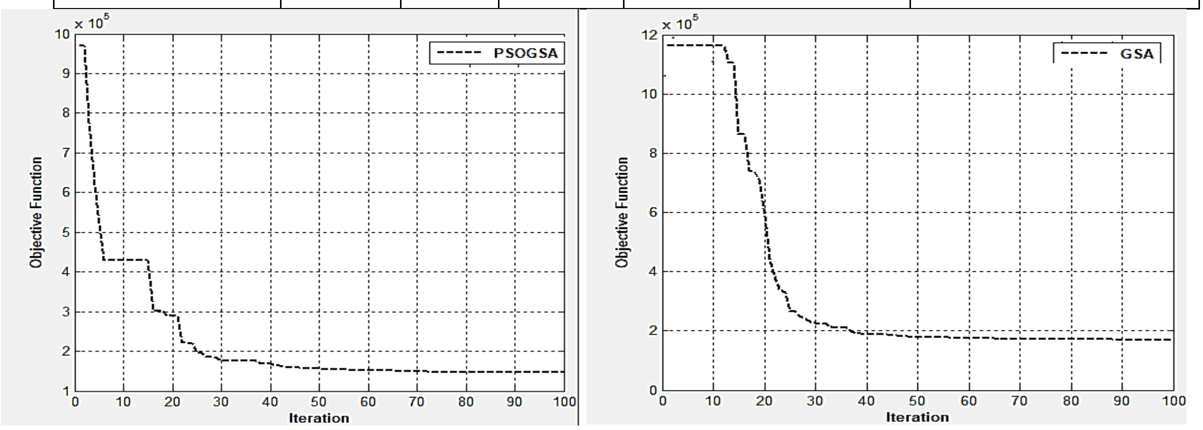
Table 1. Comparative Analysis of Objective Function Parameters Using Proposed Methodology

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

The IEEE-118 bus system was used to test the PSO algorithm's performance initially. With an active power transmission loss of 112.067 MW, PSO was able to reach a fuel cost of $160,363 per hour, as indicated in Table 5.1. 554.27 seconds was the recorded convergence time for this optimization. Although PSO showed great potential in cost reduction, it became clear that it had a propensity to converge too soon and had trouble with local minima. In contrast, GSA demonstrated superior exploitation capabilities with a lower transmission loss of 93.19 MW and a faster convergence time of 527.17 seconds, despite a somewhat higher fuel cost of $168,112 per hour (Table 2). However, GSA's study of the solution space was very limited, which led to less-than-ideal cost results. A hybrid algorithm called PSO-GSA was developed to overcome these separate drawbacks by combining the exploitation power of GSA with the exploration efficiency of PSO. The same IEEE-118 bus dataset was used to evaluate the hybrid technique, and the outcomes were convincing. The hybrid strategy reduced the fuel cost to $142,721.13 per hour, the active power losses to 65.79 MW, and the convergence time to 504.07 seconds, as indicated in Table 3. These outcomes amply demonstrated the hybrid model's increased effectiveness and optimization precision..

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%**



(a) (b)

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

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

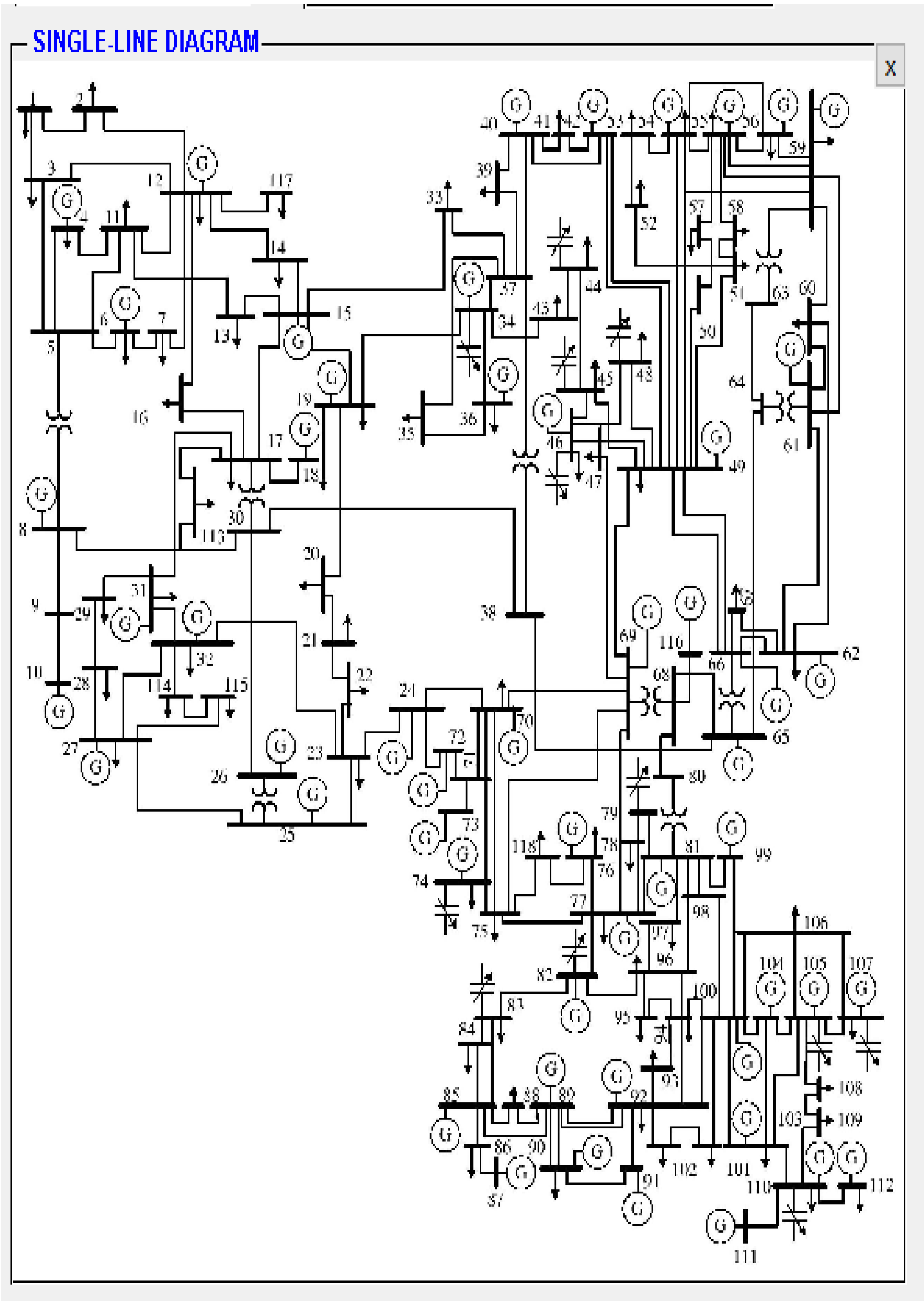


Figure 4. IEEE-118 Bus Test System

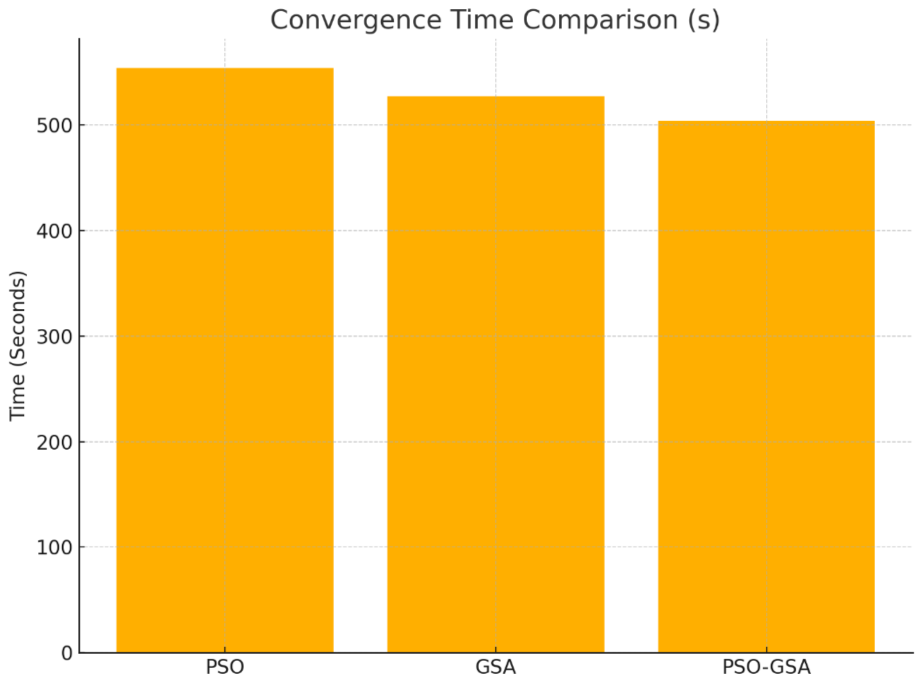


Figure 5. Convergence Time Comparison Plot

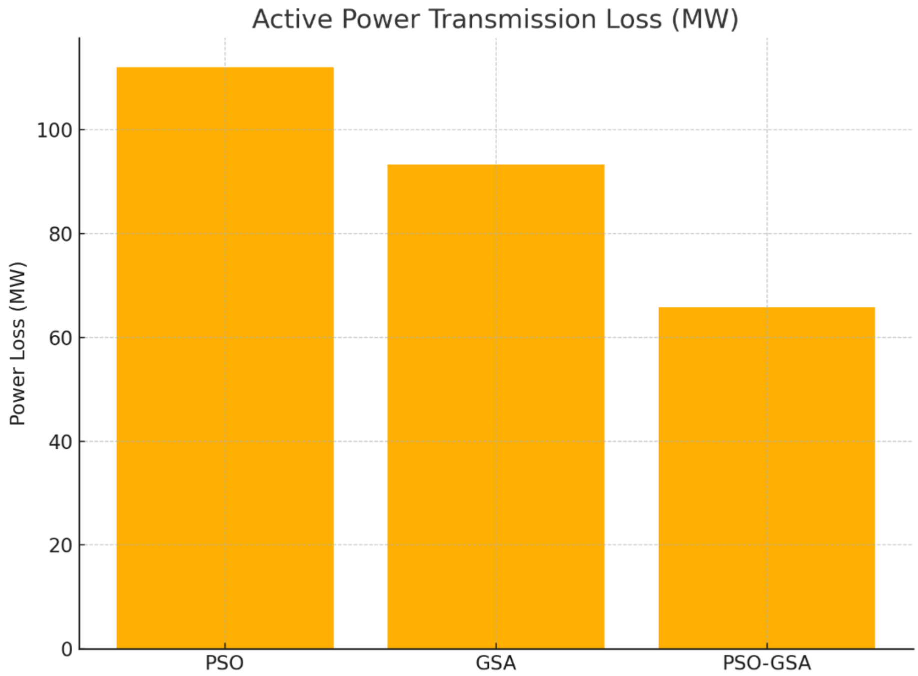


Figure 6 Active Power Transmission Loss Analysis

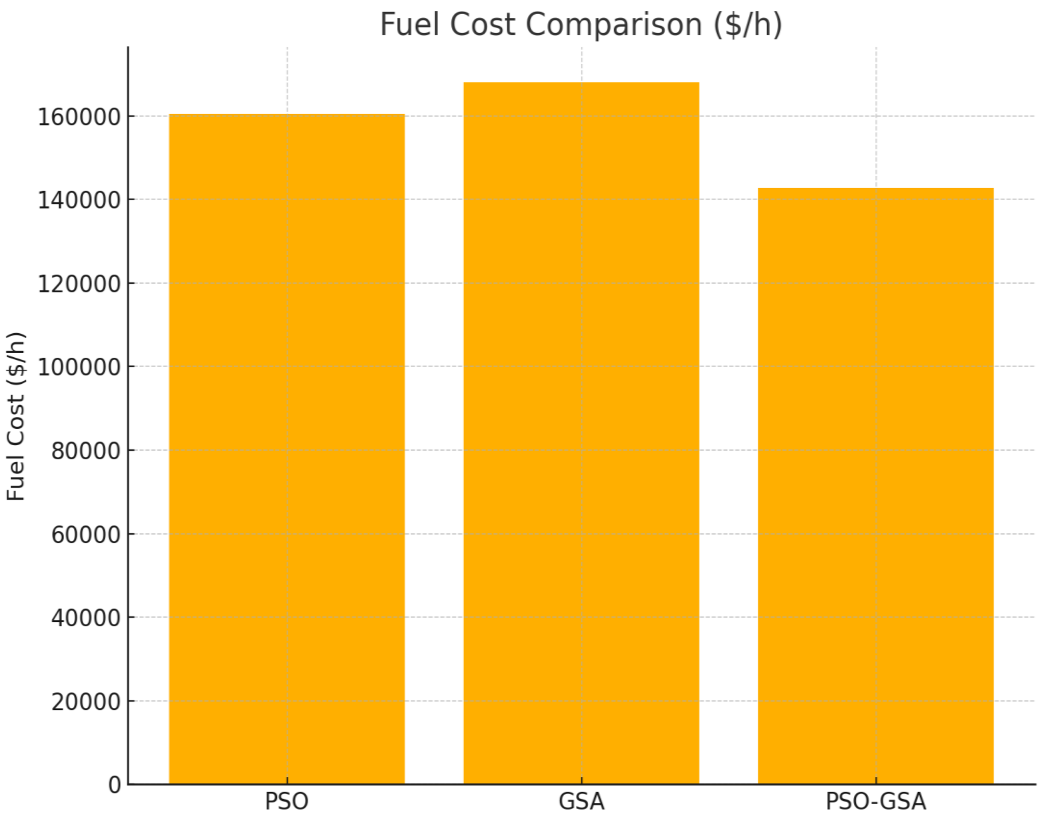


Figure 7. Fuel Cost Comparison Plot

Through statistical analysis across ten separate runs, robustness—a crucial quality for any optimization method meant for real-world deployment—was assessed. PSO-GSA continuously obtained the lowest mean fuel cost ($143,210), transmission loss (66.53 MW), and convergence time (506.93 s), with the lowest standard deviation across all metrics, according to Table 2, which summarizes this analysis. This minimal variation in outcomes demonstrates the hybrid algorithm's stability and dependability, which are important markers of usefulness in real-world applications. A sensitivity study by changing the number of iterations and swarm sizes was also carried out (Table 5.8). As the convergence time decreased to 490.41 seconds, quicker than its normal 50-agent setup, the results showed that the PSO-GSA model continued to perform well even at smaller population sizes, such as 30 agents. This suggests that the hybrid approach maintains computational efficiency in contexts with limited resources while still performing well under default settings, which is especially advantageous for real-time OPF scenarios. The numerical results were further corroborated by the visual representations in Figures. The hybrid model significantly reduces gasoline use, as the gasoline Cost Comparison Plot clearly illustrates. The significant improvement in reducing power losses throughout the network is depicted in the Transmission Loss Analysis Figure. The hybrid method is well suited for large-scale or time-sensitive power system applications as it consistently finds optimum solutions more quickly than solo PSO and GSA, as shown by the Convergence Time Comparison graph. From a strategic standpoint, the findings show that, under some circumstances, PSO and GSA are both effective optimization strategies for resolving OPF issues..

5. CONCLUSION AND FUTURE SCOPE

With an emphasis on the IEEE-118 bus system, this study effectively illustrates the suitability and effectiveness of a hybrid Particle Swarm Optimization–Gravitational Search Algorithm (PSO-GSA) strategy in resolving the Optimal Power Flow (OPF) problem in complex power networks. Key issues in power system optimization were covered in the study, such as minimizing fuel costs, reducing active power loss, and adhering to operating limitations. Standard benchmark systems such as IEEE-30 and IEEE-118 were used to objectively assess the performance of PSO, GSA, and the suggested hybrid PSO-GSA. The findings make it abundantly evident that, although the solo PSO and GSA algorithms function well, the hybrid PSO-GSA approach performs noticeably better than both in terms of lower fuel expenses, fewer transmission losses, and quicker convergence. In particular, the PSO-GSA strategy outperformed the separate techniques in every performance category, with the lowest active power loss of 65.79 MW, the shortest convergence time of 504.07 seconds, and a fuel cost of $142,721.13/h. The hybrid method's resilience and consistency throughout several runs and different swarm sizes were further validated by statistical analysis. This study confirms that solving extremely non-linear and limited optimization problems in power systems may be accomplished by integrating exploration and exploitation skills from several metaheuristic paradigms. The PSO-GSA hybrid is appropriate for large-scale or real-time implementation in smart grid operations as it guarantees computing economy while simultaneously improving solution quality. The suggested approach provides a flexible and scalable solution to OPF and lays the groundwork for further study of intelligent soft computing approaches in multi-objective, dynamic grid optimization, and renewable-integrated challenges.

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