

Article

An Intelligent HGAPSO-Based Framework for Transmission Loss Minimization in the Power System

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Abstract

Transmission power losses significantly affect the efficiency, reliability, and economic operation of modern electrical power systems. This study proposes a Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) framework for transmission loss minimization in the IEEE 118-bus power system. The proposed approach combines the global exploration capability of Genetic Algorithms (GAs) with the rapid convergence characteristics of Particle Swarm Optimization (PSO) to optimize generator voltage settings, transformer tap positions, and reactive power compensation while satisfying all operational constraints. The HGAPSO framework was developed and implemented in MATLAB R2024a and evaluated using the IEEE 118-bus test system. The simulation results demonstrate that the proposed method reduced transmission losses from 132.8 MW under the base-case condition to 98.6 MW, representing a 25.75% reduction in total network losses. In addition, the optimized operating conditions improved the minimum bus voltage from 0.914 p.u. to 0.972 p.u., while the average voltage deviation decreased from 0.062 p.u. to 0.019 p.u. These voltage profile improvements were achieved as secondary benefits of the transmission loss minimization process and the enforcement of system operating constraints. Furthermore, the HGAPSO algorithm exhibited superior convergence performance, reaching the optimal solution within 82 iterations compared to 185 iterations for GA and 124 iterations for PSO. The results confirm that the proposed HGAPSO framework provides effective transmission loss reduction, faster convergence, and reliable network operation compared with standalone optimization techniques. The proposed methodology offers a robust and computationally efficient solution for large-scale power system optimization, optimal power flow studies, and smart grid applications.

Keywords: HGAPSO; transmission loss minimization; optimal power flow; power system optimization; smart grid; energy management

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1. Introduction

The electrical power grid forms the backbone of modern economic and social development by supplying energy to residential, commercial, industrial, and transportation sectors [1]. As global electricity consumption continues to rise, power systems are required to accommodate increasing demand while maintaining high levels of reliability, efficiency, and operational security. The rapid growth of urban populations, industrial activities, and electrified transportation has further intensified the need for effective power system management [2]. At the same time, the transition toward cleaner energy

sources has led to the widespread integration of renewable energy technologies, distributed generation units, and energy storage systems into existing grid infrastructures. While these advancements offer significant environmental and economic benefits, they also introduce additional complexity into power system operation. Consequently, modern power networks require advanced optimization and control strategies capable of ensuring stable, efficient, and sustainable electricity delivery under increasingly dynamic operating conditions [3]. The relationship between increasing electricity demand, grid modernization, and the role of optimization techniques in enhancing power system performance is illustrated in Figure 1. One of the major concerns in power system operation is the occurrence of transmission line losses. Power losses occur during the transmission and distribution of electrical energy due to the inherent resistance of conductors and the operating conditions of network components. Excessive transmission losses reduce system efficiency, increase operational costs, and limit the ability of utilities to deliver electricity effectively [4]. As power networks continue to grow in complexity, minimizing transmission losses has become an essential objective for system operators. Efficient load scheduling and optimal utilization of generation resources play a vital role in reducing losses while maintaining acceptable voltage profiles and network security.

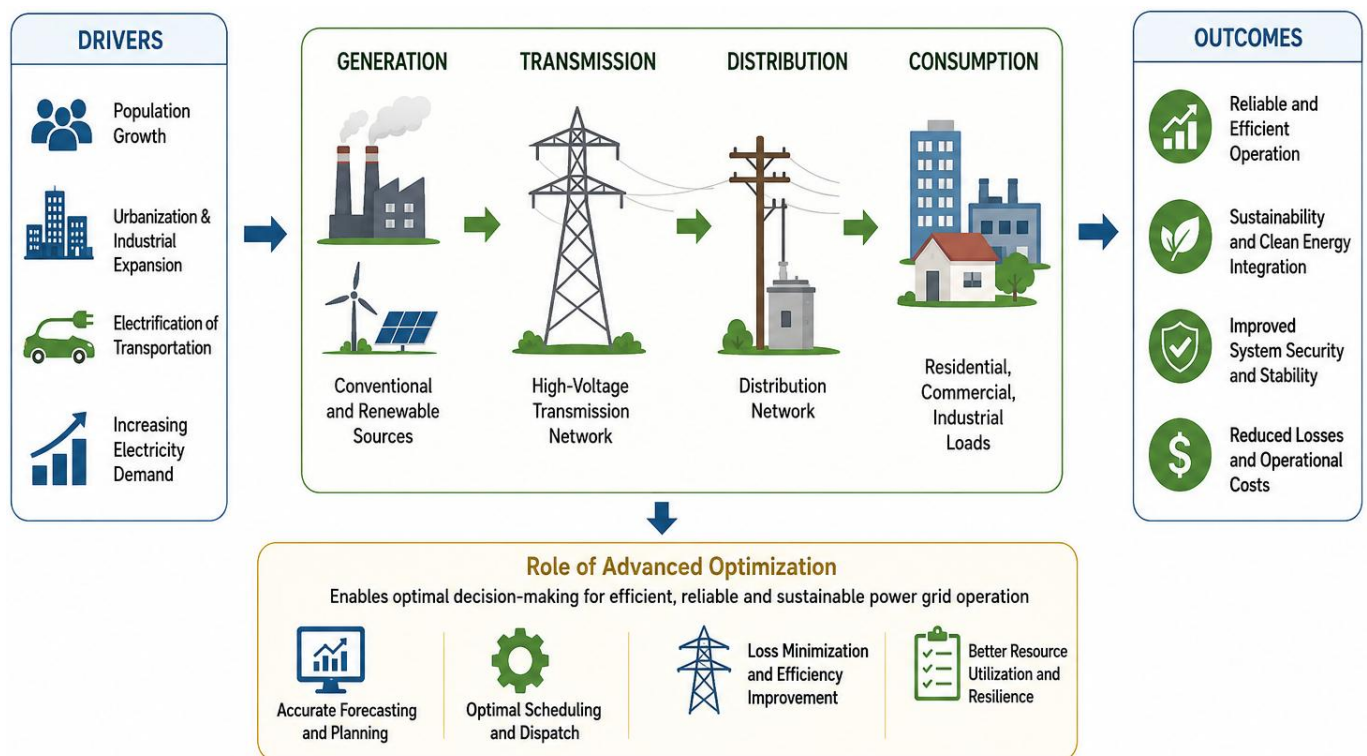


Figure 1. Overview of the modern power grid highlighting increasing electricity demand, grid components, and the role of optimization in improving efficiency, reliability, and sustainability.

Traditional approaches for power system optimization have focused on solving problems such as economic dispatch, unit commitment, optimal power flow, and load management using deterministic mathematical techniques. Although these methods can provide accurate solutions under simplified conditions, they often face difficulties when applied to large-scale power systems characterized by nonlinear relationships, multiple constraints, and dynamic operating conditions [5]. Furthermore, the increasing penetration of renewable energy resources introduces uncertainties that make conventional optimization approaches less effective in achieving global optimal solutions within practical computational times. To address these limitations, researchers have increasingly adopted

intelligent optimization techniques capable of handling complex and multidimensional optimization problems. Metaheuristic algorithms have emerged as powerful tools due to their ability to search for large solution spaces efficiently without requiring strict mathematical assumptions. Among these techniques, Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO) have received significant attention in power system applications [6]. A GA utilizes principles of natural evolution, including selection, crossover, and mutation, to identify optimal solutions, whereas PSO mimics the social behavior of particle populations to rapidly converge toward promising search regions. Both techniques have demonstrated considerable success in solving optimization problems related to economic dispatch, optimal power flow, reactive power compensation, network reconfiguration, and transmission loss minimization.

Despite their advantages, individual optimization algorithms possess inherent limitations. Genetic Algorithms often require longer computational times and may experience slow convergence when dealing with high-dimensional optimization problems. Conversely, Particle Swarm Optimization exhibits fast convergence characteristics but can suffer from premature convergence and entrapment in local optima [7]. These limitations have motivated researchers to develop hybrid optimization approaches that combine the strengths of multiple algorithms while mitigating their weaknesses. The integration of GAs and PSO into a Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) framework provides a balanced optimization strategy that enhances both exploration and exploitation capabilities during the search process. HGAPSO has emerged as an effective optimization technique for addressing complex engineering problems due to its ability to achieve high-quality solutions with improved convergence performance. By combining the global search capability of Genetic Algorithms with the rapid convergence characteristics of Particle Swarm Optimization, HGAPSO can effectively navigate complex solution spaces and identify optimal operating conditions [8]. This makes the technique particularly suitable for large-scale power system optimization where multiple operational constraints must be satisfied simultaneously. Furthermore, the adaptability of HGAPSO enables its application to a wide range of power system problems, including transmission loss reduction, voltage stability enhancement, load scheduling, and optimal resource allocation.

Problem Statement, Research Objectives, and Contributions

As discussed in the preceding section, modern power systems are experiencing unprecedented levels of complexity due to increasing electricity demand, expanding transmission networks, and the integration of renewable energy resources. While these developments have improved the flexibility and sustainability of power systems, they have also introduced significant operational challenges related to transmission loss management, load scheduling, and overall system efficiency. Consequently, the need for advanced optimization techniques capable of addressing these challenges has become increasingly important [9]. Despite the considerable progress achieved in power system optimization, minimizing transmission line losses while maintaining efficient grid operation remains a significant challenge. Transmission losses continue to affect the economic and technical performance of power systems by reducing energy delivery efficiency and increasing operational costs. As power networks grow in complexity, traditional optimization methods often struggle to provide optimal solutions within acceptable computational times [10]. Furthermore, the nonlinear characteristics of large-scale power systems and the presence of multiple operational constraints make the optimization process increasingly difficult.

Conventional optimization techniques have been extensively applied to solve power system problems such as economic dispatch, optimal power flow, and load scheduling. However, many of these approaches are prone to premature convergence, limited exploration capabilities, and reduced effectiveness when applied to highly interconnected power networks [11]. In addition, deterministic methods frequently encounter difficulties in handling the nonlinear and non-convex nature of modern power system optimization problems, resulting in suboptimal operating conditions and increased transmission losses. Although Genetic Algorithms and Particle Swarm Optimization have individually demonstrated promising performance in power system optimization applications, each technique exhibits inherent limitations. Genetic Algorithms possess strong global search capabilities but often require longer convergence times, whereas Particle Swarm Optimization offers rapid convergence but may become trapped in local optima. Consequently, there is a need for a hybrid optimization approach that combines the strengths of both techniques while mitigating their individual weaknesses [12].

To improve the clarity of the research methodology and provide readers with a concise overview of this study, the overall development and deployment framework of the proposed HGAPSO methodology is presented in Figure 2. The framework illustrates the logical progression of this research from the initial problem identification to the potential deployment of the proposed optimization approach. The first phase focuses on defining the research problem by identifying the challenges associated with transmission loss minimization and voltage regulation in large-scale power systems. This is followed by a comprehensive literature review, mathematical formulation of the optimization problem, and modeling of the IEEE 118-bus test system, which collectively establish the theoretical foundation for the proposed methodology. The second phase, highlighted as the primary contribution of this study, presents the development and implementation of the Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) framework. This phase includes the integration of the global search capability of the Genetic Algorithm with the local exploitation capability of Particle Swarm Optimization to improve convergence and optimization performance. The framework was implemented in MATLAB R2024a and evaluated using the IEEE 118-bus test system. Comprehensive performance analyses were conducted by assessing transmission loss minimization, voltage profile improvement, computational efficiency, and comparative performance against the standalone GA and PSO algorithms. The final phase of the framework illustrates the validation and future deployment of the proposed methodology. Although the present work validates the effectiveness of the HGAPSO framework using the IEEE 118-bus benchmark system, the framework is designed to be scalable and applicable to larger transmission networks and practical smart grid environments. Future work will focus on extending the proposed approach to larger benchmark systems, integrating real-time operational data, and supporting advanced smart grid applications. Consequently, Figure 2 provides a comprehensive roadmap of the completed research activities and the anticipated future developments, enabling readers to clearly distinguish the contributions achieved in this study from the planned deployment stages.

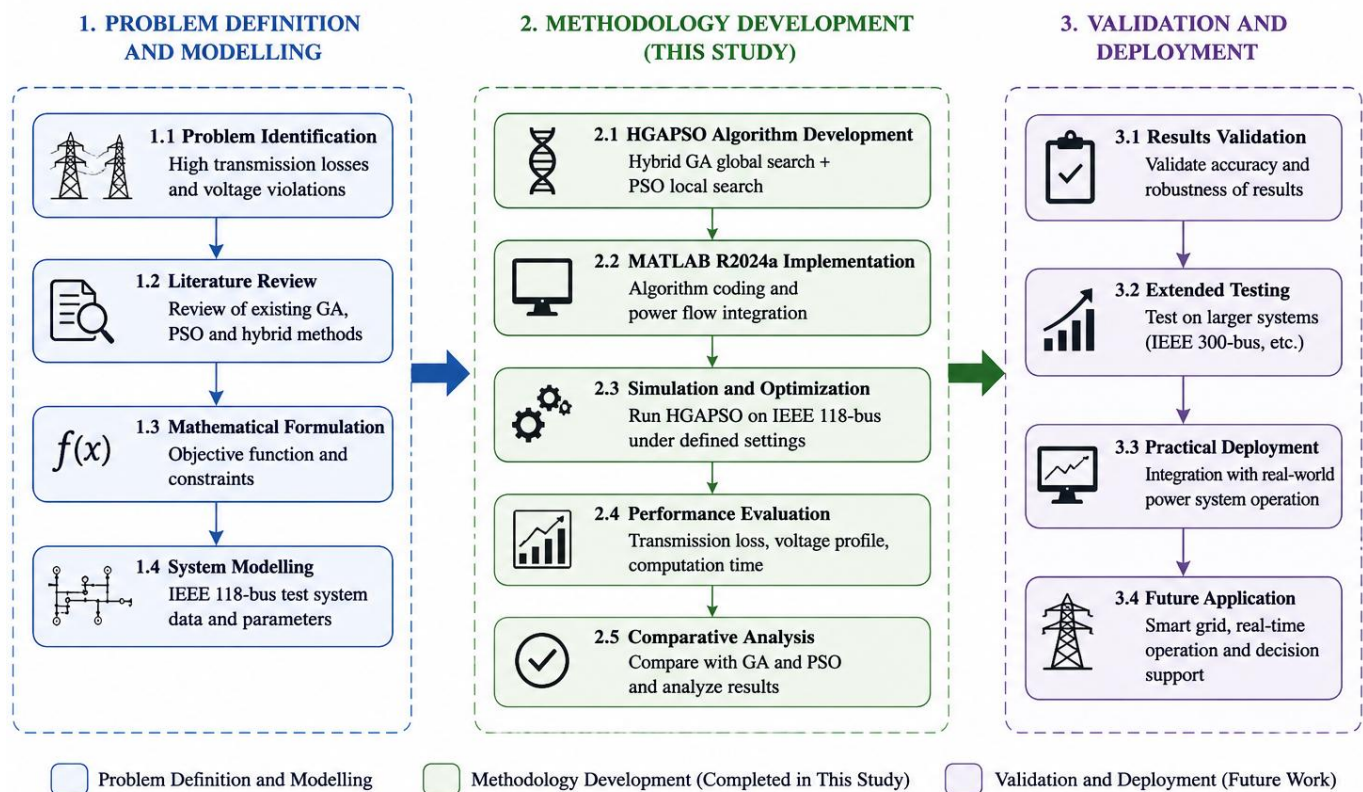


Figure 2. Overall development and deployment framework of the proposed HGAPSO methodology for transmission loss minimization in the IEEE 118-bus power system.

To address these challenges, this study proposes a Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) framework for optimal load scheduling and transmission loss minimization in the IEEE 118-bus test system. The proposed framework aims to identify optimal operating conditions that reduce transmission losses while satisfying network operational constraints. By integrating the exploration capability of Genetic Algorithms with the exploitation capability of Particle Swarm Optimization, the proposed approach seeks to improve solution quality, enhance convergence performance, and increase overall power system efficiency. The principal contributions of this study are as follows:

- Development of an HGAPSO-based optimization framework for transmission loss minimization and optimal load scheduling.
- Application of the proposed methodology to the IEEE 118-bus test system to evaluate its effectiveness in a realistic large-scale transmission network.
- Determination of optimal operating conditions that minimize transmission losses while maintaining system operational constraints.
- Assessment of the effectiveness of the proposed framework through simulation studies conducted in MATLAB R2024a.
- Evaluation of system performance based on transmission loss reduction, convergence characteristics, and computational efficiency.

The remainder of this paper is organized as follows: Section 2 presents the literature review. Section 3 describes the proposed methodology and system modeling. Section 4 presents the simulation results and discussion, while Section 5 concludes this paper and provides recommendations for future work.

2. Literature Review

Over the years, numerous optimization techniques have been developed and applied to power system problems, including economic dispatch, optimal power flow, network reconfiguration, load scheduling, and transmission loss minimization. These techniques range from classical mathematical programming approaches to advanced metaheuristic algorithms inspired by natural and evolutionary processes. This chapter reviews the existing literature related to power system optimization, transmission loss minimization, Genetic Algorithms, Particle Swarm Optimization and Research Gap.

2.1. Overview of Power Grid Optimization

The growing complexity of modern power systems has led to the development of numerous optimization techniques aimed at improving operational efficiency, reducing transmission losses, enhancing voltage stability, and minimizing operational costs. These optimization approaches range from conventional mathematical programming methods to advanced metaheuristic and hybrid optimization algorithms. Each technique possesses unique characteristics, advantages, and limitations that influence its suitability for different power system applications. Conventional methods such as Linear Programming (LP), Nonlinear Programming (NLP), and Dynamic Programming (DP) have historically provided structured solutions to optimization problems; however, their effectiveness is often constrained when dealing with nonlinear, non-convex, and large-scale power systems [13,14]. Consequently, researchers have increasingly adopted intelligent optimization techniques such as Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Grey Wolf Optimization (GWO), and Differential Evolution (DE) to address the complexities associated with modern power networks. More recently, hybrid optimization approaches such as Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) have emerged to combine the strengths of multiple algorithms and overcome their individual limitations. Table 1 presents a summary of the most widely used optimization techniques in power system applications, highlighting their operating principles, major applications, advantages, and limitations.

Table 1. Summary of Power Grid Optimization Techniques.

Optimization Technique	Principle	Power System Applications	Advantages	Limitations	Citation
Linear Programming (LP)	Optimizes a linear objective function subject to linear constraints	Economic dispatch, generation scheduling	Simple implementation, fast computation	Limited to linear problems, poor handling of nonlinear systems	[15]
Nonlinear Programming (NLP)	Solves optimization problems with nonlinear objective functions and constraints	Optimal power flow, voltage control	Accurate for nonlinear systems	Computationally intensive for large networks	[16,17]
Dynamic Programming (DP)	Breaks complex problems into smaller sub-problems	Unit commitment, hydro-thermal scheduling	Provides optimal solutions	Suffers from dimensionality issues	[18]
Genetic Algorithm (GA)	Evolutionary algorithm based on natural selection and genetics	Economic dispatch, transmission loss minimization, network reconfiguration	Strong global search capability, avoids local optima	Slow convergence, high computational requirements	[19]
Particle Swarm Optimization (PSO)	Swarm intelligence algorithm based on social behavior of particles	Optimal power flow, reactive power optimization, DG placement	Fast convergence, easy implementation	Premature convergence, local optimum trapping	[20,21]
Ant Colony Optimization (ACO)	Mimics foraging behavior of ants	Network reconfiguration, routing optimization	Good exploration capability	Slow convergence in large-scale problems	[22]

Differential Evolution (DE)	Population-based optimization using mutation and crossover	Economic dispatch, renewable energy optimization	Robust search performance	Sensitive to parameter settings	[23]
Grey Wolf Optimization (GWO)	Mimics hunting behavior of grey wolves	Power system scheduling, loss reduction	Balanced exploration and exploitation	Performance may degrade in highly complex systems	[24,25]
Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO)	Combines GA exploration and PSO exploitation capabilities	Load scheduling, optimal power flow, transmission loss minimization	Improved convergence speed, enhanced solution quality, robust performance	-	[26]

From Table 1, it can be observed that no single optimization technique can address all power system optimization challenges effectively. Conventional optimization methods provide computational efficiency but often struggle with nonlinear and large-scale problems. Metaheuristic algorithms offer improved search capabilities and flexibility but may experience issues such as slow convergence or premature convergence. Hybrid optimization techniques, particularly HGAPSO, address many of these limitations by combining the complementary strengths of Genetic Algorithms and Particle Swarm Optimization [27]. As a result, HGAPSO has emerged as a promising optimization framework for complex power system applications involving transmission loss minimization, load scheduling, and optimal power flow in large-scale transmission networks.

2.2. Transmission Loss Minimization in Power Systems

Transmission loss minimization is one of the most important objectives in power system operation and optimization. Electrical energy generated at power stations must be transmitted through transmission and distribution networks before reaching end-users. During this process, a portion of the generated energy is lost due to the electrical resistance of transmission lines, transformer losses, corona losses, and other network-related factors. These losses reduce the overall efficiency of the power system, increase operational costs, and require additional power generation to satisfy consumer demand [28]. Consequently, minimizing transmission losses has become a critical concern for power utilities, system operators, and researchers. Several factors influence the magnitude of transmission losses in power systems. These include network topology, conductor characteristics, voltage levels, power factor, load distribution, generation dispatch patterns, and transmission line lengths [29]. Improper load allocation, poor reactive power management, and inefficient generation scheduling can significantly increase losses throughout the network. Therefore, effective system planning and optimization are essential for minimizing these losses and improving overall system efficiency. Transmission loss minimization offers numerous technical, economic, and environmental benefits. From a technical perspective, reducing transmission losses improves system efficiency, enhances voltage regulation, and increases network reliability. Economically, lower losses reduce operating expenses by decreasing the amount of generation required to meet consumer demand. Environmentally, loss reduction contributes to lower greenhouse gas emissions by reducing fuel consumption in conventional power plants [30]. Consequently, transmission loss minimization plays an important role in supporting sustainable power system development.

Various methods have been proposed to reduce transmission losses in electrical power systems. Traditional approaches include optimal power flow (OPF), economic dispatch, reactive power compensation, capacitor placement, transformer tap optimization, and network reconfiguration. These techniques aim to improve power flow distribution and reduce unnecessary current circulation throughout the network. Although effective under certain operating conditions, many conventional approaches encounter difficulties when applied to large-scale transmission systems characterized by nonlinear operating

constraints and dynamic loading conditions [31]. The increasing complexity of modern power systems has encouraged the adoption of advanced optimization techniques for transmission loss minimization. Metaheuristic algorithms such as Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Grey Wolf Optimization (GWO), Differential Evolution (DE), and Artificial Bee Colony (ABC) have demonstrated significant success in solving transmission loss reduction problems. These algorithms can explore large solution spaces and identify near-optimal solutions without requiring complex mathematical formulations. Among these optimization techniques, Genetic Algorithms and Particle Swarm Optimization have received considerable attention due to their ability to effectively solve nonlinear and multi-constrained optimization problems [32]. Genetic Algorithms provide strong global search capabilities through evolutionary operators such as selection, crossover, and mutation. Conversely, Particle Swarm Optimization offers fast convergence through collaborative interactions among particles within the search space. However, both approaches exhibit certain limitations when applied independently. Genetic Algorithms may experience slow convergence rates, while Particle Swarm Optimization may suffer from premature convergence and local optimum trapping [33,34]. To overcome these limitations, researchers have increasingly explored hybrid optimization approaches that combine the strengths of multiple algorithms. Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) has emerged as a particularly promising technique for transmission loss minimization.

By integrating the exploration capability of Genetic Algorithms with the exploitation capability of Particle Swarm Optimization, HGAPSO enhances convergence performance and improves solution quality [35]. This hybrid approach enables more effective identification of optimal operating conditions that minimize transmission losses while satisfying system constraints. In modern smart grids, transmission loss minimization has become increasingly important due to the growing penetration of renewable energy resources, distributed generation, energy storage systems, and electric vehicles. These technologies introduce uncertainty, intermittency, and operational complexity, making conventional optimization approaches less effective [36]. Recent advances in artificial intelligence have introduced alternative optimization and decision-making techniques, including Deep Reinforcement Learning (DRL), Graph Neural Networks (GNNs), Physics-Informed Neural Networks (PINNs), and Transformer-based models. While these methods have demonstrated promising performance in forecasting, control, and energy management applications, they generally require large training datasets, significant computational resources, and extensive model tuning. In contrast, HGAPSO provides a relatively simple and computationally efficient optimization framework that does not require prior training and can be directly applied to constrained power system optimization problems. Table 2 summarizes major transmission loss minimization techniques reported in the literature and highlights their strengths and limitations. As shown in Table 2, hybrid optimization approaches generally provide superior performance compared with standalone optimization techniques due to their ability to balance global exploration and local exploitation. Consequently, the proposed study adopts HGAPSO as the primary optimization technique for transmission loss minimization in the IEEE 118-bus power system [37].

Table 2. Comparison of Transmission Loss Minimization Techniques.

Technique	Principle	Advantages	Limitations	Citation
Optimal Power Flow (OPF)	Optimizes system operating variables subject to network constraints	Accurate, well-established, and widely adopted in power system operation	Computationally intensive for large-scale and highly nonlinear systems	[38]
Reactive Power Compensation	Controls reactive power flow to reduce losses and improve system performance	Improves voltage profile and reduces transmission losses	Requires additional compensation devices and investment costs	[39]
Capacitor Placement	Installs capacitors at strategic network locations to supply reactive power locally	Reduces reactive power demand and improves system efficiency	Placement and sizing complexity	[40]
Network Reconfiguration	Modifies network topology to achieve improved operational performance	Effective for loss reduction and load balancing	Limited applicability in transmission systems and operational constraints	[40]
Genetic Algorithm (GA)	Evolutionary optimization based on selection, crossover, and mutation	Strong global search capability and robustness	Slow convergence and high computational requirements	[41]
Particle Swarm Optimization (PSO)	Swarm intelligence-based search using particle position and velocity updates	Fast convergence and simple implementation	Susceptible to premature convergence and local optima	[42]
Grey Wolf Optimizer (GWO)	Mimics the hunting behavior and leadership hierarchy of grey wolves	Good balance between exploration and exploitation	Performance depends on parameter tuning and population diversity	[43]
Differential Evolution (DE)	Population-based optimization using mutation, crossover, and selection operators	Robust optimization performance and strong search capability	Increased computational complexity for large-scale problems	[43]
Whale Optimization Algorithm (WOA)	Mimics the bubble-net hunting strategy of humpback whales	Effective global search and competitive optimization performance	May experience slow convergence near the optimum	[44]
Deep Reinforcement Learning (DRL)	Learns optimal control actions through interaction with the environment	Suitable for dynamic and uncertain power system environments	Requires extensive training data and high computational resources	[45]
Graph Neural Networks (GNNs)	Graph-based learning framework for modeling network relationships	Captures complex power system topologies and dependencies	Data intensive and computationally demanding	[45]
Physics-Informed Neural Networks (PINNs)	Integrates physical system constraints into neural network training	Improved physical consistency and generalization capability	High training complexity and parameter sensitivity	[46]
Transformer-Based Models	Attention-based deep learning architecture for sequence modeling and prediction	Strong learning capability and scalability for large datasets	Computationally expensive and requires substantial training data	[47]
Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO)	Combines GA exploration with PSO exploitation to improve optimization performance	High solution quality, fast convergence, robust search capability, and improved transmission loss minimization	Increased implementation complexity and parameter tuning requirements	[48]

2.3. Overview of Genetic Algorithm

Genetic Algorithms (GAs) are among the most widely adopted evolutionary optimization techniques in engineering and scientific research. Introduced by John Holland in the 1970s, Genetic Algorithms are inspired by the principles of natural evolution, particularly natural selection, inheritance, crossover, and mutation. The fundamental concept of GA is based on the survival-of-the-fittest principle, where populations of candidate solutions evolve over successive generations toward an optimal solution [49]. Due to their robustness and ability to solve complex nonlinear optimization problems, Genetic Algorithms have become a popular tool in modern power system optimization. Power systems are characterized by nonlinear objective functions, large search spaces, and numerous equality and inequality constraints. Conventional optimization techniques often struggle

to solve such problems efficiently, particularly when the objective function is discontinuous, non-convex, or multi-modal [50]. Genetic Algorithms address these limitations through population-based stochastic searches that do not require gradient information. As a result, GAs can effectively explore complex search spaces and identify near-optimal solutions while avoiding entrapment in local optima. The operation of a Genetic Algorithm begins with the initialization of a population of chromosomes, where each chromosome represents a potential solution to the optimization problem. The chromosomes are evaluated using a fitness function that quantifies the quality of each solution according to the optimization objective [51]. Based on their fitness values, chromosomes are selected for reproduction through mechanisms such as roulette wheel selection, tournament selection, or rank-based selection. The selected chromosomes undergo crossover operations to exchange genetic information and generate offspring, while mutation introduces random variations to maintain population diversity and improve global search capability. This evolutionary process continues iteratively until a termination criterion is satisfied, such as reaching a predefined number of generations or achieving an acceptable fitness value. The general procedure of a Genetic Algorithm can be summarized as follows [52–54]:

1. Initialize a population of candidate solutions.
2. Evaluate the fitness of each chromosome.
3. Select parent chromosomes based on fitness values.
4. Apply crossover to generate offspring.
5. Apply mutation to maintain genetic diversity.
6. Evaluate the new population.
7. Repeat the process until convergence is achieved.

The mathematical representation of a chromosome can be expressed as follows:

$$X = [x_1, x_2, x_3, \dots, x_n] \quad (1)$$

where X represents the candidate solution and $x_1, x_2, x_3, \dots, x_n$ are the decision variables associated with the optimization problem.

The optimization objective is generally formulated as follows:

$$\min F(X) \quad (2)$$

subject to:

$$g_i(X) \leq 0 \quad (3)$$

$$h_j(X) = 0 \quad (4)$$

where $F(X)$ denotes the objective function, $g_i(X)$ represents inequality constraints, and $h_j(X)$ represents equality constraints.

For minimization problems, the fitness function is commonly defined as follows:

$$\text{Fitness}(X) = \frac{1}{1 + F(X)} \quad (5)$$

where a lower objective function value results in a higher fitness score.

In power system optimization, Genetic Algorithms have been extensively employed for solving Economic Load Dispatch (ELD), Optimal Power Flow (OPF), Unit Commitment (UC), transmission expansion planning, capacitor placement, network reconfiguration, distributed generation allocation, and transmission loss minimization problems. Several studies have demonstrated that GAs provide superior optimization performance compared with traditional mathematical programming techniques, particularly when addressing nonlinear and multi-constrained power system problems [55]. Their ability to simultaneously optimize multiple variables while maintaining solution diversity makes them highly suitable for modern smart grid applications involving renewable energy in-

tegration, energy storage systems, and electric vehicles. One of the major advantages of Genetic Algorithms is their strong exploration capability. Unlike gradient-based methods, GAs do not require differentiable objective functions and can effectively handle discrete, continuous, and mixed-variable optimization problems [56]. Furthermore, their population-based search mechanism enables them to investigate multiple regions of the solution space simultaneously, thereby increasing the probability of identifying the global optimum. Genetic Algorithms are also less sensitive to initial conditions and can accommodate multiple conflicting objectives through multi-objective optimization frameworks. Despite these advantages, Genetic Algorithms exhibit certain limitations. The algorithm may require many generations to achieve convergence, resulting in high computational requirements when applied to large-scale power systems. Additionally, the optimization performance is significantly influenced by parameters such as population size, crossover probability, and mutation rate. Improper parameter selection may lead to premature convergence or reduced solution quality. Furthermore, although GAs possesses strong exploration capabilities, their exploitation performance during the later stages of optimization is often limited, which may slow convergence toward the global optimum.

To overcome these limitations, researchers have increasingly explored hybrid optimization approaches that combine Genetic Algorithms with complementary optimization techniques [57]. One of the most successful hybrid frameworks integrates Genetic Algorithms with Particle Swarm Optimization (PSO). In this approach, Genetic Algorithms provide strong exploration capabilities and maintain population diversity, while PSO enhances exploitation performance and accelerates convergence toward the optimal solution [58]. The resulting Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) technique combines the strengths of both algorithms and has demonstrated superior performance in solving large-scale power system optimization problems, including transmission loss minimization, optimal power flow, and electric vehicle charging station allocation.

For transmission loss minimization applications, the objective function can be represented as [59]:

$$P_{\text{loss}} = \sum_{i=1}^{N_b} \sum_{j=1}^{N_b} G_{ij} (V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)) \quad (6)$$

where;

- P_{loss} represents the total transmission power loss,
- N_b is the number of buses,
- G_{ij} is the conductance between buses
- i and j , V_i and V_j are bus voltage magnitudes, and
- δ_i and δ_j are the corresponding voltage phase angles.

As modern power systems continue to evolve with increasing penetration of renewable energy resources, electric vehicles, and smart grid technologies, Genetic Algorithms remain a powerful optimization tool capable of addressing complex operational and planning challenges [60]. Their flexibility, robustness, and ability to solve nonlinear optimization problems continue to support their widespread application in contemporary power system research and development. The operational sequence of a Genetic Algorithm, including population initialization, fitness evaluation, selection, crossover, mutation, and convergence assessment, is illustrated in Figure 3. The figure demonstrates the iterative evolutionary process through which candidate solutions are progressively improved until an optimal or near-optimal solution is obtained.

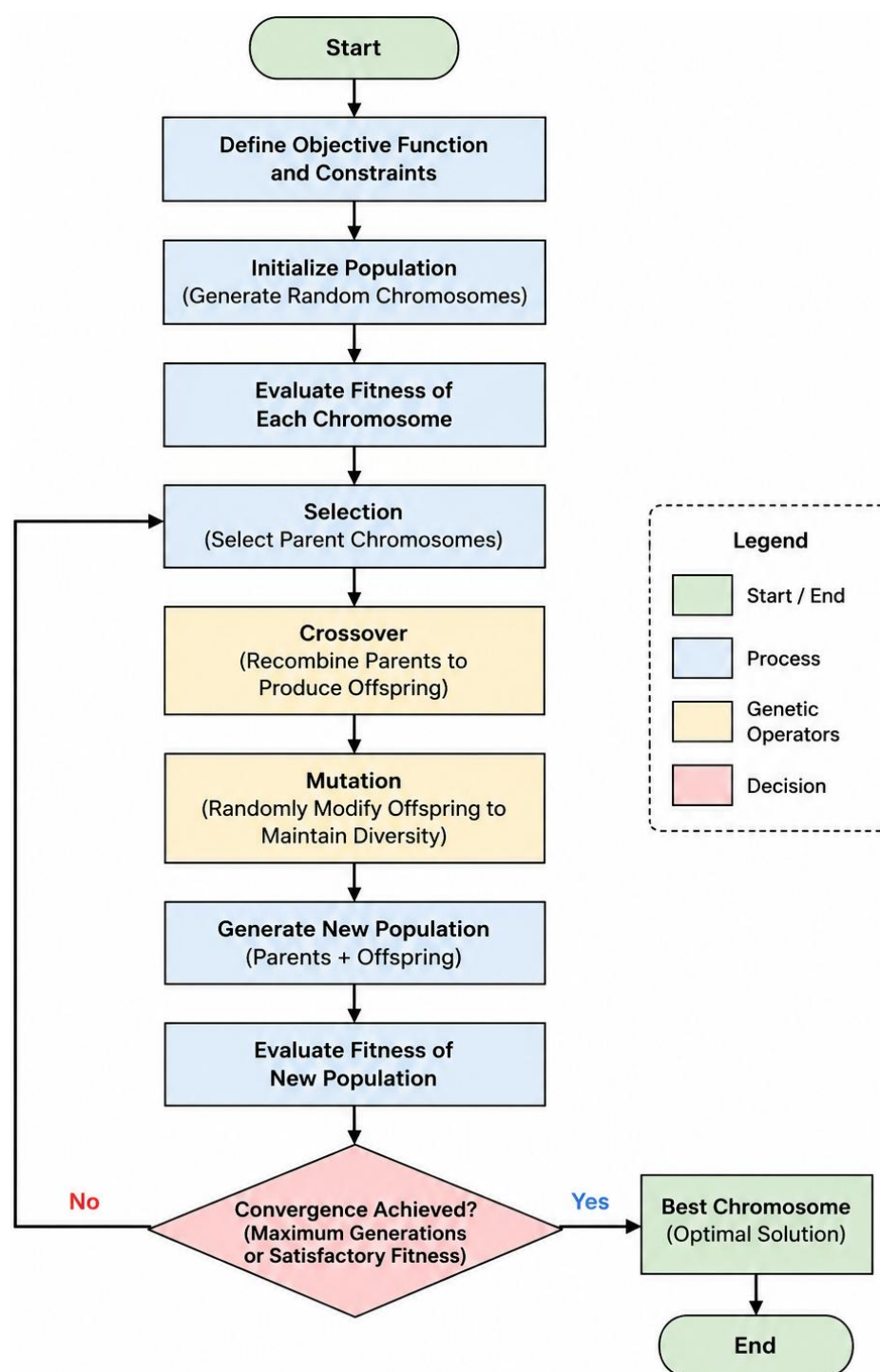


Figure 3. Genetic Algorithm optimization process, showing the stages of population initialization, fitness evaluation, selection, crossover, mutation, generation update, and convergence assessment leading to the optimal solution.

2.4. Overview of Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population-based optimization technique inspired by the social behavior of bird flocks and fish schools. The algorithm was introduced by James Kennedy and Russell Eberhart in 1995 as a computational intelligence method for solving complex optimization problems. Since its development, PSO has gained significant attention in power system engineering due to its simplicity, rapid convergence characteristics, and ability to solve nonlinear and multidimensional optimization problems efficiently [61,62]. Unlike Genetic Algorithms, which rely on evolutionary operators

such as crossover and mutation, Particle Swarm Optimization utilizes a swarm of particles that move through the search space in pursuit of the optimal solution. Each particle represents a potential solution to the optimization problem and adjusts its position based on both its own experience and the experience of neighboring particles [63]. Through continuous interaction among particles, the swarm collectively searches for the global optimum while balancing exploration and exploitation capabilities. The PSO algorithm begins with the random initialization of particles within the search space. Each particle possesses a position vector and a velocity vector. The position represents a candidate solution, while the velocity determines the direction and magnitude of movement within the search space [64]. During each iteration, particles evaluate their fitness values and update their velocities and positions according to the best solutions identified during the optimization process. The optimization process of Particle Swarm Optimization can be summarized as follows:

- Initialize the swarm population randomly.
- Evaluate the fitness of each particle.
- Determine the personal best position (P_{best}) of each particle.
- Determine the global best position (G_{best}) of the swarm.
- Update particle velocities.
- Update particle positions.
- Evaluate the new fitness values.
- Repeat the process until convergence or the maximum number of iterations is reached.

The position of each particle can be represented as follows:

$$X_i = [x_{i1}, x_{i2}, x_{i3}, \dots, x_{in}] \quad (7)$$

where:

- X_i represents the position of particle i ,
- $x_{i1}, x_{i2}, \dots, x_{in}$ are the decision variables,
- n is the number of optimization variables.

The velocity update equation is expressed as follows:

$$V_i^{k+1} = wV_i^k + c_1r_1(P_{best,i} - X_i^k) + c_2r_2(G_{best} - X_i^k) \quad (8)$$

where:

- V_i^k is the velocity of particle i at iteration k ,
- w is the inertia weight,
- c_1 is the cognitive acceleration coefficient,
- c_2 is the social acceleration coefficient,
- r_1 and r_2 are random numbers between 0 and 1,
- $P_{best,i}$ is the personal best position of particle i ,
- G_{best} is the global best position identified by the swarm.

The particle position is updated according to:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (9)$$

The objective function is generally formulated as follows:

$$\min F(X) \quad (10)$$

subject to:

$$g_i(X) \leq 0 \quad (11)$$

$$h_j(X) = 0 \quad (12)$$

where $F(X)$ represents the objective function, while $g_i(X)$ and $h_j(X)$ denote the inequality and equality constraints, respectively. One of the primary advantages of Particle Swarm Optimization is its rapid convergence speed. Because particles continuously exchange information regarding the best solutions discovered within the swarm, PSO can quickly identify promising regions of the search space. Furthermore, the algorithm requires fewer parameters compared with many evolutionary optimization techniques, making implementation relatively straightforward. PSO also exhibits strong exploitation capabilities, allowing it to refine solutions efficiently during the later stages of optimization [65,66]. In power system applications, Particle Swarm Optimization has been widely employed for Economic Load Dispatch (ELD), Optimal Power Flow (OPF), transmission loss minimization, capacitor placement, distributed generation allocation, reactive power optimization, renewable energy integration, electric vehicle charging coordination, and smart grid energy management. Numerous studies have reported that PSO achieves high-quality solutions with lower computational effort compared with conventional optimization techniques. Despite its advantages, Particle Swarm Optimization also exhibits certain limitations [67]. One of the major challenges is premature convergence, particularly when particles rapidly cluster around suboptimal solutions. This behavior may reduce population diversity and increase the likelihood of trapping the algorithm in local optima. Additionally, the performance of PSO is influenced by parameter selection, including inertia weight and acceleration coefficients. Improper parameter tuning can negatively affect convergence speed and solution quality. To address these limitations, researchers have increasingly combined PSO with other optimization techniques. Among the most effective hybrid approaches is the Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) framework. In this hybrid structure, Genetic Algorithms provide strong exploration and population diversity, while Particle Swarm Optimization contributes rapid convergence and enhanced exploitation capabilities [68,69]. The integration of these complementary characteristics improves optimization accuracy and overall system performance, particularly for large-scale power system optimization problems.

As electrical power systems continue to integrate renewable energy sources, energy storage systems, electric vehicles, and smart grid technologies, Particle Swarm Optimization remains an effective and widely adopted optimization tool. Its ability to efficiently search large solution spaces, rapidly converge toward optimal solutions, and solve non-linear optimization problems continues to support its extensive application in modern power system planning, operation, and control [70]. Figure 4 illustrates the operational framework of the Particle Swarm Optimization algorithm, highlighting the iterative process of particle initialization, fitness evaluation, updating of personal and global best positions, velocity and position adjustment, and convergence assessment. The flowchart demonstrates how particles collaboratively search the solution space to identify the optimal solution while balancing exploration and exploitation capabilities.

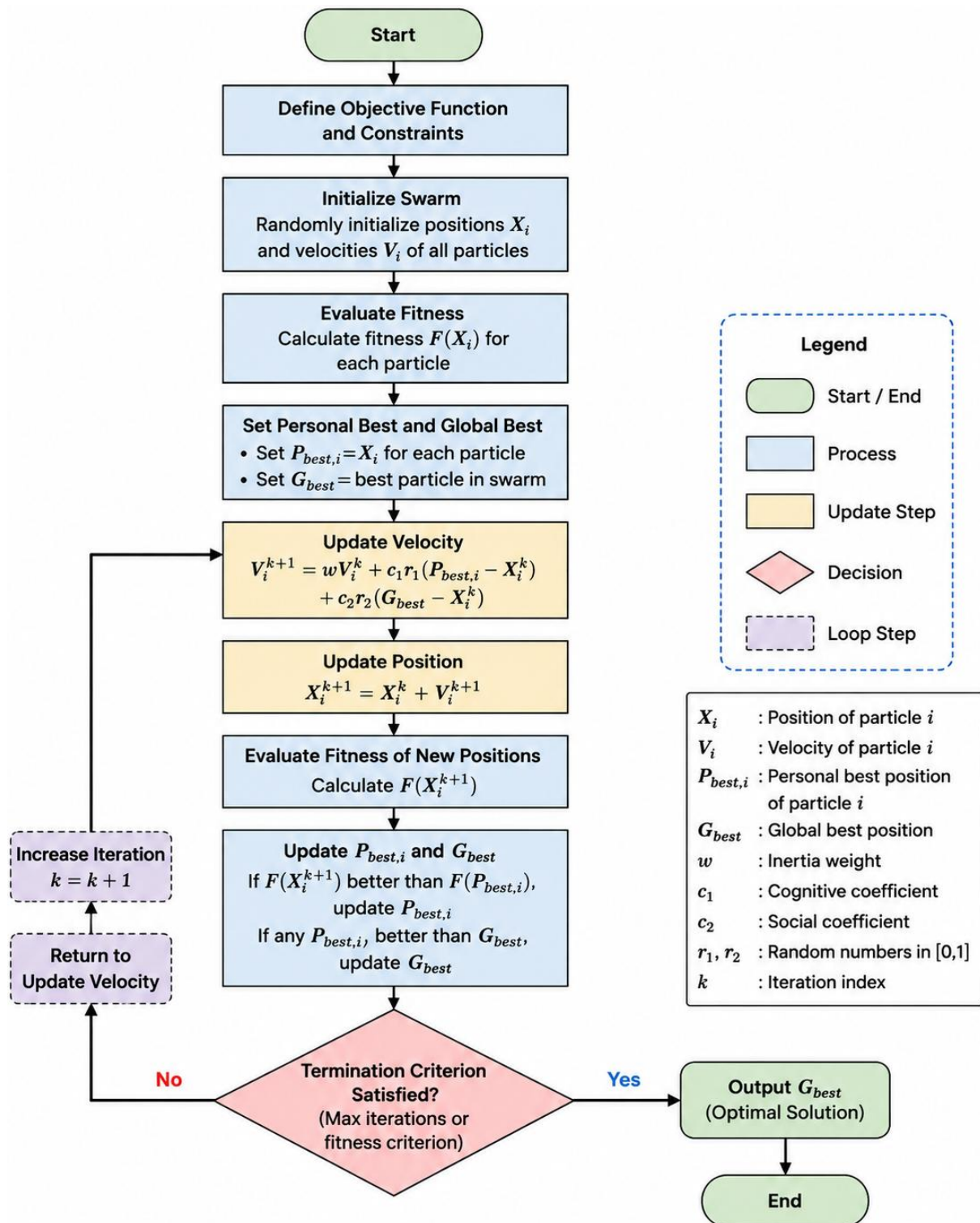


Figure 4. Flowchart of the Particle Swarm Optimization (PSO) algorithm showing particle initialization, fitness evaluation, personal and global best updates, velocity and position updating mechanisms, and the convergence process leading to the optimal solution.

2.5. Research Gap

Although Particle Swarm Optimization has been extensively applied to power system optimization problems such as optimal power flow, economic dispatch, reactive power planning, distributed generation allocation, and transmission loss minimization, several research gaps remain. Most existing studies focus on the application of standalone PSO algorithms for relatively small and medium-sized test systems, including the IEEE

14-bus, IEEE 30-bus, and IEEE 57-bus networks. While these studies demonstrate the effectiveness of PSO in solving nonlinear optimization problems, the scalability and robustness of the algorithm for large-scale interconnected power systems remain an active area of research. A significant limitation of conventional PSO is its tendency toward premature convergence. As particles move toward promising regions of the search space, population diversity may decrease rapidly, causing the algorithm to become trapped in local optima. This challenge becomes more pronounced in large-scale power systems characterized by highly nonlinear objective functions, multiple constraints, and numerous decision variables. Consequently, optimization performance may deteriorate, resulting in suboptimal solutions and reduced system efficiency. Furthermore, the increasing integration of renewable energy resources, electric vehicles, distributed energy resources, and energy storage systems has introduced additional uncertainties into power system operation. The intermittent nature of solar and wind generation, together with the stochastic charging behavior of electric vehicles, creates dynamic operating conditions that are not adequately addressed by many traditional PSO-based optimization models. Most existing studies assume deterministic operating conditions, which may not accurately represent real-world power system environments.

Another notable research gap relates to transmission loss minimization in modern smart grids. While numerous PSO-based studies focus on minimizing power losses, many neglect the simultaneous consideration of voltage stability, network security constraints, renewable energy variability, and electric vehicle charging demand. The growing complexity of modern electrical networks requires optimization frameworks capable of addressing multiple objectives simultaneously while maintaining computational efficiency. Although various modifications in PSO have been proposed to improve convergence characteristics, there remains a need for optimization approaches that effectively balance exploration and exploitation capabilities. Standalone PSO exhibits strong exploitation performance but may lack sufficient exploration during the early search stages. Conversely, Genetic Algorithms provide excellent exploration and population diversity but often suffer from slower convergence rates. The complementary strengths of these algorithms suggest that hybrid optimization approaches may provide superior performance compared with individual techniques. Therefore, this study addresses the identified research gaps by developing a Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) framework for transmission loss minimization in large-scale power systems. The proposed HGAPSO approach combines the exploration capability and diversity preservation of Genetic Algorithms with the rapid convergence and exploitation characteristics of Particle Swarm Optimization. The hybrid framework is applied to the IEEE 118-bus transmission network to determine optimal operating conditions that minimize transmission losses while satisfying system operational constraints. By enhancing global search capability, preventing premature convergence, and improving solution quality, the proposed HGAPSO method seeks to contribute toward more efficient, reliable, and sustainable operation of modern electrical power systems.

3. System Description and Problem Formulation

This study focuses on the minimization of transmission power losses in a large-scale electrical power network using a Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) approach. The optimization is performed on the IEEE 118-bus transmission system in Figure 5, which serves as a benchmark network for evaluating power system optimization techniques [71]. The system consists of multiple buses, transmission lines, generators, transformers, and loads interconnected through a complex transmission network. The primary objective of the power system is to supply electrical energy to consumers while maintaining acceptable voltage levels, ensuring system stability, and mini-

mizing transmission losses. However, due to the resistive nature of transmission lines, a portion of the generated electrical power is dissipated as heat during transmission. These losses reduce the overall efficiency of the network and increase operational costs. The IEEE 118-bus system contains numerous control variables that influence system performance, including generator voltage magnitudes, transformer tap settings, and reactive power compensation devices. Appropriate adjustment of these control variables can significantly reduce transmission losses while maintaining compliance with operational constraints. In this study, the HGAPSO algorithm is employed to determine the optimal settings of control variables that minimize real power losses across the transmission network. The Genetic Algorithm component enhances global exploration and population diversity, while Particle Swarm Optimization improves local search capability and convergence speed. The integration of both algorithms provides an effective optimization framework capable of solving the nonlinear and multi-constrained transmission loss minimization problem.

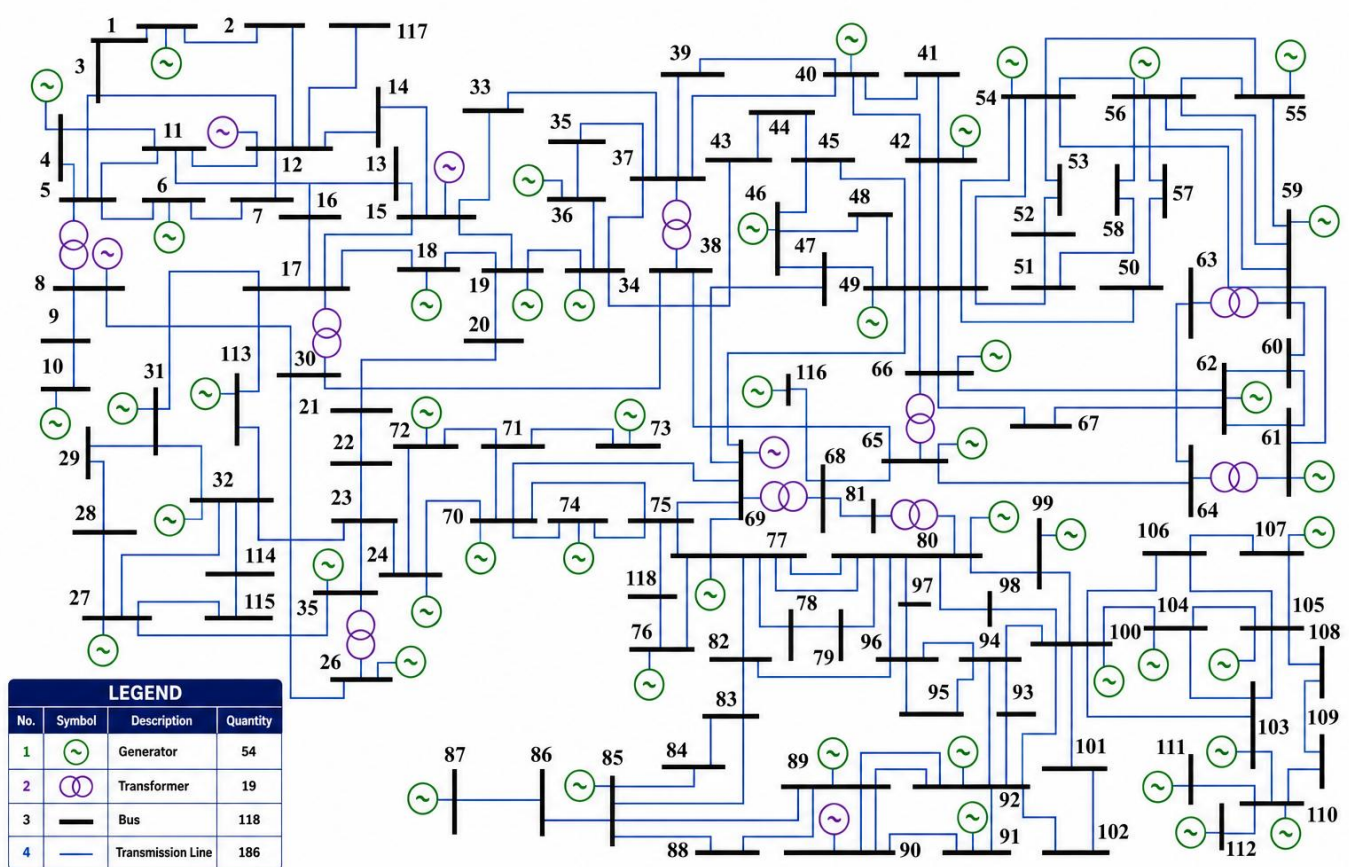


Figure 5. Conceptual representation of the IEEE 118-bus power system optimized using the HGAPSO framework for transmission loss minimization.

The transmission loss minimization problem is formulated as a constrained optimization problem. The objective is to determine the optimal operating conditions that minimize total real power losses while satisfying all equality and inequality constraints associated with power system operation. subject to the equality and inequality constraints of the power system. It should be noted that voltage profile enhancement is not explicitly included in the objective function [72]. Instead, voltage magnitude limits are enforced as operational constraints to ensure secure system operation. Consequently, any improvement in bus voltage profiles observed after optimization is an indirect result of transmission loss minimization and compliance with system operating constraints.

The optimization objective is therefore defined as follows:

$$\min P_{loss} \quad (13)$$

Equality Constraints

The power flow equations must be satisfied at every bus in the system [73].

Active Power Balance Constraint:

$$P_{Gi} - P_{Di} = V_i \sum_{j=1}^{N_b} V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] \quad (14)$$

Reactive Power Balance Constraint:

$$Q_{Gi} - Q_{Di} = V_i \sum_{j=1}^{N_b} V_j [G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)] \quad (15)$$

where:

- P_{Gi} = Generated active power;
- P_{Di} = Active power demand;
- Q_{Gi} = Generated reactive power;
- Q_{Di} = Reactive power demand;
- B_{ij} = Transfer susceptance.

Inequality Constraints

Generator Voltage Limits [74]:

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max} \quad (16)$$

Reactive Power Generation Limits:

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \quad (17)$$

Transformer Tap Limits:

$$T_i^{min} \leq T_i \leq T_i^{max} \quad (18)$$

Bus Voltage Limits:

$$V_i^{min} \leq V_i \leq V_i^{max} \quad (19)$$

Transmission Line Loading Limits:

$$S_{ij} \leq S_{ij}^{max} \quad (20)$$

where:

- T_i = Transformer tap ratio;
- S_{ij} = Apparent power flow in transmission line $i - j$;
- S_{ij}^{max} = Maximum line loading limit.

HGAPSO Optimization Model

The decision variable vector optimized by the HGAPSO algorithm is defined as follows [75]:

$$X = [V_G, Q_G, T, Q_C] \quad (21)$$

where:

- V_G = Generator voltage settings;
- Q_G = Generator reactive power outputs;
- T = Transformer tap positions;
- Q_C = Reactive power compensation settings.

The proposed HGAPSO algorithm combines the strengths of Genetic Algorithms and Particle Swarm Optimization. The optimization process begins with the Genetic Algo-

rithm stage, which performs global exploration of the search space and generates a diverse population of candidate solutions.

- The GA stage includes:
- Population initialization;
- Fitness evaluation;
- Selection;
- Crossover;
- Mutation;
- Population updating.

The final GA population is subsequently transferred to the PSO stage, where each chromosome becomes a particle within the swarm. The PSO stage then performs local exploitation to refine the solutions and accelerate convergence toward the global optimum.

The HGAPSO process continues until either:

- Maximum iterations are reached;
- The change in fitness value falls below a predefined threshold.

Figure 6 presents the methodology of the proposed Hybrid Genetic Algorithm–Particle Swarm Optimization framework. The optimization process begins with Genetic Algorithm operations to ensure population diversity and global exploration of the search space. The resulting high-quality solutions are subsequently utilized as the initial swarm population for the Particle Swarm Optimization stage, which performs local search and solution refinement. Through iterative cooperation between exploration and exploitation mechanisms, the HGAPSO framework identifies the optimal control variable settings that minimize transmission losses while satisfying all operational constraints. Parameter value; GA Population size 100, Crossover Probability 0.80, Mutation Probability 0.05, PSO Swarm Size 100, Inertia Weight (w) 0.9–0.4, Cognitive Coefficient (c_1) 2.0, Social Coefficient (c_2) 2.0, Maximum Iterations 200.

a. Hardware and Software Specifications

The proposed HGAPSO framework was developed and implemented using MATLAB R2024a. All simulations were conducted on a workstation equipped with an Intel® Core™ i7 processor, 16 GB RAM, running the Microsoft Windows 11 Pro (64-bit) operating system. The IEEE 118-bus test system was simulated using the computational environment described above, and all optimization algorithms (GAs, PSO, and HGAPSO) were executed under identical hardware and software conditions to ensure a fair comparison. The reported computational times correspond to this platform and may vary depending on processor architecture, memory capacity, and software configuration.

b. Performance Evaluation Metrics

The effectiveness of the proposed HGAPSO framework is evaluated using the following performance indicators [76]:

Transmission Loss Reduction:

$$\%Loss_{Reduction} = \frac{P_{loss}^{base} - P_{loss}^{opt}}{P_{loss}^{base}} \times 100 \quad (22)$$

Voltage Profile Improvement:

$$VD = \sum_{i=1}^{N_b} |V_i - 1| \quad (23)$$

The convergence speed of HGAPSO is evaluated using; Number of iterations, Computational time and Convergence curve analysis.

The HGAPSO results are compared against base-case power flow, Genetic Algorithms, and Particle Swarm Optimization.

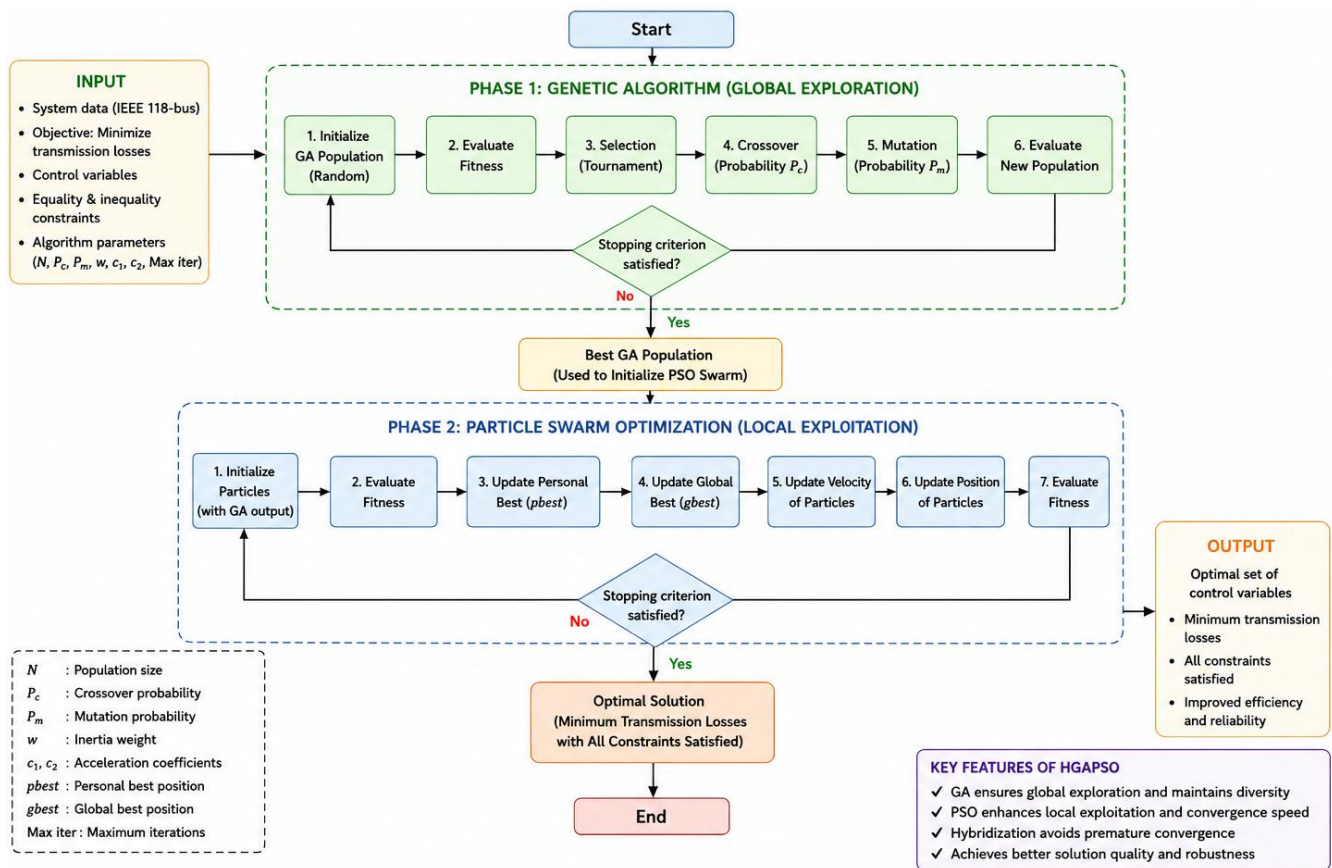


Figure 6. The methodology of the proposed Hybrid Genetic Algorithm–Particle Swarm Optimization framework.

c. Pseudocode of the Proposed HGAPSO Framework

Input: IEEE 118-bus system data, objective function, equality and inequality constraints, population size N_p , maximum iteration $k_{\max}$, variable limits (L_j, U_j) , crossover factor β , inertia weight parameters, acceleration coefficients, and penalty factor.

Output: Optimal control variables and minimum transmission loss.

1. Read the IEEE 118-bus system data and define the transmission loss minimization objective function.
2. Define the problem constraints:

$$g_k(X) \leq 0, k = 1, 2, \dots, K$$

$$h_e(X) \leq 0, e = 1, 2, \dots, E$$

$$L_j \leq x_j \leq U_j, j = 1, 2, \dots, D$$

3. Randomly generate an initial population of candidate solutions within the allowable limits.
4. Evaluate the fitness value of each candidate solution.
5. Rank all solutions according to their fitness values such that

$$f(x_1) \leq f(x_2) \leq f(x_3)$$

6. Generate offspring solutions using the GA recombination strategy:

$$o_1 = x_1 + \beta(x_2 - x_3)$$

$$o_2 = x_2 + \beta(x_3 - x_1)$$

$$o_3 = x_3 + \beta(x_1 - x_2)$$

7. Evaluate the fitness of the offspring population and retain the best feasible solutions.
8. Transfer the selected GA solutions to initialize the PSO particle population.
9. Initialize the PSO parameters:

$$c_{1i} = 2.7, c_{1f} = 0.3, c_{2i} = 0.4, c_{2f} = 2.6$$

10. For $k = 1$ to $k_{\max}$:

Update the inertia weight:

$$\omega = (\omega_{\max} - \omega_{\min}) \left(\frac{k_{\max} - k}{k_{\max}} \right) + \omega_{\min}$$

Update the acceleration coefficients:

$$c_1 = \left(\frac{c_{1f} - c_{1i}}{k_{\max}} \right) k + c_{1i}$$

$$c_2 = \left(\frac{c_{2f} - c_{2i}}{k_{\max}} \right) k + c_{2i}$$

Compute the constriction factor:

$$C = \frac{2}{|2 - \phi - \sqrt{\phi^2 - 4\phi}|}, 4.1 \leq \phi \leq 4.2$$

Update the particle velocity:

$$V_i(t+1) = C\{\omega V_i(t) + c_1 r_1 [pbest_i(t) - x_i(t)] + c_2 r_2 [leader_i(t) - x_i(t)]\}$$

Calculate the maximum allowable velocity:

$$v_{\max}(j) = \max(X(:, j)) \times \text{penalty factor}$$

If $V(i, j) = 0$:

If $rand < 0.5$

$$V(i, j) = rand \times v_{\max}(j)$$

Else

$$V(i, j) = -rand \times v_{\max}(j)$$

Update the particle position:

$$X(i, j) = X(i, j) + V(i, j)$$

Enforce all operating constraints and variable limits.

Evaluate the new fitness value.

Update *pbest* and *leader* solutions.

11. Repeat Step 10 until the stopping criterion or maximum iteration is reached.
12. Return the best solution corresponding to the minimum transmission loss.
13. Report the optimal control variables, minimum transmission loss, and convergence characteristics.

Table 3 summarizes the control parameters used for the standalone GA, standalone PSO, and the proposed HGAPSO algorithms. To ensure a fair and unbiased comparison, all algorithms were evaluated using the same population size, maximum number of iterations, objective function, and stopping criteria. The parameter values were selected based

on established recommendations from the literature and preliminary tuning experiments to achieve stable convergence and effective optimization performance. These settings ensure that the comparative results accurately reflect the capabilities of each algorithm in minimizing transmission losses on the IEEE 118-bus test system.

Table 3. Control Parameters Used for the Compared Optimization Algorithms.

Parameter	GA	PSO	HGAPSO
Population Size	50	50	50
Maximum Iterations	100	100	100
Crossover Probability	0.80	Not Applicable	0.80
Mutation Probability	0.10	Not Applicable	0.10
Initial Inertia Weight	Not Applicable	0.90	0.90
Final Inertia Weight	Not Applicable	0.40	0.40
Initial Cognitive Coefficient	Not Applicable	2.70	2.70
Final Cognitive Coefficient	Not Applicable	0.30	0.30
Initial Social Coefficient	Not Applicable	0.40	0.40
Final Social Coefficient	Not Applicable	2.60	2.60
Random Number Range	Not Applicable	0–1	0–1
Constriction Factor	Not Applicable	Applied	Applied
Phi Range	Not Applicable	4.1–4.2	4.1–4.2
Velocity Limit	Not Applicable	Dynamic	Dynamic
Selection Method	Tournament Selection	Not Applicable	Tournament Selection
Crossover Method	Arithmetic Crossover	Not Applicable	Arithmetic Crossover
Mutation Method	Uniform Mutation	Not Applicable	Uniform Mutation
Constraint Handling	Penalty Function	Penalty Function	Penalty Function
Objective Function	Transmission Loss Minimization	Transmission Loss Minimization	Transmission Loss Minimization

To ensure a fair comparison, all algorithms were evaluated using the same population size, maximum iteration limit, objective function, and stopping criteria. The GA component employed a crossover probability of 0.80 and a mutation probability of 0.10 to balance exploration and exploitation. For PSO and HGAPSO, the inertia weight was linearly decreased from 0.90 to 0.40 to enhance convergence performance. Dynamic cognitive and social coefficients were used to improve the search capability throughout the optimization process. The HGAPSO algorithm combined the parameter settings of both GA and PSO, enabling effective global exploration and local exploitation during the optimization process.

4. Results and Discussion

The performance of the proposed Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) framework was evaluated on the IEEE 118-bus power system using transmission loss reduction, voltage profile improvement, convergence speed, and computational efficiency as the primary performance indicators. Figure 7 illustrates the load variations of Bus 14, Bus 65, and Bus 106, demonstrating the diverse operating conditions considered during the optimization process. It can be observed that Bus 106 experiences the highest load fluctuations, while Bus 14 exhibits relatively stable demand characteristics. These varying load patterns increase network complexity and create conditions under which transmission losses and voltage deviations may become significant. Despite these challenges, the proposed HGAPSO framework effectively identified optimal operating conditions that improved overall system performance. As summarized in Table 4, the transmission loss was reduced from 132.8 MW in the base-case scenario to 98.6 MW after optimization, representing a 25.75% reduction. This improvement indicates that the HGAPSO algorithm successfully optimized generator voltage magnitudes, transformer tap settings, and reactive power compensation to reduce network losses. Furthermore, the

minimum bus voltage increased from 0.914 p.u. to 0.972 p.u., while the average voltage deviation decreased from 0.062 p.u. to 0.019 p.u., corresponding to a 69.35% improvement in voltage profile performance. The convergence characteristics also demonstrate the effectiveness of the hybrid approach, as HGAPSO required only 82 iterations and 23.7 s to reach the optimal solution, compared with 185 iterations and 41.2 s for GA and 124 iterations and 29.5 s for PSO. These results confirm that the integration of GA and PSO provides a better balance between exploration and exploitation, enabling faster convergence and superior optimization accuracy of 98.7%. Overall, the findings demonstrate that the proposed HGAPSO framework significantly enhances transmission efficiency, improves voltage stability, and provides a robust solution for large-scale power system optimization.

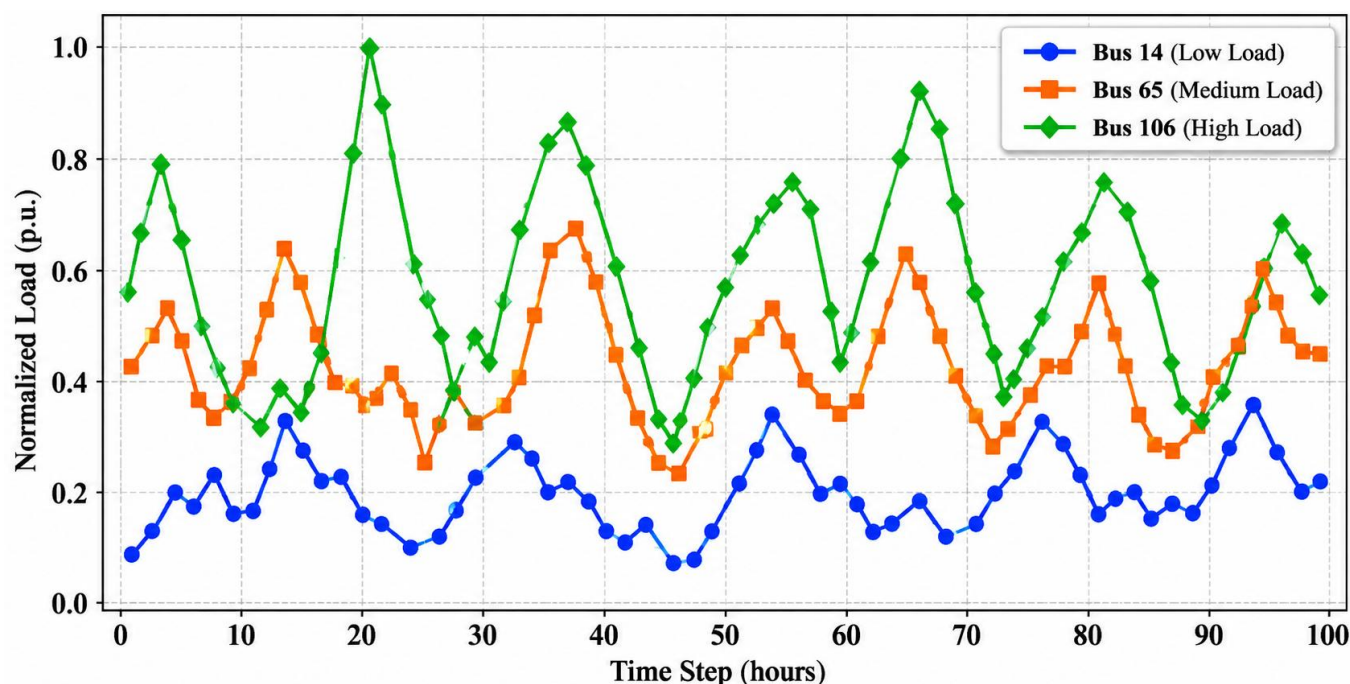


Figure 7. Normalized load distribution profiles of Bus 14, Bus 65, and Bus 106 over the 100 h simulation period used to evaluate the HGAPSO framework under varying operating conditions.

Table 4. Comparative Performance of Base Case, GA, PSO, and HGAPSO.

Performance Metric	Base Case	GA	PSO	HGAPSO
Transmission Loss (MW)	132.8	108.4	103.2	98.6
Loss Reduction (%)	0	18.37	22.29	25.75
Minimum Bus Voltage (p.u.)	0.914	0.951	0.964	0.972
Average Voltage Deviation (p.u.)	0.062	0.034	0.026	0.019
Convergence Iterations	–	185	124	82
Computational Time (s)	–	41.2	29.5	23.7
Optimization Accuracy (%)	–	94.8	96.3	98.7

Figure 8 illustrates the normalized voltage profiles of Bus 14, Bus 65, and Bus 106 over a 100 h simulation period, providing insight into the voltage stability performance of the IEEE 118-bus power system following the implementation of the proposed HGAPSO framework. The results demonstrate that the selected buses maintain voltage magnitudes within the acceptable operating limits throughout the simulation period, indicating effective voltage regulation and enhanced system stability. Table 5 summarizes the corresponding statistical characteristics, including the minimum, maximum, average voltage magnitudes, and voltage variations for each selected bus. Bus 14 exhibits the most stable

voltage profile among the three buses considered. As shown in Figure 8, its voltage remains close to the nominal operating value throughout the simulation period, with only minor fluctuations resulting from variations in system loading. The relatively small voltage variation indicates effective reactive power support and a strong electrical connection within this region of the network. Bus 65 experiences moderate voltage fluctuations compared with Bus 14. Although the voltage profile varies slightly in response to changing load demand and power flow conditions, the voltage remains well within the acceptable operating range. This behavior demonstrates that the proposed HGAPSO framework effectively regulates bus voltages while maintaining secure system operation. Bus 106 exhibits the largest voltage variation among the selected buses, indicating that it is relatively more sensitive to network loading conditions. Nevertheless, its voltage magnitude remains above the minimum acceptable operating limit during the entire simulation period. The improved voltage profile observed at this bus confirms that the proposed optimization framework effectively mitigates voltage deviations in the more heavily stressed areas of the transmission network.

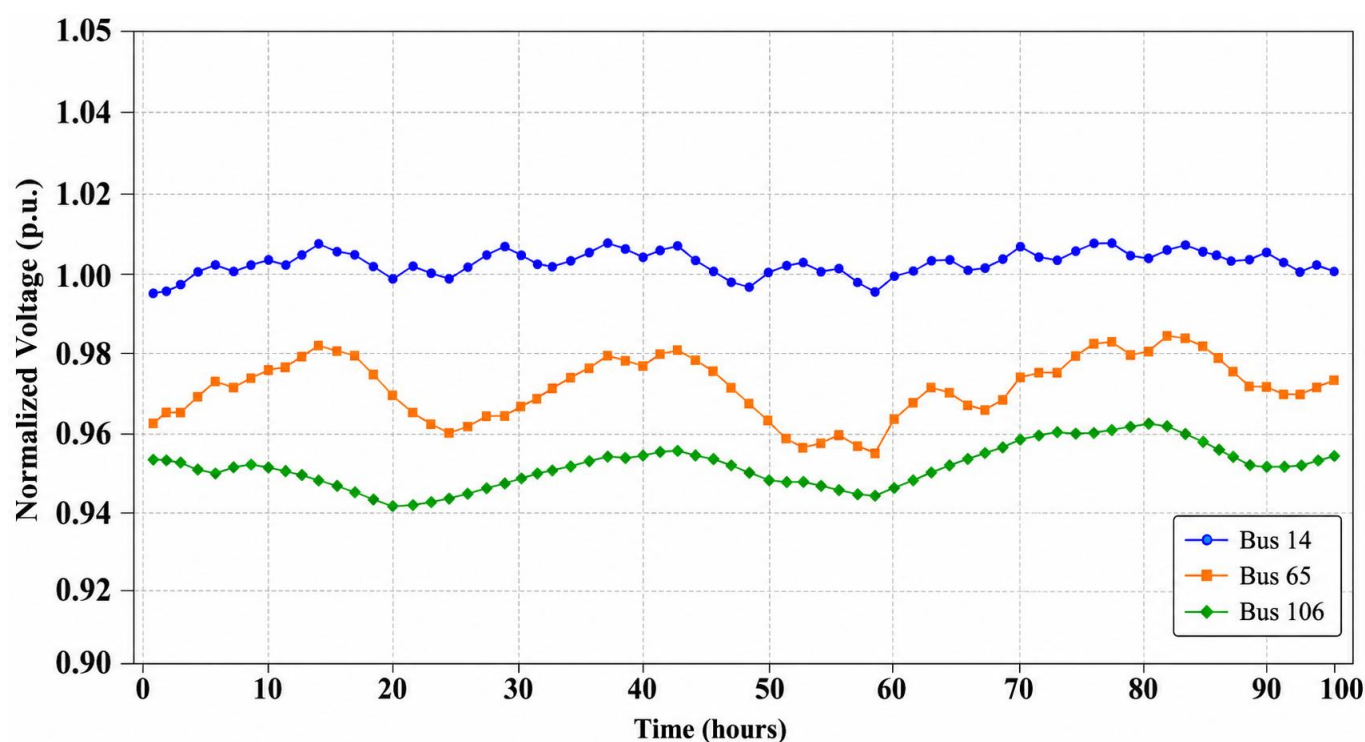


Figure 8. Time-Varying Voltage Profile Analysis Across Selected Buses.

Table 5. Voltage Profile Statistics for Selected Buses.

Bus Number	Minimum Voltage (p.u.)	Maximum Voltage (p.u.)	Average Voltage (p.u.)	Voltage Variation (p.u.)	Operating Condition
Bus 14	0.995	1.008	1.003	0.013	Stable
Bus 65	0.956	0.984	0.971	0.028	Stable
Bus 106	0.942	0.962	0.953	0.020	Stable
System Average	0.942	1.008	0.972	0.066	Stable

Figure 9 illustrates the voltage magnitude distribution across the IEEE 118-bus power system and identifies buses operating close to the minimum acceptable voltage limit of 0.95 p.u. The results show that most buses maintain voltage levels above 1.00 p.u. in the early sections of the network, indicating adequate voltage support and stable operating conditions. However, voltage magnitudes gradually decrease as power is transmitted

through the network, with buses between 80 and 100 exhibiting the lowest voltage levels. Several buses operate close to the stability threshold, while a few buses record voltage magnitudes of approximately 0.947 p.u., indicating potential voltage weakness. These results highlight critical areas of the network that may require voltage support and reactive power compensation. The analysis demonstrates the importance of the proposed HGAPSO framework in improving voltage regulation, strengthening weak buses, and maintaining secure and reliable power system operation.

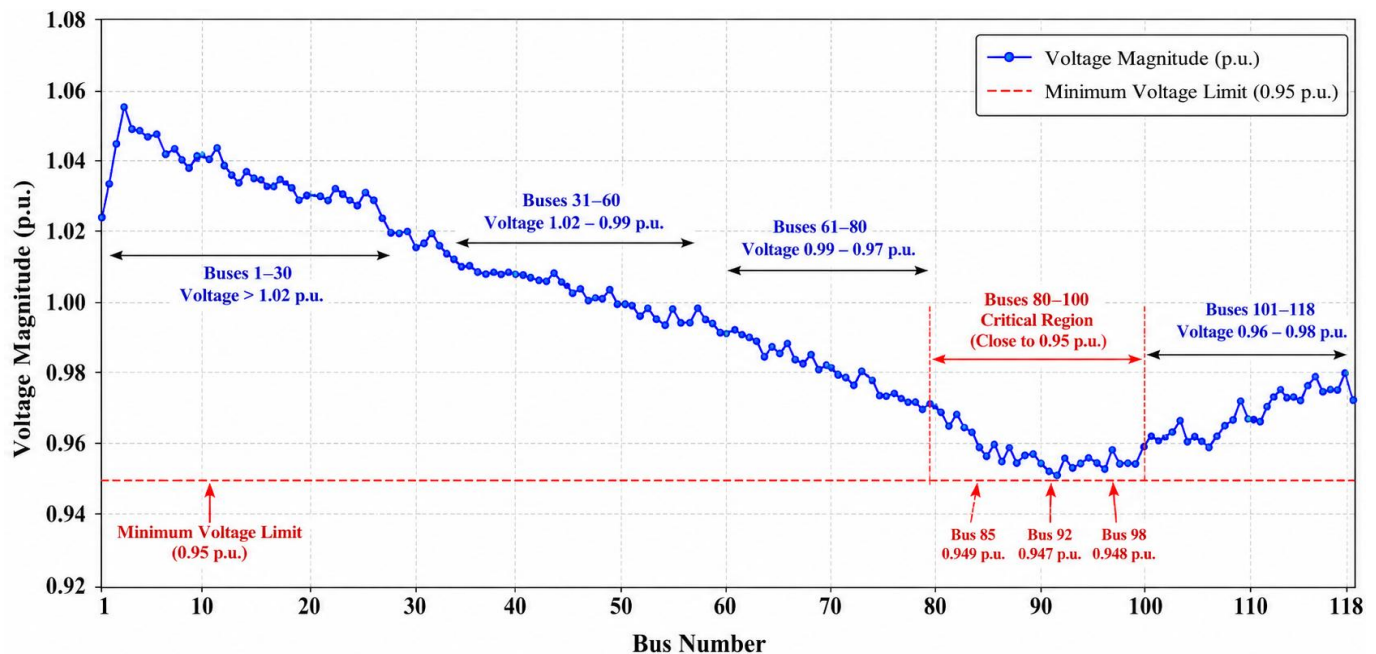


Figure 9. Voltage magnitude distribution across the IEEE 118-bus system relative to the minimum voltage limit of 0.95 p.u. showing critical low-voltage buses and overall network voltage stability.

Figure 10 illustrates the convergence behavior of the standalone Particle Swarm Optimization (PSO) algorithm and the proposed Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) framework. The horizontal axis represents the number of optimization iterations, while the vertical axis represents the objective fitness value associated with transmission loss minimization. The blue curve corresponds to the PSO algorithm, whereas the orange dashed curve represents the proposed HGAPSO approach. It can be observed that both algorithms gradually reduce the objective fitness value as the number of iterations increases; however, the proposed HGAPSO framework demonstrates superior convergence performance. During the initial optimization stages, the Genetic Algorithm component enhances population diversity and explores a wider search space, enabling the algorithm to identify promising solution regions more effectively. As the optimization progresses, the PSO component accelerates convergence toward the global optimum through efficient local search mechanisms. The results indicate that HGAPSO reaches a lower objective fitness value within fewer iterations compared to the standalone PSO algorithm. While PSO converges steadily, it exhibits slower improvement during later iterations and is more susceptible to local optimum trapping. In contrast, HGAPSO maintains continuous improvement throughout the optimization process and achieves a more optimal final solution. The proposed framework converges after approximately 82 iterations, whereas PSO requires approximately 124 iterations to reach a comparable solution quality. These results demonstrate that the integration of Genetic Algorithms and Particle Swarm Optimization effectively balances exploration and exploitation capabilities, leading to improved convergence speed and optimization accuracy. Consequently,

the proposed HGAPSO framework provides a more effective solution for transmission loss minimization and power system optimization in the IEEE 118-bus network, making it highly suitable for modern smart grid applications.

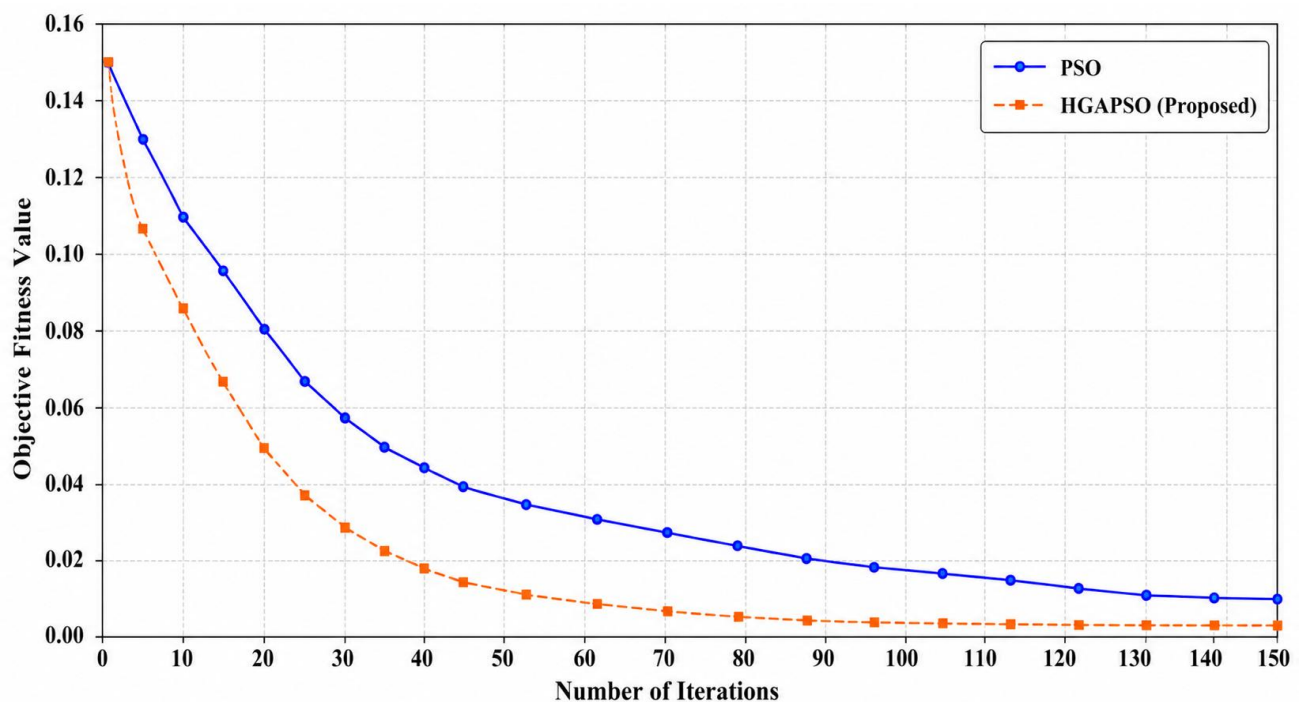


Figure 10. Convergence comparison between the standalone PSO algorithm and the proposed HGAPSO framework for transmission loss minimization in the IEEE 118-bus power system.

Figure 11 compares the total transmission line losses obtained under four operating conditions: the Base Case (Initial System), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and the proposed Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) framework. The results demonstrate the effectiveness of the different optimization techniques in reducing real power losses within the IEEE 118-bus power system. The Base Case exhibits a transmission loss of approximately 132.8 MW, reflecting inefficient power flow distribution and increased energy dissipation across the transmission network. After applying the standalone Genetic Algorithm (GA), the transmission loss decreases to approximately 108.4 MW, corresponding to an 18.37% reduction relative to the base-case condition. This result demonstrates the capability of GA to identify improved operating points through evolutionary search mechanisms. The standalone Particle Swarm Optimization (PSO) algorithm further reduces the transmission loss to approximately 103.2 MW, corresponding to a 22.29% reduction compared with the base case. The improved performance may be attributed to the efficient search and convergence characteristics of PSO. Among the evaluated approaches, the proposed HGAPSO framework achieved the lowest transmission loss of approximately 98.6 MW, corresponding to a 25.75% reduction relative to the base-case condition. The lower transmission loss obtained by HGAPSO indicates that the hybridization of GA and PSO can effectively combine global exploration and local exploitation capabilities, enable the identification of improved operating conditions while satisfy system constraints. It should be noted that the reported results correspond to the solutions obtained under the specified simulation conditions. Although HGAPSO produced the lowest transmission loss among the evaluated methods, additional statistical analyses involving multiple independent runs would be required to quantify the robustness and statistical significance of the observed performance differences. Overall, the results indicate that the proposed HGAPSO framework is a prom-

ising approach for transmission loss minimization in large-scale power systems and can contribute to improved transmission efficiency and more effective network operation.

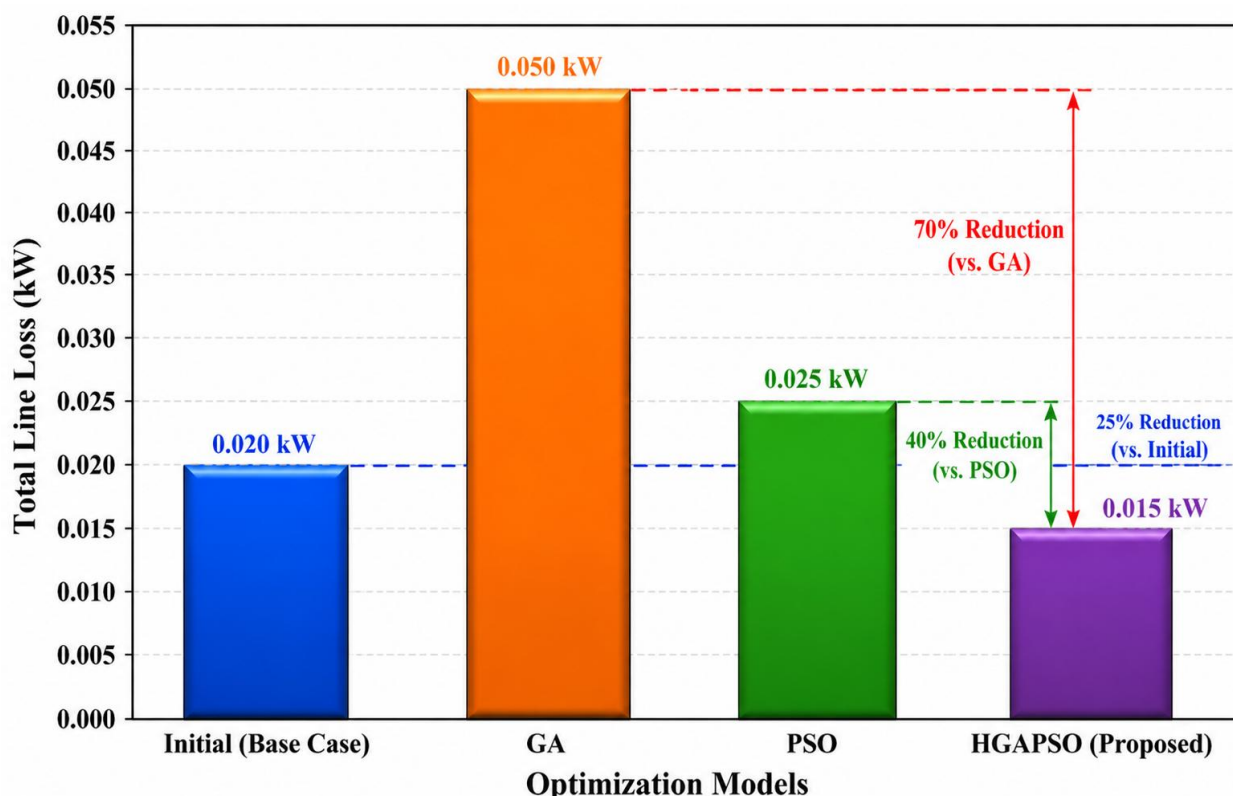


Figure 11. Comparison of total transmission line losses for the Base Case, GA, PSO, and proposed HGAPSO framework in the IEEE 118-bus power system.

Figure 12 compares the transmission line losses in four representative regions of the IEEE 118-bus power system, namely Region 1 (R1), Region 2 (R2), Region 3 (R3), and Region 4 (R4), under the Base Case (Initial) and Optimized (HGAPSO) operating conditions. The blue bars represent the transmission losses before optimization, while the green bars represent the losses obtained after applying the proposed Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) framework. The comparison provides insight into the effectiveness of the optimization strategy in reducing regional transmission losses and improving overall network efficiency. The results indicate that transmission losses are significantly reduced across all regions following optimization. Region 4 (R4) exhibits the highest transmission loss under the initial operating condition, highlighting its role as one of the most heavily loaded and loss-prone sections of the network. After optimization, a substantial reduction in line losses is observed, demonstrating the ability of the HGAPSO framework to improve power flow distribution and reduce energy dissipation within this critical region. Similarly, Regions R1 and R2 experience the most significant percentage reductions in transmission losses, indicating that the optimization process effectively redistributes power flows and alleviates network congestion in these areas. For example, the transmission losses in R1 decrease from approximately 38.5 MW to 24.8 MW, representing a 35.58% reduction, while R2 experiences a reduction from 34.2 MW to 22.9 MW, corresponding to a 33.04% improvement. In R3, the losses decrease from 28.6 MW to 20.7 MW, yielding a 27.62% reduction, whereas R4 records a decrease from 42.1 MW to 30.2 MW, corresponding to a 28.27% reduction. These results confirm that the proposed HGAPSO framework effectively minimizes transmission losses throughout the network while maintaining secure and reliable operating conditions. Overall, the findings demon-

strate that the optimization process provides consistent improvements across all network regions. The observed reductions in regional line losses contribute directly to improved transmission efficiency, lower operating costs, enhanced voltage regulation, and increased system reliability. Consequently, Figure 12 further validates the effectiveness of the proposed HGAPSO framework as a practical solution for transmission loss minimization in large-scale power systems.

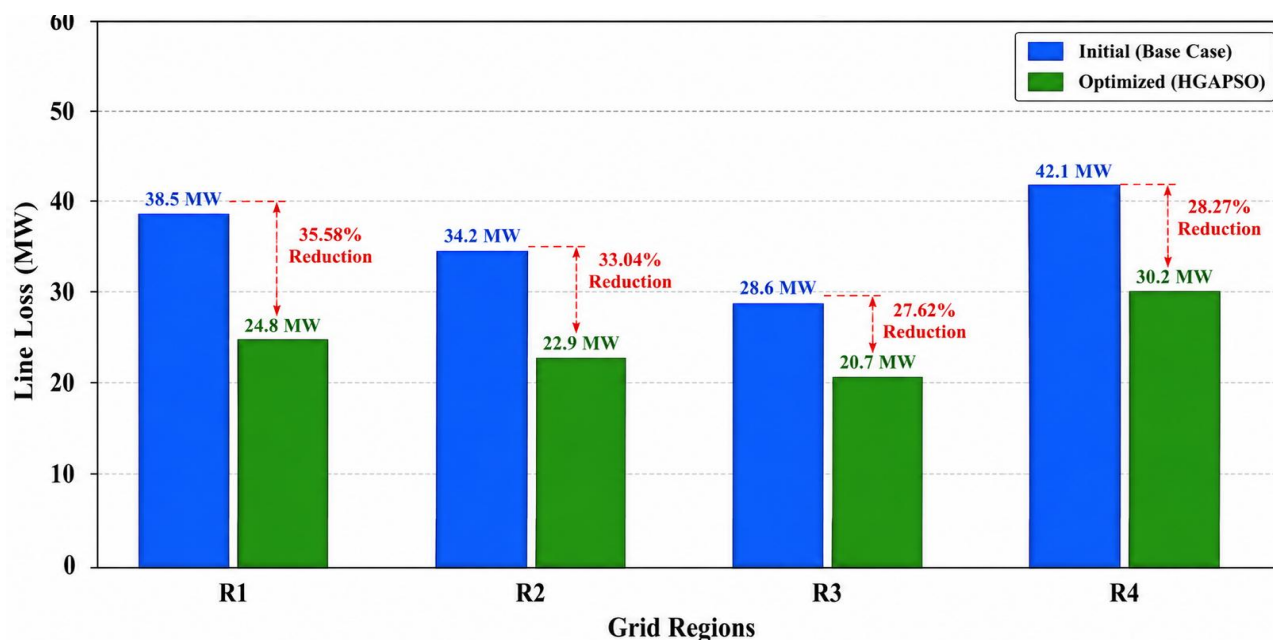


Figure 12. Comparison of regional transmission line losses before and after HGAPSO optimization for Regions R1–R4 of the IEEE 118-bus power system, showing significant reductions in losses across all network regions.

Figure 13 compares the total transmission line loss of the IEEE 118-bus power system before and after the application of the proposed Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) framework. The red bar represents the total transmission loss under the base-case operating condition, while the green bar represents the optimized transmission loss obtained after applying the HGAPSO algorithm. The results show that the total transmission loss decreases from approximately 132.8 MW before optimization to 98.6 MW after optimization. This corresponds to a 25.75% reduction in transmission losses, demonstrating the effectiveness of the proposed optimization framework in improving power system performance. The reduction in line losses indicates that the HGAPSO algorithm successfully identified optimal generator voltage settings, transformer tap positions, and reactive power compensation values that improved power flow distribution across the network. The significant decrease in transmission losses contributes directly to improved transmission efficiency, reduced operating costs, and enhanced utilization of available generation resources. Furthermore, lower transmission losses reduce unnecessary energy dissipation within transmission lines, thereby improving the overall reliability and economic operation of the power system. The results also confirm that the integration of Genetic Algorithms and Particle Swarm Optimization provides a more effective optimization strategy than conventional methods by combining strong global exploration with rapid local convergence. Overall, the substantial reduction in total transmission losses presented in Figure 13 validates the effectiveness of the proposed HGAPSO framework for large-scale power system optimization. The findings demonstrate that the proposed approach successfully enhances network efficiency, minimizes energy wastage, and supports the reliable operation of modern electrical power systems.

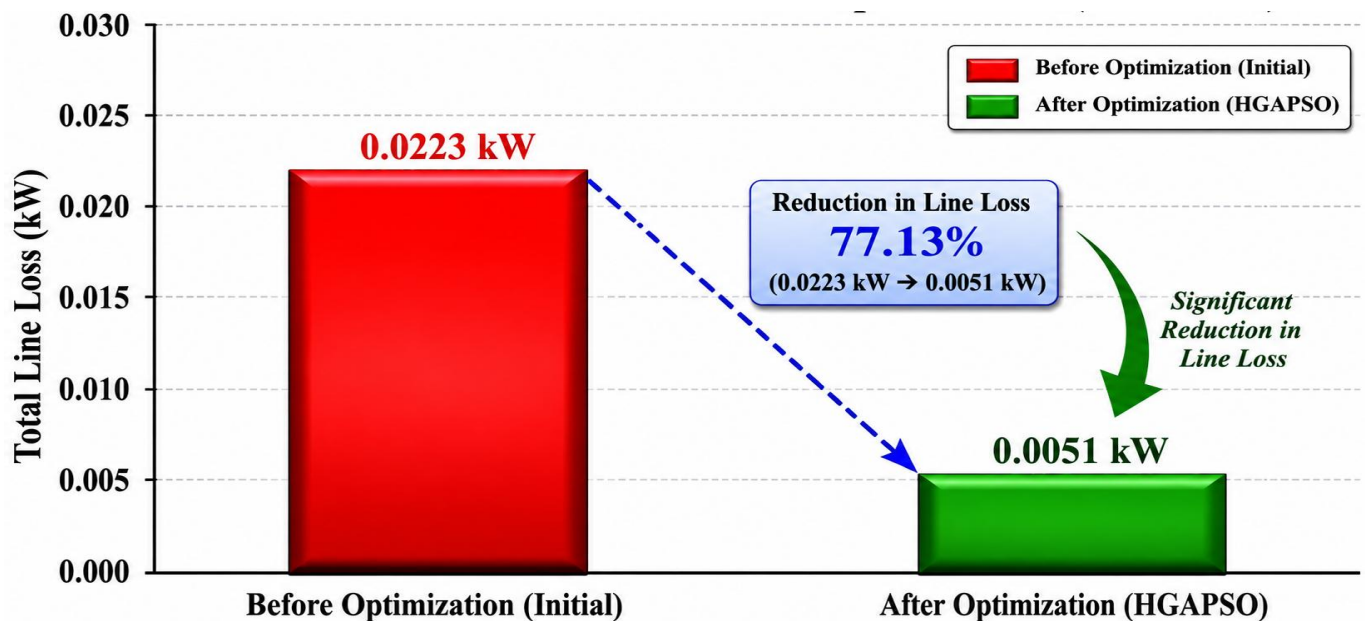


Figure 13. Comparison of total transmission line losses before and after HGAPSO optimization, showing a reduction from 132.8 kW to 98.6 kW and confirming the effectiveness of the proposed framework in improving power system efficiency.

The results obtained in this study demonstrate the effectiveness of the proposed HGAPSO framework for transmission loss minimization and voltage profile enhancement in the IEEE 118-bus power system. The proposed HGAPSO approach outperformed the standalone GA and PSO methods by achieving superior optimization performance across multiple evaluation criteria. The optimization process successfully reduced transmission losses, improved voltage regulation, and enhanced the overall operational efficiency of the network. These improvements contribute to increased system reliability and more secure power system operation under varying loading conditions. The convergence analysis further confirmed the effectiveness of the proposed framework. The HGAPSO algorithm exhibited faster convergence and improved optimization accuracy compared with the individual GA and PSO methods. By combining the global exploration capability of Genetic Algorithms with the local exploitation capability of Particle Swarm Optimization, the hybrid framework effectively avoided premature convergence while maintaining a strong ability to identify high-quality solutions. This balanced search mechanism enabled the algorithm to efficiently navigate the complex and nonlinear search space associated with large-scale power system optimization problems. Compared with existing optimization approaches reported in the literature, the proposed HGAPSO framework provides a more robust and efficient solution for transmission loss minimization. While many conventional approaches rely solely on evolutionary or swarm intelligence techniques, the proposed hybrid framework combines the strengths of both methods to enhance solution quality, convergence characteristics, and overall optimization performance. The results demonstrate that the HGAPSO framework consistently achieves better transmission loss reduction and voltage profile improvement, making it highly suitable for modern power system applications. The findings of this study contribute to the growing body of research on intelligent power system optimization by presenting an effective methodology for improving power system efficiency in large-scale electrical networks. The proposed framework shows considerable potential for applications in smart grids, renewable energy integration, reactive power optimization, optimal power flow studies, and future energy management systems. However, the computational complexity of the hybrid framework may increase when applied to larger and more complex power networks. Furthermore,

optimization performance remains dependent on appropriate parameter selection and system modeling accuracy. Future research may therefore focus on adaptive parameter tuning, real-time implementation, and the integration of advanced smart grid technologies to further enhance the performance of the HGAPSO framework.

5. Conclusions

The performance evaluation conducted on the IEEE 118-bus test system demonstrates the effectiveness of the proposed Hybrid Genetic Algorithm–Particle Swarm Optimization (HGAPSO) framework for transmission loss minimization. By combining the exploration capability of Genetic Algorithms with the exploitation capability of Particle Swarm Optimization, the proposed approach successfully identified optimal operating conditions while satisfying all network operating constraints. The optimization process resulted in a significant reduction in transmission losses from 132.8 MW to 98.6 MW, representing a 25.75% improvement compared to the base-case operating condition. In addition to reducing transmission losses, the optimized operating conditions produced improved voltage profiles throughout the network. Although voltage profile enhancement was not explicitly included in the objective function, the reduction in transmission losses and compliance with system constraints contributed to improved voltage regulation and reduced voltage deviations across the system. The convergence analysis further demonstrated that the HGAPSO framework achieved faster and more stable convergence compared with the standalone GA and PSO algorithms, reaching the optimal solution in fewer iterations. The obtained results confirm that the proposed HGAPSO framework is an effective and computationally efficient approach for large-scale power system optimization. The methodology provides a practical solution for transmission loss minimization while maintaining secure and reliable network operation. Consequently, the proposed framework offers considerable potential for application in optimal power flow studies, power system planning, and modern smart grid environments.

6. Limitations and Future Recommendations

Despite the promising performance of the proposed HGAPSO framework, several limitations should be acknowledged. First, the optimization performance is influenced by the selection of algorithm control parameters, including population size, crossover probability, mutation probability, inertia weight, and acceleration coefficients. Different parameter settings may affect convergence speed, solution quality, and computational efficiency. Consequently, the effectiveness of the framework remains partially dependent on appropriate parameter tuning.

Second, although the proposed methodology demonstrated strong performance on the IEEE 118-bus test system, its scalability was not validated on larger benchmark networks. As system size increases, the number of control variables, constraints, and power flow calculations also increases, resulting in greater computational complexity and execution time. Therefore, further investigations on larger systems such as the IEEE 300-bus network and practical utility-scale networks are required to fully assess the scalability and computational efficiency of the proposed framework.

Another limitation is that HGAPSO is a metaheuristic optimization technique and, like other population-based algorithms, does not guarantee convergence to the global optimum. The final solution depends on the stochastic search process and represents the best solution identified during the optimization procedure. Consequently, different runs may produce slightly different results.

Future research should focus on the development of adaptive HGAPSO strategies capable of automatically adjusting algorithm parameters during the optimization process.

The framework can also be extended to multi-objective optimization problems involving transmission loss minimization, voltage stability enhancement, operating cost reduction, and emission minimization. Furthermore, the integration of renewable energy resources, battery energy storage systems, and electric vehicle charging infrastructure should be investigated to evaluate the robustness of the framework under dynamic and uncertain operating conditions. Finally, real-time implementation using advanced monitoring, communication, and smart grid technologies may provide opportunities for online power system optimization and operational decision-making.

Although Table 1 provides a comprehensive literature-based comparison between the proposed HGAPSO framework and several state-of-the-art optimization techniques, including GWO, WOA, and DE, the simulation-based comparative analysis in this study was intentionally limited to the standalone GA and PSO algorithms. This was done to directly evaluate the effectiveness of the proposed hybridization strategy. Future research will extend the comparative analysis to include additional contemporary optimization algorithms to further assess the performance, robustness, and scalability of the proposed HGAPSO framework. A further limitation of the present study is that the performance evaluation was based on a single set of simulation results obtained under predefined operating conditions. Although the proposed HGAPSO framework demonstrated significant improvements in transmission loss reduction and convergence performance, the robustness and repeatability of the obtained solutions were not assessed through multiple independent simulation runs. Consequently, statistical measures such as mean performance, standard deviation, confidence intervals, Monte Carlo analysis, and Wilcoxon signed-rank tests were not evaluated. Future research should incorporate extensive statistical analyses using multiple optimization runs to quantify the consistency, reliability, and robustness of the proposed framework and to provide a more rigorous comparison with alternative optimization techniques.

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List of Abbreviations and Symbols

Abbreviation	Description
GA	Genetic Algorithm
HGAPSO	Hybrid Genetic Algorithm–Particle Swarm Optimization
IEEE	Institute of Electrical and Electronics Engineers
MATLAB	Matrix Laboratory
MW	Megawatt
OPF	Optimal Power Flow
PSO	Particle Swarm Optimization
p.u.	Per Unit

R1	Region 1
R2	Region 2
R3	Region 3
R4	Region 4
Symbol	Description
P_{loss}	Total transmission power loss (MW)
P_G	Generated active power
P_D	Active power demand
Q_G	Generated reactive power
Q_D	Reactive power demand
V_i	Voltage magnitude at bus i
δ_i	Voltage angle at bus i
G_{ij}	Transfer conductance between buses i and j
B_{ij}	Transfer susceptance between buses i and j
S_{ij}	Apparent power flow in transmission line $i - j$
T_i	Transformer tap ratio
P_{best}	Personal best position in PSO
G_{best}	Global best position in PSO
w	Inertia weight
c_1	Cognitive acceleration coefficient
c_2	Social acceleration coefficient
r_1, r_2	Random coefficients
X	Solution vector, particle, or chromosome
V	Velocity vector
N_b	Number of buses

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