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Original Article

Hybrid Optimization of AC Transmission Expansion Planning for Augmenting Renewable Energy Integration: A Case Study of Kerala State Electricity Board's Subsystem

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***Abstract** - The incorporation of renewable energy sources into power systems is the key factor in achieving de-carbonization, promising a future of energy that is not only cleaner but also more sustainable. This paper presents a multi-objective hybrid optimization method for AC Transmission Expansion Planning (TEP) in electrical power systems incorporating renewable energy sources using the IEEE 24 Reliability Test System. This is an extended work of Multi-Objective Hybrid Optimization for Renewable Energy Integrated Electrical Power Transmission Expansion Planning in DC systems proposed by the authors. The method combines the Genetic Algorithm and the Grey Wolf Optimization known as Grey Wolf with the Genetic Algorithm (GWGA), taking advantage of both methods to optimize the cost and load-shedding factors of power transmission systems with the objective of minimizing transmission losses. The results show that GWGA consistently reduces losses from 2.65 MW to 1.91 MW between the 100^{th} and 500^{th} iterations, demonstrating remarkable stability and convergence compared to all other conventional algorithms. A real system using a modelled subsystem of the Kerala State Electricity Board (KSEB) central zone for optimized TEP using GWGA is also done, and the results are presented. The results achieve the lowest transmission loss with an optimum value of 1.45 MW from 300 iterations onwards. It also minimizes power transmission expansion costs and reduces the risk of load shedding, enhancing the cost-effectiveness of renewable energy integration. This research work also addresses the difficulties encountered in the TEP electrical power system through the optimization of reinforcement lines, generators, and renewable energy sources. The findings presented here can potentially inform future transmission expansion strategies within the KSEB and serve as a model for similar systems globally.*

***Keywords** - Genetic Algorithm, Grey Wolf Optimization, Multi-objective, Renewable energy integration, Transmission expansion planning*.

1. Introduction

Electric power systems play a fundamental role in supporting modern society, powering our homes, businesses and industries. The expanding transmission network would enable optimal, efficient, reliable and cost-feasible delivery of growing power demand [1, 2]. Whereas in the conventional era, the primary goal of TEP was merely to minimize the total investment cost, with power market restructuring, other metrics such as congestion management, nodal pricing, social welfare, and reliability indices have gained more relevance [3, 4]. Transmission planning is a complex process that involves the optimization of new transmission lines, substations and related equipment used to add load and overcome system limitations.To reduce carbon emissions and meet the growing electricity demand, there has been a remarkable expansion of renewable energy generation like wind and solar, providing a cleaner and more sustainable energy future. However, it is not easy to integrate these sources into the power grid. The variable nature of weather-dependent renewable energy sources poses huge challenges to providing a stable energy supply. A robust, high-efficiency transmission infrastructure is required to support this requirement [5-7]. This challenge is more complicated when there is a need to integrate renewable energy sources while meeting environmental goals and keeping the grid stable with various contingencies.In this context, optimization techniques have emerged as an essential tool to help the transmission system planners in their decision-making process. Conventional optimization techniques are sometimes inadequate for addressing scenarios that involve multi-objective problems and complex systems. This is where hybrid optimization techniques come into play, offering the potential to combine the strengths of different optimization algorithms to tackle these challenges effectively.The Kerala State Electricity Board (KSEB) is the leading authority in regulating power supply and distribution across Kerala. The total installed generation capacity of 31.03.2024 is 2307.59 MW; the wind and solar contribute to 2.03 MW and 49.24 MW, respectively. The load demand on average is 3978 MW. Because of increased electricity demands due to urbanization and industrialization, KSEB faces major challenges in delivering reliable, efficient, cost-effective electrical transmission.

Therefore, strategic development plans for expanding transmission infrastructure are essential to successfully attaining this objective. The emphasis on sustainability has increased, and therefore, the inclusion of solar and wind power into the grid has now become the top of KSEB's agenda. Including renewable energy sources remains crucial to meet growing energy needs while reducing dependence on fossil fuels, meeting environmental goals through reduced greenhouse gas emissions, and moving toward renewable energy goals. Renewable energy variability must be managed, and grid stability must be improved to enable steady energy distribution across Kerala; thus, successful transmission planning is required.The paper is structured as follows: Section 2 details the Literature Survey, Section 3 presents the AC-TEP problem definition, Section 4 details Hybrid GWO and GA for AC-TEP Optimization, Section 5 discusses the Results and Discussion, Section 6 provides the Real System Modelling and Analysis, and Section 7 concludes the work.

2. Literature Survey

Optimization methods are essential in solving the problems of TEP because of the non-convex, non-linear, and combinatorial problem characteristics. Conventional approaches are faced with the challenges of computational complexity and solution quality [8]. These are overcome using heuristic and metaheuristic methods. Hybrid methods also involve more than one optimization strategy, which is found to enhance the convergence rate as well as the precision of solutions [9, 10]. Including renewable energy sources further complicates TEP, requiring sophisticated optimization techniques that can consider power demand and generation uncertainties. Selection of the optimization technique is a key aspect that heavily determines investment cost, system reliability and computational intensity, thus representing a vital component in formulating efficient TEP planning.Many research studies have confirmed that TEP is a very complicated, mixed-integer, nonlinear and non-convex problem that requires advanced optimization techniques [11]. Traditional mathematical techniques, such as Mixed-Integer Linear Programming (MILP) and Generalized Benders Decomposition (GBD), have been widely applied; however, they face significant issues related to scalability and computational complexity issues. To avoid such computational problems, evolutionary algorithms and other metaheuristic strategies have been proposed as well. In order to improve the robustness and adaptability of the search in various network conditions, a new evolutionary algorithm combined with a dynamic selection probability is presented [12]. Similarly, Biogeography-Based Optimization (BBO), reported in [13], is much superior towards the TEP solution, especially in the case of simultaneous expansion of transmission lines and reactive power support. Analogously, a study in [14] combines the Generalized Benders Decomposition (GBD) technique with the Linearized Alternating Current (AC) power flow model and offers superior accuracy compared to the conventional DC-based approach yet takes an enhancement of its application to scale.

To demonstrate the need for speed-up techniques in optimization, the Branch and Cut Bender’s Decomposition (BCBD) algorithm is applied to the task of solving security-constrained TEP, followed by a comparison to commercial solvers. The complexity of TEP demands advanced search techniques with the capacity to handle multi-objective constraints, network contingencies and renewable integration [15, 16].It is evident from these findings that TEP requires the need for meta-heuristic algorithms. Their efficacy in large solution space explorations, nonlinearity handling and computational step optimization make them particularly specialized for modern power system planning problems. Research at further levels needs to focus on developing hybrid metaheuristic frameworks that integrate heuristic search methods with mathematical optimization to enhance their efficiency and scalability. Grey Wolf Optimizer (GWO) offers one of the most promising algorithms to be employed in solving advanced optimization problems such as TEP.

GWO is based on the grey wolf model for leadership and hunting as well as having the capacity to optimally trade-off exploration and exploitation, making it very effective for solving large scale non-convex power system problems [17]. Multi-Strategy Ensemble GWO (MEGWO) incorporates more than one search technique to improve global and local search performance [18]. Also, various modifications, such as parallel and hybrid forms, have been attempted to increase their efficiency and strength in solving complex optimization problems [19]. In an effort to enhance the performance of GWO, an Improved Grey Wolf Optimizer (I-GWO) was introduced to solve issues regarding premature convergence and lack of adequate population diversity [20]. The Firefly algorithm (FF) is a method of optimization based on the behavior and movement of fireflies. The literature has reported that it will work in the IEEE 24 Bus, IEEE 118 Bus and the Iranian 400 KV transmission grid, where it optimizes the investment cost, reliability and congestion cost [21]. Because of its usefulness as a general-purpose method in swarm intelligence, FF has been efficiently hybridized and modified for wider use in various engineering branches [22, 23]. Genetic Algorithms (GA) have gained significant attention in optimization research due to their ability to be applied in many areas. New advancements in GA include improving genetic operators, fitness functions, and hybridization with other techniques to improve efficiency [24]. GA has been successfully hybridized with other techniques to improve retrieval efficiency and computational speed in many applications [25, 26]. Particle Swarm Optimization (PSO) is a popular heuristic global optimization method based on fish and bird schooling behavior. It is valued for its ease of use, low parameter tuning and simplicity. To address PSO's shortcomings such as premature convergence and local optima trapping, a number of variants have been proposed [27].

One such improvement incorporates Social Learning processes into PSO (SL-PSO), allowing particles to learn from their more successful neighbors rather than relying on prior knowledge. Both low-dimensional and high-dimensional problems have been successfully optimized using this technique [28]. The Artificial Bee Colony (ABC) algorithm, which is based on the food-gathering behavior of honeybees, is competitive with other population-based algorithms and usually needs fewer control parameters [29]. ABC has also been used in TEP and proved effective when hybridized with AI methods such as Tabu Search and Artificial Neural Networks [30]. Yet, ABC has exploitation and convergence speed challenges, and thus several modifications ensue [31, 32]. The Coronavirus Search Optimizer Algorithm (COVSA) has been utilized to solve TEP by taking into account economic dispatch, uncertainty in load, and uncertainty in distributed generation [33].

It can potentially be used in complex power systems because it has proven to perform better than traditional techniques like Branch and Bound problems [34]. Using a DC power flow model, the Cuckoo Search Algorithm (CSA) has also been used for TEP optimization, demonstrating effectiveness in reducing investment costs while meeting future load requirements [35]. To guarantee network resilience, the Ant Colony Optimization (ACO) technique has been studied for transmission planning, incorporating distribution generation and N-1 contingency analysis [36]. In several benchmark systems, the Social Spider Algorithm (SSA), another bio-inspired technique, has been applied to static TEP problems with appreciable cost savings [37]. The Binary Bat Algorithm (BBA) has been proposed to solve AC-based TEP problems, which employs AC optimal power flow calculations for optimizing transmission expansion [38]. Another nature-based method, the Bacterial Foraging Algorithm, has been used in a deregulated market scenario, including demand response programs and distributed generation, to minimize the total expansion costs and enhance grid flexibility [39]. The Arithmetic Optimization Algorithm (AOA), a newer method, has also been investigated in recent research for solving mixed-integer nonlinear TEP problems [40]. These optimization techniques have unique advantages in terms of reliability economy and computational efficiency, and they all provide varying solutions to the TEP problems. Hybrid optimization techniques have been developed to address the TEP issues with individual approaches by combining several strategies to enhance solution quality and computational efficiency. A hybrid approach making use of Memetic Algorithms (MA) to solve the Dynamic Transmission Expansion Planning (DTEP) problem. It combines PSO with Hill Climbing for global exploration and local improvement [41]. A recent study introduced the Bee-Benders Hybrid Algorithm (BBHA), which optimizes energy storage and transmission expansion planning by combining the Bees Algorithm and Bender's decomposition. This metaheuristic solution ensures fast convergence and parallelization while still ensuring optimality when running over extended horizons [42].

A new hybrid metaheuristic framework has been developed for DTEP with the integration of load-shedding formulation and co-optimization of shunt compensation. It has been checked using the IEEE 24-bus test case and compared to Static (STEP) and Quasi-dynamic (QTEP) models. The findings support that the hybrid method offers better expansion solutions accounting for dynamic system constraints [43]. These hybrid optimization techniques improve the accuracy and efficiency of TEP solutions, overcoming the difficulties presented by the complexity of the problem. New studies on TEP incorporating renewable energy took into account various optimization approaches, handling uncertainty, and dynamic planning techniques [44, 45]. One of the most prominent subjects of recent studies is the integration of Renewable Energy Sources (RES), such as wind and solar PV, into TEP models. Few publications highlight the variable generation challenge, demand variability, and distributed generation impacts on transmission systems [46-54].

In general, recent advances in TEP methods are focused on metaheuristic optimization, integration of renewable energy, uncertainty modeling, and dynamic planning models. Discussion of topics such as stochastic optimization, multi-period planning, and AC power flow considerations can further guide future research towards practical transmission planning problems.As per the literature review, traditional optimization methods have issues such as scalability, computational inefficiency, premature convergence, and susceptibility to local optima when used in systems with high levels of renewable energy penetration. These limitations highlight the urgent need for advanced optimization methods that can address the dynamic, multi-objective and large-scale nature of TEP problems. These factors motivated proposing an innovative hybrid optimization method.The motivation for this research lies in bridging the gap between theoretical advancements and practical applications in TEP. Using real transmission system data will be key to validating the

feasibility of the proposed methodology in a real-world context. This motivated me to collect real data from the Kerala State Electricity Board (KSEB) for this study, ensuring the applicability and reliability of the optimization technique in addressing the unique challenges of the region.
A research gap was identified in the lack of fully hybrid optimization approaches for TEP with renewable energy integration, as existing studies primarily combine a single optimization method with local search techniques.

Also, hybrid optimization has not been explored in TEP using real-world data, as existing studies are based on single optimization methods only. This paper presents a hybrid optimization technique for transmission expansion planning, addressing the challenges of handling nonlinear problems in electrical power systems considering factors such as cost, reliability, load shedding, transmission losses and renewable energy integration. The proposed approach is validated on the IEEE 24-bus Reliability Test System and a real-world subsystem of the KSEB transmission network.

3. AC-TEP Problem Definition

The GWGA proposed by the authors, which is used in this work for AC TEP combines GWO and GA to effectively optimize the cost and the load-shedding factors of power transmission systems with the objective of minimizing transmission losses. The performance of GWGA is evaluated against several conventional and advanced optimization techniques, including PSO, ABC, FF, GA, and GWO, as well as two recent algorithms widely discussed in the TEP literature: CSA and COVSA. The methodology highlights its effectiveness in addressing key performance criteria, including cost reduction, loss minimization, and enhanced renewable energy integration, validated through application to the IEEE 24 AC bus system.

A comprehensive analysis of the real subsystem of the KSEB’s Central Zone is also presented. The subsystem under consideration is a small-scale representation of the broader transmission network, providing a representative case study for applying advanced optimization methodologies. By hybridizing GWO and GA, the authors aim to provide a robust solution for optimizing power transmission networks. The GWGA algorithm provides more accurate and efficient solutions to TEP problems with renewable energy sources in power systems.The objective of the problem is to determine the expansion strategy z that minimizes both the total investment and operational costs while maximizing the optimal power flow with minimal losses. The Investment Cost (IC) is represented by Equation (1) and accounts for the cost associated with reinforcements to the branch connecting bus i to bus j. The Operational Cost (OC) is formulated as a Linear Programming (LP) problem aimed at optimizing the economic dispatch of generators, thereby reducing load shedding [12].

Minimize the cost function,

$$g(z) = \sum_{(i,j)\epsilon\mu} C_{ij}\, n_{ij} \; + \; K \sum_{m=1}^{NL} I_m^2\, R_m \qquad (1)$$

Subject to

$$B(z) = 0$$

$$C(z) = 0$$

$$0 \leq n_{ij} \leq n_{ijmax}$$

The unit cost C_{ij} corresponds to the cost of strengthening the branch connecting bus i to bus j, and μ represents the set of all possible branches within the system network. Bus i to bus j can have a maximum reinforcement added as indicated by n_{ijmax}. Function B(z) indicates load shedding, while C(z) represents overload [12]. The loss coefficient K is determined using the formula, K=8760 *NYE*C kWh, where NYE stands for the estimated lifetime of the expansion network (years), and C kWh is the cost of one kWh ($/kWh), R_m is the resistance of the m^{th} line, I_m represents current flow through the m^{th} line, and NL refers to the number of the existing lines. AC Power flow analysis is conducted for the IEEE 24 bus system [30].

4. Hybrid GWO and GA for AC- TEP Optimization

The Grey Wolf Optimization is a metaheuristic algorithm inspired by grey wolves' hunting tactics in nature. It is founded on the premise that wolves utilize various tactics, including social order, pursuing, encircling and attacking to hunt their prey. In GWO, these hunting strategies are employed to optimize an objective function. The algorithm starts with a pool of candidate solutions known as the search agents. Depending on their fitness and the location of the search space, the search agents are iteratively updated. However, the classic GWO algorithm has certain limitations even though it performs well for various optimization problems. For instance, it might have a limited capacity for local searches, slow convergence, and poor solving accuracy.The GWO algorithm may be combined with other optimization algorithms to overcome these shortcomings.

An example of such an algorithm is the genetic algorithm, a traditional metaheuristic that draws inspiration from natural selection and genetic inheritance principles. Genetic Algorithm operates by evolving a population of potential solutions over generations. Each generation is formed by applying crossover and mutation operators and selecting the fittest members of the last generation. By combining GWO with GA, a hybrid optimization algorithm that leverages the best of both algorithms can be constructed. The GWO algorithm can guarantee a good local search ability, while the GA algorithm can guarantee a robust global search ability.

In the hybrid algorithm, the GWO algorithm is the local search operator, while the GA algorithm is the global search operator. The hybrid GWO-GA algorithm starts with a starting population of candidate solutions. The GWO algorithm is utilized to optimize the fitness of each candidate solution within the population. The fittest solutions are then selected and used to create a new generation using the GA algorithm. The GA algorithm generates new solutions by applying selection, crossover and mutation operators to the fittest individuals of the previous generation.

This iteration continues until a stopping criterion is met.Here, the bounding factor is given by Equation (2), where b_{max} and b_{min} denote the upper and lower bounds of the solution, respectively, and the crossover rate r_c is set as 0.6. Additionally, a distance factor 'd' that is based on the best position and current position of the solution is introduced and can be evaluated as given by Equation (3), where α_{po} is the best position of the solution, and ζ_{po} is the current position of the solution.

$$b = \sqrt{mean(b_{\max} - b_{\min})^2} \tag{2}$$

$$d = \sqrt{mean(\alpha_{po} - \varsigma_{po})^2} \tag{3}$$

Moreover, the distance threshold d_{th} can be evaluated by Equation (4), where Iter represents the present iteration and $Iter_{max}$ indicates the maximum iteration.

$$d_{th} = r_c \times b \times \frac{Iter}{Iter_{\max}} \tag{4}$$

Additionally, GWO can be used to update the solution if the distance d exceeds d_{th}. If not, the GA algorithm's principle must be applied to the crossover operation, and Equation (5), provides the updated solution.

$$Z_2^* = \frac{child1 + child2}{2} \tag{5}$$

Consequently, Z* is the optimal TEP solution, achieving balanced power generation and reduced costs to satisfy the power system's demands. Figure 1 displays the suggested GWGA algorithm's flow chart. The algorithm then enters a loop where it iterates through each search agent and checks whether to perform a GWO or a crossover operation based on the distance factor 'd'. If 'd' is greater than the maximum threshold 'd $_{max}$', the search agent's position is updated using the GWO.

Otherwise, a crossover operation is performed to create two offspring, which are then mutated and evaluated. The algorithm then applies GWO to the best offspring and replaces the worst search agent in the population with it if it is better. The algorithm also updates the best three search agents if any offspring outperforms them.The algorithm stops when the stopping criterion is achieved and returns the optimal solution found so far.

5. Results and Discussions

The IEEE 24 RTS model shown in Figure 2 utilized in this study comprises 11 number of synchronous generators, 17 load points, and 38 branches; the maximum generation capacity is 3405 MW, while the total demand is 2850 MW. In the optimization process for TEP, the chromosome size is set to 61. The initial 38 chromosomes serve as a representation of the number of branches. The subsequent 11 chromosomes, from 39 to 49, signify the specific nodes at which generators are connected. Lastly, the final 12 chromosomes, from 50 to 61, denote the nodes where renewable energy sources, such as wind turbines and PV arrays, are incorporated. The wind turbines are modelled with 1.5 MW General Electric (GE) wind turbines [47]. The PV arrays are Characterized by their module area and efficiency [52].

Various design parameters taken for calculating the electrical energy from the PV array are Area = 1.3264m^2, Efficiency = 15%. Geographical factors, including land requirements for wind farms, solar irradiance for PV integration, and other location-specific constraints, have not been taken into account.The model has been simulated in MATLAB. The results obtained have been analyzed and compared with traditional algorithms, including GA, PSO, ABC, FF, GWO, CSA and COVSA, focusing on the cost function and load shedding function and transmission losses. The suggested model offers an optimal TEP solution that balances power generation and cost to guarantee that the power system can meet the demand.

5.1. Cost Function and Load Shedding Analyses

The performance comparison is conducted using two evaluation metrics: transmission cost in dollars and load shedding in MW. The proposed GWGA method is compared with traditional algorithms, including GA, PSO, FF, ABC, GWO, as well as CSA and COVSA, based on the above metrics, as shown in Figures 3 and 4, respectively. The population size is taken as 10, and the number of iterations is considered to be 200. The results indicate that the proposed GWGA method outperforms all other methods for both metrics at various population sizes and iterations, demonstrating superior convergence speed and effectiveness in reducing computational time. To further analyze the method's performance, the number of iterations is increased to 500 for a population size of 10. The corresponding analysis is presented in Table 1 and Table 2, respectively and illustrated in Figure 5 and Figure 6. This extension emphasizes the effectiveness of the proposed method in minimizing computational time and achieving faster convergence.

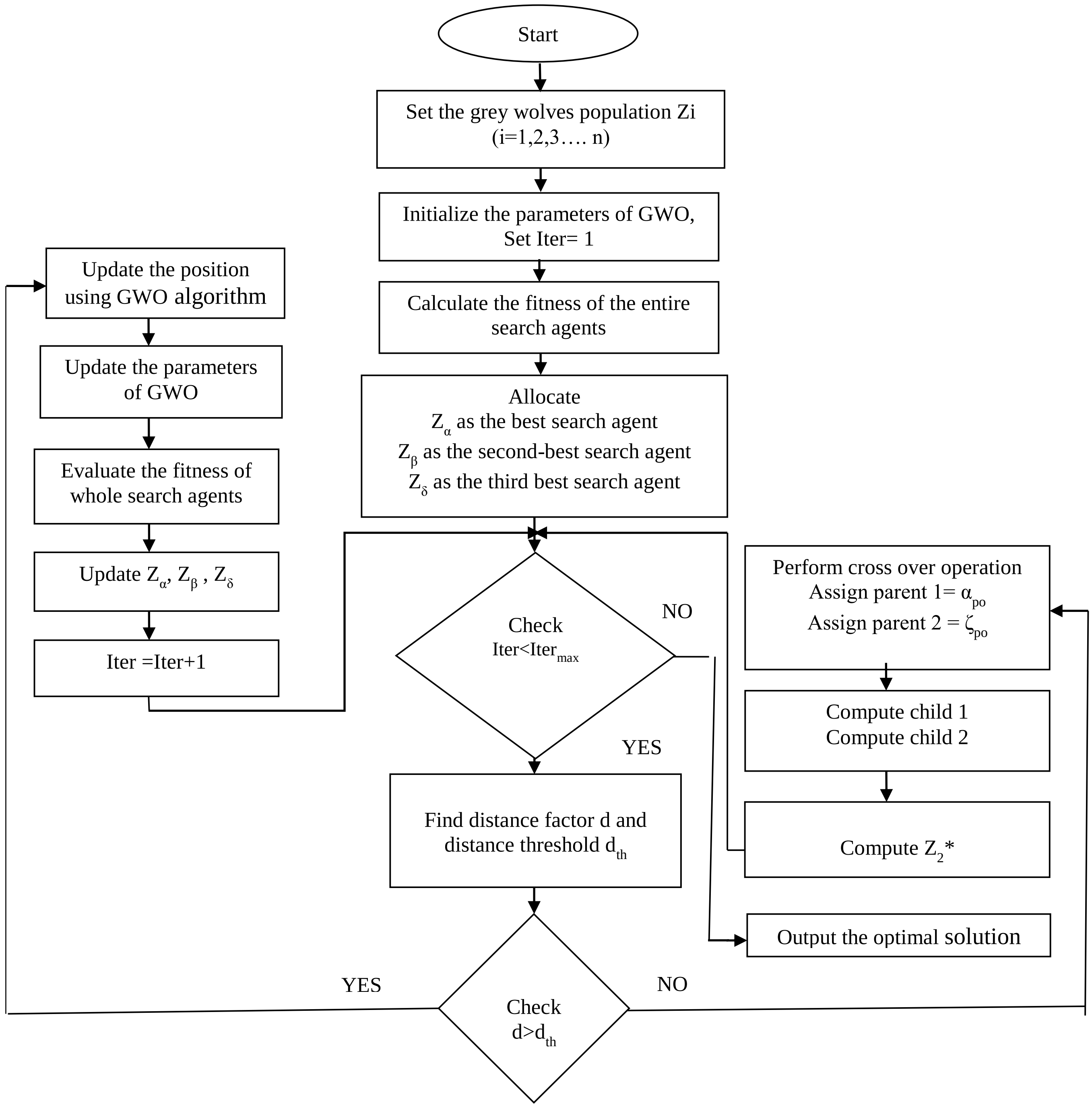

Fig. 1 Flow chart of the GWGA algorithm

The analysis of Tables 1 and 2 shows that the proposed GWGA algorithm consistently outperforms other optimization methods both in minimizing transmission expansion cost and load shedding across all iterations taken into consideration, showcasing its robustness and effectiveness in optimizing power system expansion planning. The performance analysis for cost function and load shedding is performed for different population sizes (10, 30, 60, 80, and 100) over 200 iterations, with results shown in Tables 3 and 4, respectively. The proposed GWGA model consistently outperforms the other methods for both evaluation metrics across all population sizes. The percentage of performance improvement of the GWGA method compared to conventional algorithms, CSA, and COVSA, concerning the cost function and load shedding, is provided in Tables 5 and 6, respectively.

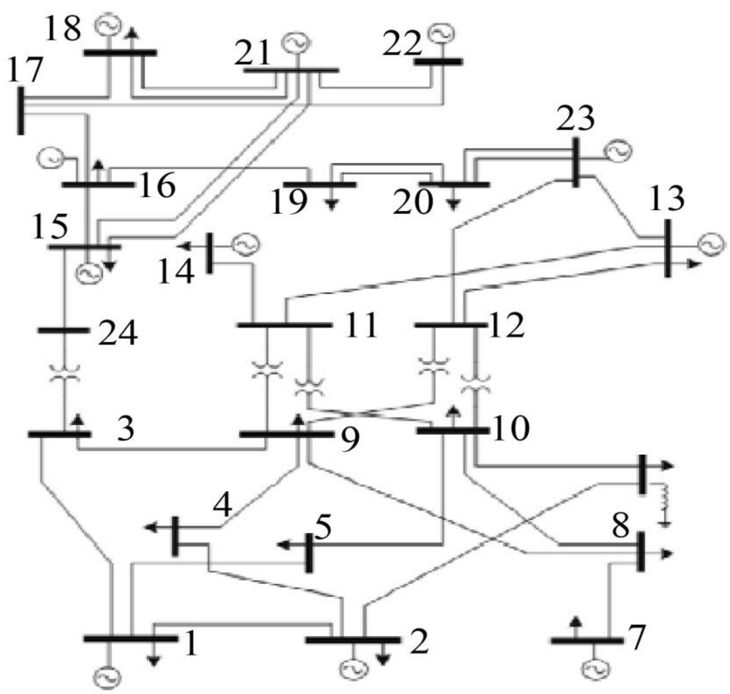

Fig. 2 Single diagram of IEEE 24 bus reliability test system

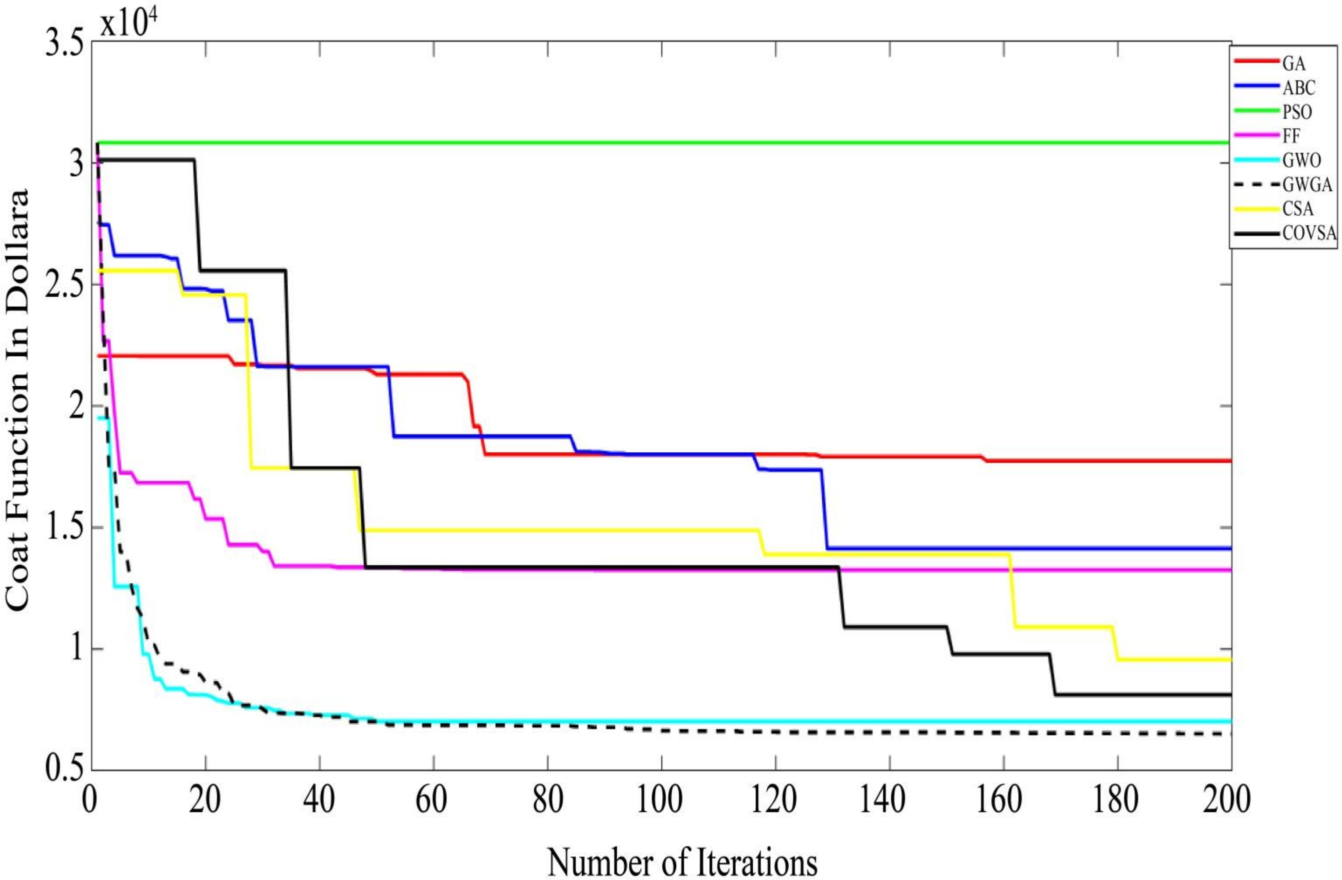

Fig. 3 Analysis of cost function for different optimization techniques from 0 to 200 iterations

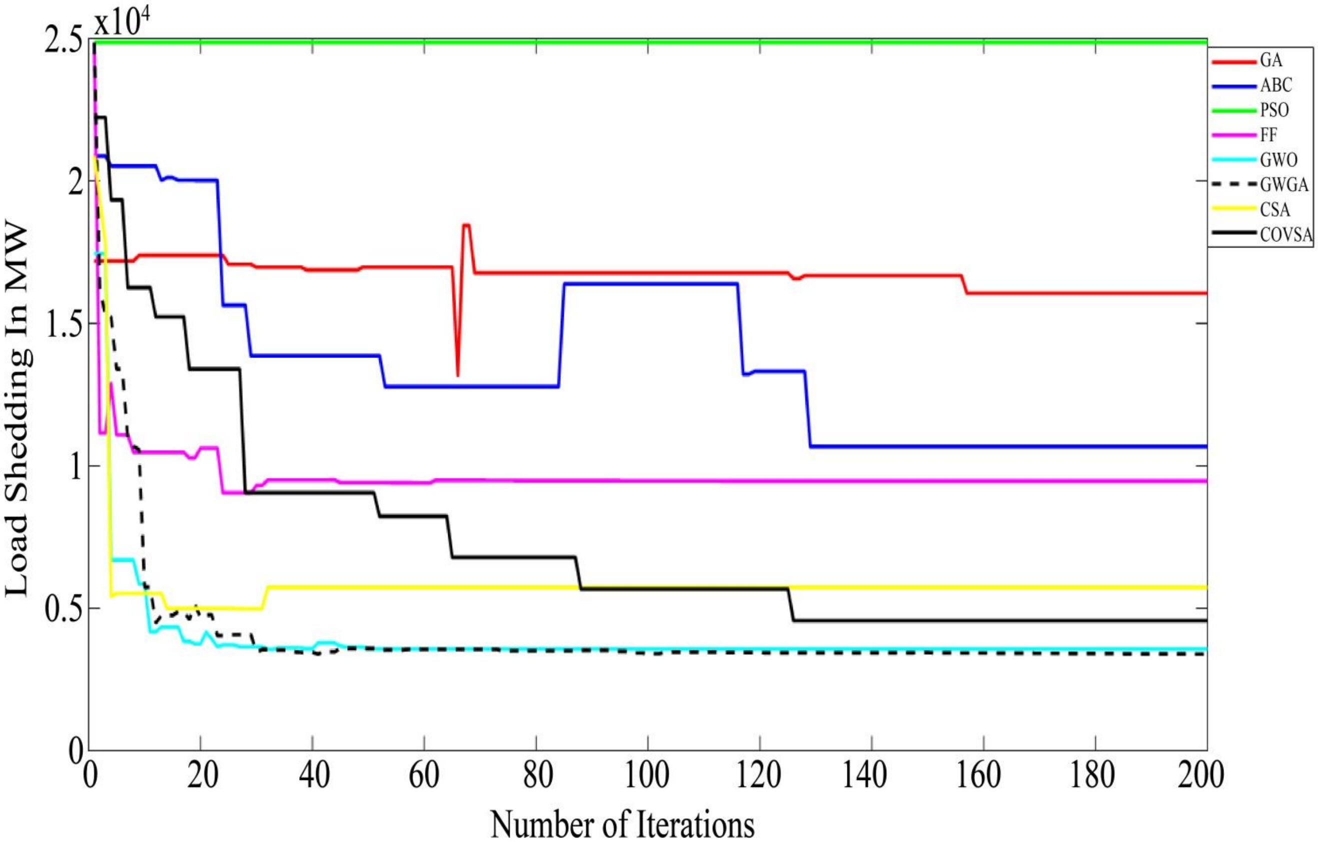

Fig. 4 Analysis of load shedding for different optimization techniques from 0 to 200 iterations

Table 1. Analysis of cost function using different optimization techniques with varying iterations

Optimization Algorithm	Number of iterations				
	100	**200**	**300**	**400**	**500**
	Transmission Expansion Cost in Dollars				
GA	18011	17740	17640	17540	17540
ABC	18011	14139	14131	14001	14000
PSO	30834	30834	30834	30834	30834
FF	13258	13254	13000	12998	12998
GWO	7023	7022	7022	7022	7022
CSA	14891	9567	9657	9679	9567
COVSA	13367	8124	8123	8123	8123
GWGA	6647	6521	6500	6499	6499

Table 2. Analysis of load shedding using different optimization techniques with varying iterations

Optimization Algorithm	Number of iterations				
	100	**200**	**300**	**400**	**500**
	Load Shedding in MW				
GA	16780	16063	16062	16056	16056
ABC	16780	10680	10671	10671	10699
PSO	24870	24869	24870	24870	24870
FF	9478	9473	9472	9468	9468
GWO	3408	3576	3576	3576	3576
CSA	5735	5735	5835	5835	5836
COVSA	5678	4567	4566	4566	4566
GWGA	3400	3397	3396	3396	3396

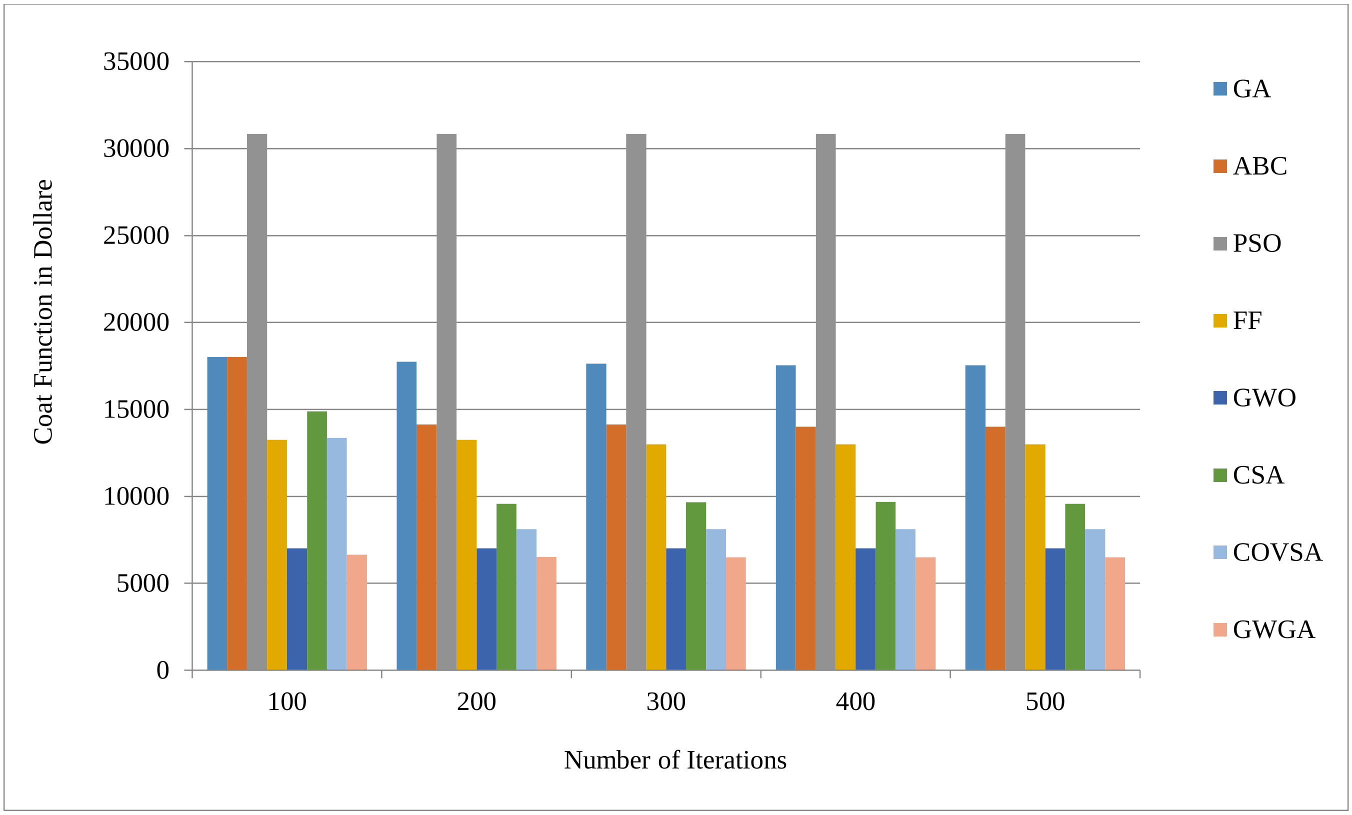

Fig. 5 Analysis of cost function for different optimization techniques across 100 to 500 iterations

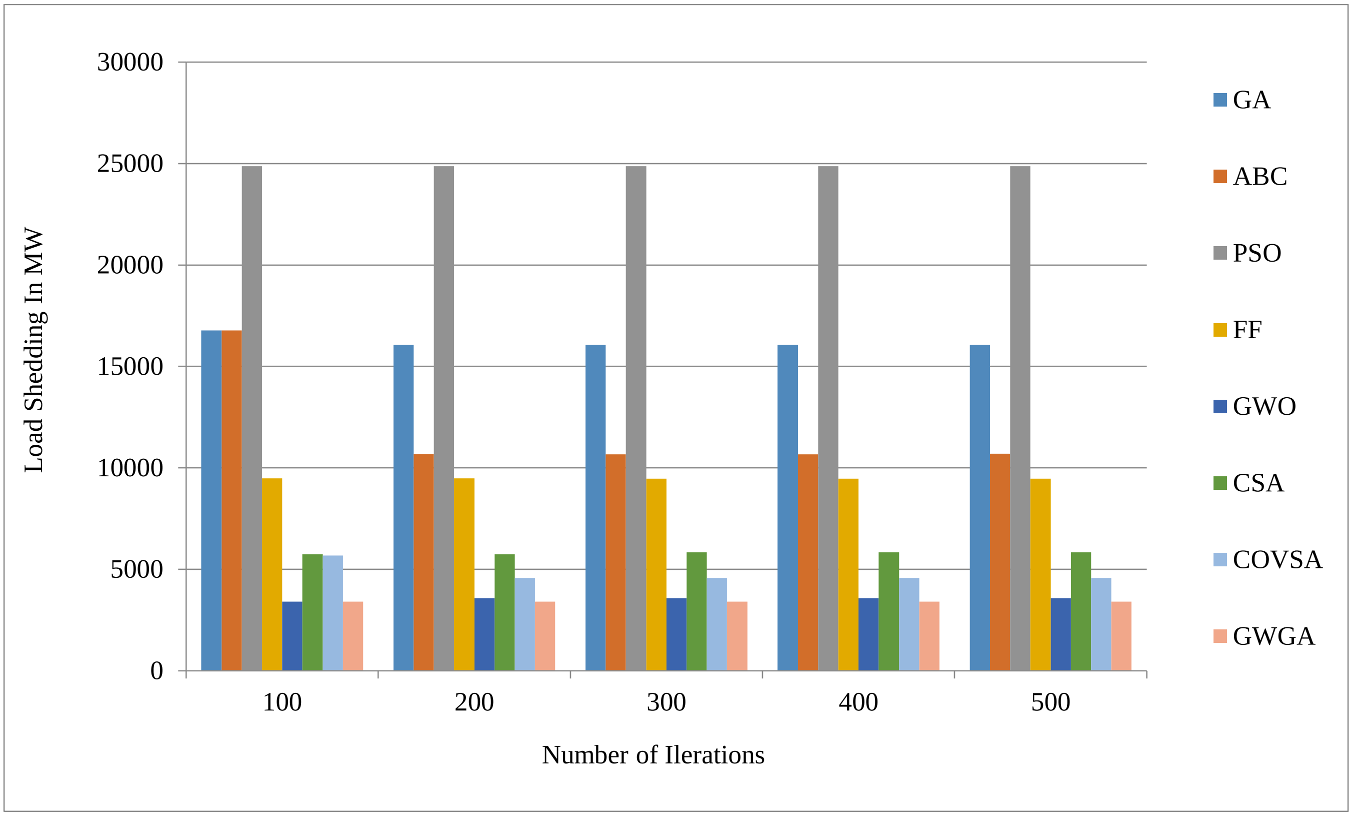

Fig. 6 Analysis of load shedding for different optimization techniques across 100 to 500 iterations

Table 3. Analysis of cost function using different optimization techniques with varying population size

Optimization Algorithm	Population Size				
	10	30	60	80	100
	Transmission Expansion Cost in Dollars				
GA	17740	18814	18912	18999	18514
ABC	14139	15710	16503	16914	15912
PSO	30834	31124	31415	31114	27012
FF	13254	13753	13883	13911	13498
GWO	7022	7410	7488	7573	7461
CSA	9567	9557	9560	9561	9561
COVSA	8124	9021	8524	8545	8543
GWGA	6521	6613	6633	6689	6584

Table 4. Analysis of load shedding using different optimization techniques with varying population size

Optimization Algorithm	Population Size				
	10	30	60	80	100
	Load Shedding in MW				
GA	16063	16414	16439	15649	15632
ABC	10680	11193	11987	11793	11743
PSO	24869	25951	25999	25154	24914
FF	9473	9582	9581	9483	9480
GWO	3576	4125	4138	3934	3926
CSA	5735	5435	5437	6000	6171
COVSA	4567	4589	4600	4609	4613
GWGA	3397	4107	4119	3925	3918

Table 5. Performance improvement of GWGA in cost function compared to conventional algorithms (%)

Optimization Algorithm	Population Size				
	10	30	60	80	100
GA	63.24	64.85	64.93	64.79	64.44
ABC	53.88	57.91	59.81	60.45	58.62
PSO	78.85	78.75	78.89	78.5	75.63
FF	50.8	51.92	52.22	51.92	51.22
GWO	7.13	10.76	11.42	11.67	11.75
CSA	31.84	30.8	30.62	30.04	31.14
COVSA	19.73	26.69	22.18	21.72	22.93

Table 6. Performance improvement of GWGA in load shedding compared to conventional algorithms (%)

Optimization Algorithm	Population Size				
	10	30	60	80	100
GA	78.85	74.98	74.94	74.92	74.94
ABC	68.19	63.31	65.64	66.72	66.64
PSO	86.34	84.17	84.16	84.4	84.27
FF	64.14	57.14	57.01	58.61	58.67
GWO	5.01	0.44	0.46	0.23	0.2
CSA	40.77	24.43	24.24	34.58	36.51
COVSA	58.19	48.66	48.59	51.68	52.72

Table 5 provides a comparative analysis of the performance improvement achieved by the GWGA in terms of the cost function when compared to conventional algorithms, namely GA, ABC, PSO, FF, GWO, CSA and COVSA. The analysis is performed across various population sizes of 10, 30, 60, 80, and 100. The results clearly indicate that GWGA consistently outperforms the other algorithms in optimizing the cost function across all population sizes. Lower transmission expansion cost has the advantages of reduced electricity tariffs and improved financial sustainability for power utilities. The improvement achieved by GWGA over GA ranges from 63.24% at a population size of 10 to 64.93% at a population size of 60. to GWO, performance improvements ranging from 7.13% at a population size of 10 to 11.75% at a population size of 100. The improvement over CSA is consistent, ranging from 30.04% to 31.84% and the improvement over COVSA peaks at 26.69% for a population size of 30 while stabilizing around 22% for higher population sizes. GWGA demonstrates consistent and superior performance across all population sizes, indicating its robustness and scalability. The choice of population size appears to have an impact on performance, with GWGA consistently showing remarkable results and highlighting its potential for practical applications in real-world scenarios. Further research could explore fine-tuning GWGA parameters to optimize its performance even further.

The results from Table 6 indicate that GWGA consistently outperforms other conventional algorithms in terms of minimizing load shedding across all population sizes. GWGA shows substantial improvements over GA, with performance ranging from 74.92% at a population size of 80 to 78.85% at a population size of 10. Compared to GWO, the improvement ranges from 5.01% at a population size of 10 to 0.20% at a population size of 100. GWGA achieves the lowest load shedding across all population sizes, demonstrating its superior optimization capability in minimizing power system disruptions. Lower load shedding enhances power system reliability, minimizes economic losses, and ensures a stable and uninterrupted electricity supply.

5.2. Transmission Loss Analysis

The transmission losses obtained from the cost the objective function, Equation (1), for the different optimization techniques for iterations 100, 200, 300, 400 and 500 is tabulated in Table 7. The proposed GWGA algorithm notably surpassed all other algorithms, demonstrating a reduction in losses from 2.65 MW in the first iteration to 1.91 MW, which indicates remarkable stability and convergence.

The results indicate that the proposed GWGA algorithm achieves the lowest transmission losses across all iterations compared to conventional optimization methods for a population size of 60. As iterations progress from 100 to 500, GWGA consistently reduces transmission losses, reaching its best performance at 500 iterations with a loss of just 1.91 MW. This represents a significant improvement over GA, whose best transmission loss at 500 iterations is 7.40 MW, indicating a 74.19% reduction achieved by GWGA. Similarly, compared to GWO, which performs well with a loss of 2.09 MW at 500 iterations, GWGA delivers a further reduction of 8.61%, showcasing its superiority even over advanced optimization techniques. The final expansion plan generated by the proposed methodology is shown in Table 8. The comparison of the generation capacity at different nodes before and after TEP using the GWGA methodology is shown in Table 9, while Table 10 lists the nodes that are connected to renewable energy sources in order to maximize the suggested methodology.

The GWGA algorithm achieves the highest total integrated power among the optimization techniques taken into consideration. The analysis from Tables 8 to 10 highlights the enhanced performance of GWGA in TEP. Table 8 shows the optimized connectivity of transmission lines across buses, ensuring balanced network utilization. Table 9 demonstrates significant improvements in generation capacities after TEP, with notable increases at critical nodes like buses 13, 18, and 21.

The total generation capacity before TEP was 987.0 MW, while after TEP, it increased to 1587.12 MW. The total generation capacity increased by 60.80% after TEP using GWGA. Table 10 underscores GWGA's efficiency in integrating renewable energy, achieving the highest wind turbine capacity (36 MW) and fully utilizing PV arrays (7200 W) while optimizing node placements better than other techniques. These results reaffirm GWGA's effectiveness in modern power system optimization.

Table 7. Transmission losses for iterations from 100 to 500 for a population size of 60

Optimization Algorithm	**Number of Iterations**				
	100	**200**	**300**	**400**	**500**
	Transmission Loss in MW				
GA	7.56	7.52	7.46	7.41	7.4
ABC	7.65	6.82	6.78	6.76	6.36
PSO	12.56	12.46	12.45	12.44	10.8
FF	5.56	5.5	5.47	5.43	5.39
GWO	3.03	2.99	2.96	2.14	2.09
CSA	4.04	3	3.14	2.97	2.99
COVSA	5.02	5.34	4.96	4.78	4.12
GWGA	2.65	2.64	2.13	1.93	1.91

Table 8. Number of transmission lines connected to each bus after TEP

Bus Number	Number of lines
1	2
2	1
3	-
4	-
5	1
6	2
7	1
8	2
9	2
10	3
11	1
12	2
13	2
14	1

Table 9. Generation capacity comparison at different nodes before and after TEP

Generator Bus Number	Generation Capacity before TEP (MW)	Generation Capacity after TEP (MW)
2	30.4	139.95
7	75	76.54
13	206.85	278.09
15	12	44.5
16	54.25	118.34
18	100	204.19
21	100	298.83
22	300	300
23	108.5	126.68

Table 10. Node numbers of buses connected to renewable energy sources

Type of Renewable Energy Source	Technique Used	Node Number	Total Renewable Power Integrated
Wind turbine	GA	5,6, 8, 9, 11, 14, 20	31.5 MW
	ABC	1,4,9,10,11	22.5 MW
	PSO	1,3,4,5,9,11,14,17	36 MW
	FF	1,3,4,6, 8, 9,17	31.5 MW
	GWO	1,3,5,9,14,17,20	31.5 MW
	CSA	1,3,5,9,14,20	27 MW
	COVSA	1,3,4,8,9,17	27 MW
	GWGA	1,5,6,9,11, 14,17,19	36 MW
PV array	GA	17,19	4800 W
	ABC	20	2400 W
	PSO	6,10,19	7200 W
	FF	-	-
	GWO	6,11	4800 W
	CSA	6,9,17	7200 W
	COVSA	6,8,19	7200 W
	GWGA	3,4,20	7200 W

6. Real System Modelling and Analysis

The Kerala State Electricity Board has been at the forefront of power supply and distribution in the southern state of India. As electricity demand rises due to urbanization and industrialization, KSEB faces the formidable task of ensuring a reliable, efficient, cost-effective electrical transmission network. A critical aspect of achieving this objective lies in the careful planning and expansion of the transmission infrastructure. A 14-bus subsystem is modelled based on the Central Zone region of KSEB, which includes 4 generating stations, 10 load buses and 17 transmission lines, with each allowing for a maximum of three reinforcements. The total demand for this subsystem is 194 MW, while the maximum generation capacity is 238.65 MW. The data utilized has been generously provided by the KSEB. Their detailed and comprehensive datasets have been instrumental in conducting accurate analyses and validating the proposed methodology for transmission expansion planning. The details of the buses and the transmission lines are presented in Tables 11 and 12, respectively. In the optimization process for TEP, the chromosome size is set to 31. Chromosomes 1 to 17 indicate the number of branches, chromosomes 18 to 21 represent the nodes where generators are connected, and chromosomes 22 to 31 denote the nodes where renewable energy sources, such as wind turbines and Photovoltaic (PV) arrays, are integrated. To enhance system performance and sustainability, a series of meticulous analyses and simulations have been conducted using MATLAB.

6.1. Cost Function and Load Shedding Analyses of the Modelled Subsystem

In the realm of power systems, the meticulous examination of cost functions and load shedding is paramount for ensuring the efficient and sustainable operation of our electricity grids. Power systems aim to operate efficiently and economically. Cost functions help in optimizing the generation and transmission of power by considering factors such as fuel costs, maintenance, and transmission losses. Analyzing cost functions allows for identifying strategies that minimize overall operational costs. Load shedding is a control strategy employed during emergencies or situations where the demand for electrical power exceeds the available supply. By analyzing load-shedding scenarios, power system operators can improve the reliability and security of the electrical system.

Table 11. Bus details of the modelled subsystem

Bus Number	Bus type	Bus Name
1	Generator Bus	Poringal
2	Generator Bus	Sholayar
3	Load Bus	Chalakkudy
4	Load Bus	Ayyampuzha
5	Load Bus	Angamaly
6	Load Bus	Kurumassery
7	Load Bus	Aluva
8	Generator Bus	Idamalayar
9	Load Bus	Malayattoor
10	Load Bus	Kizhakkambalam
11	Generator Bus	Neriamangalam
12	Load Bus	Pothanicad
13	Load Bus	Muvattupuzha
14	Load Bus	Kalamassery

Table 12. Transmission line data of the modelled subsystem

Line No.	From Bus No.	To Bus No.
1	1	2
2	2	3
3	1	3
4	3	5
5	3	7
6	3	4
7	4	8
8	8	9
9	9	14
10	10	14
11	10	13
12	13	14
13	12	13
14	12	11
15	7	14
16	6	14
17	5	6

The cost function analysis and load shedding analysis using various optimization techniques for a population size of 10, from 0 to 200 iterations, are illustrated in Figures 7 and 8, respectively. To assess the effectiveness of the proposed methodology, the number of iterations is increased to 500, with the results tabulated in Tables 13 and 14 and represented graphically in Figure 9 and Figure 10, respectively.

Figure 7 illustrates the convergence of various optimization techniques in minimizing the cost function over 200 iterations. The GWGA algorithm demonstrates superior performance, achieving the lowest cost value with rapid convergence, indicating its high efficiency in optimizing the transmission expansion planning process.

Lower costs in TEP enable the redirection of financial resources to improve system reliability, integrate renewable energy sources, and enhance operational flexibility, ultimately contributing to a more sustainable and robust power network. Figure 8 focuses on load-shedding analysis in MW across the same set of optimization techniques. GWGA again demonstrates the best performance, achieving the lowest load-shedding values early in the iterations and maintaining this advantage throughout the process.

The results of both graphs clearly establish GWGA as the most effective method among them, excelling in both cost minimization and reliability improvement through reduced load shedding. Reduced load shedding significantly enhances system reliability, ensuring consumers a more stable power supply. This leads to fewer service interruptions, better voltage regulation, and overall improved customer satisfaction.

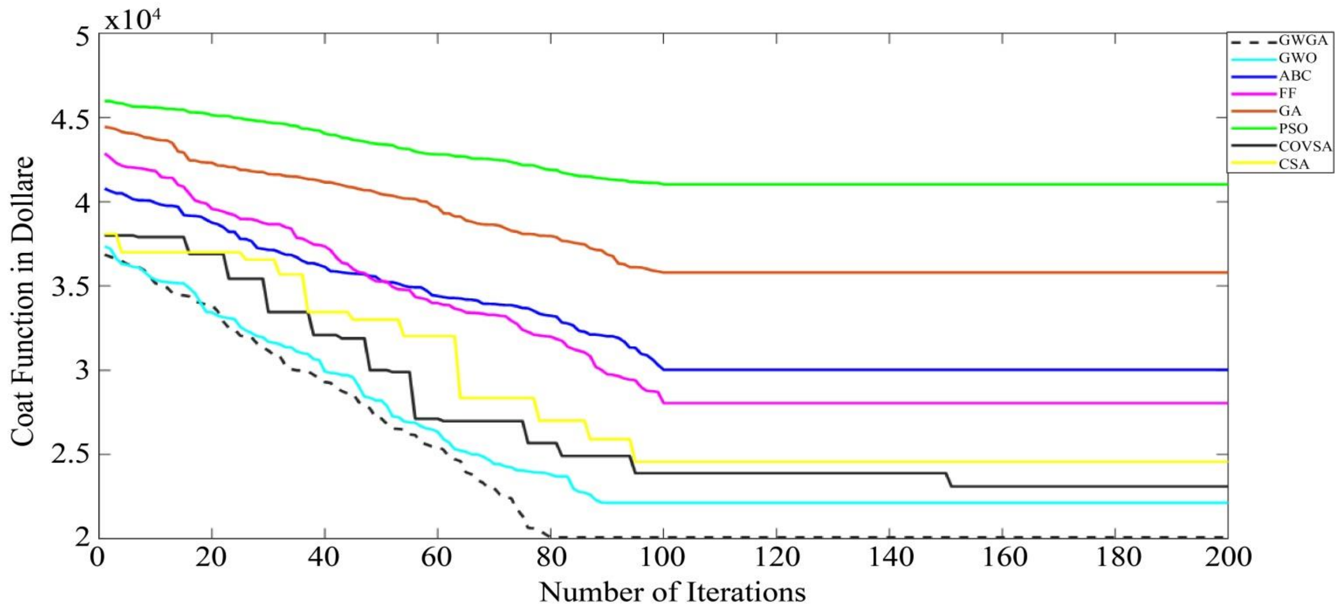

Fig. 7 Analysis of cost function for different optimization techniques from 0 to 200 iterations

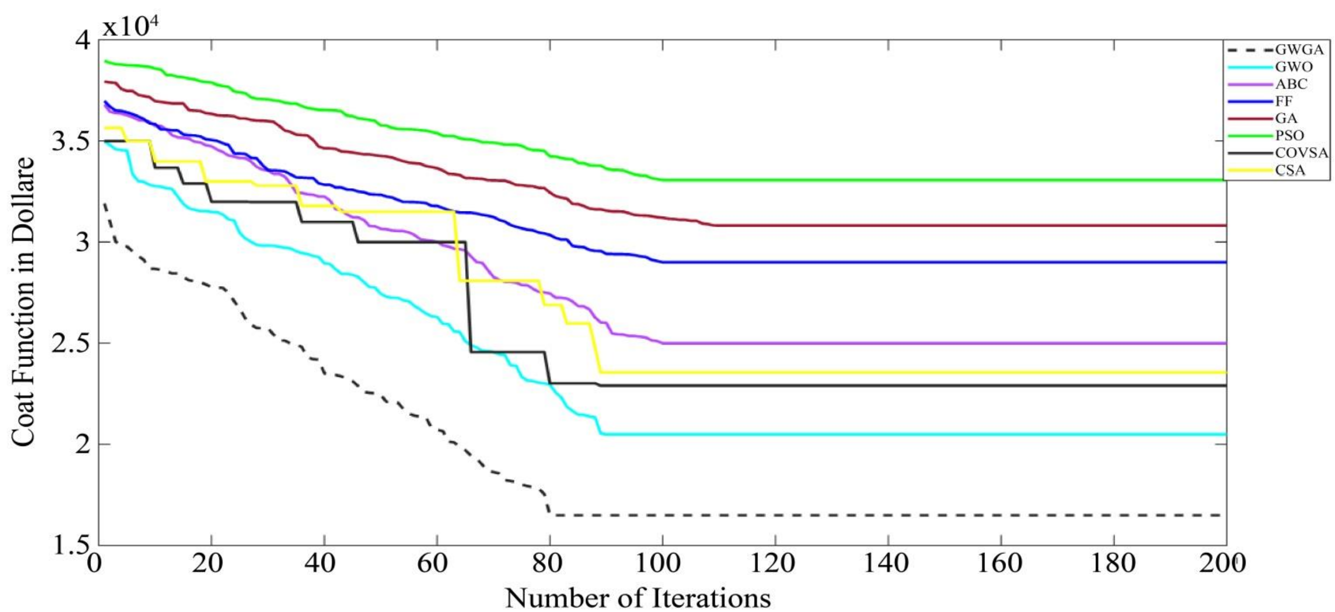

Fig. 8 Analysis of load shedding for different optimization techniques from 0 to 200 iterations

Table 13. Analysis of cost function using different optimization techniques with varying iterations

Optimization Algorithm	Number of iterations				
	100	200	300	400	500
	Transmission Expansion Cost in Dollars				
GA	35802	35802	35802	35802	35802
ABC	30031	30031	30031	30031	30030
PSO	41033	41033	40001	40000	40000
FF	28051	28051	28051	28051	28051
GWO	22139	22139	21790	21000	21000
CSA	24568	24568	24567	24567	24567
COVSA	23889	23100	23000	22026	22026
GWGA	20085	20085	20083	20083	20083

Table 14. Analysis of load shedding using different optimization techniques with varying iterations

Optimization Algorithm	Number of iterations				
	100	200	300	400	500
	Load Shedding in MW				
GA	31209	30825	30825	30824	30824
ABC	29068	29010	29006	28999	28900
PSO	33118	33064	33001	32910	32910
FF	25120	25001	25000	24891	24891
GWO	20504	20504	20503	20503	20503
CSA	23555	23555	23390	23390	23390
COVSA	22910	22910	22908	22908	22908
GWGA	16500	16500	16489	16489	16489

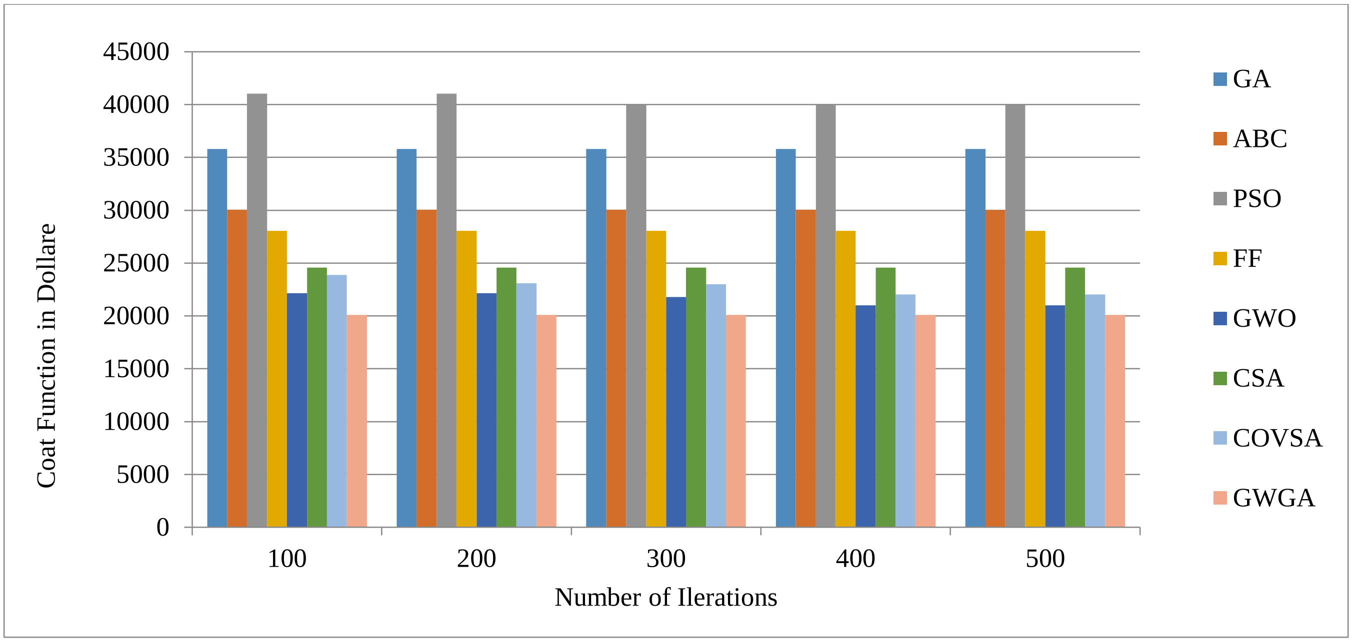

Fig. 9 Analysis of cost function for different optimization techniques across 100 to 500 iterations

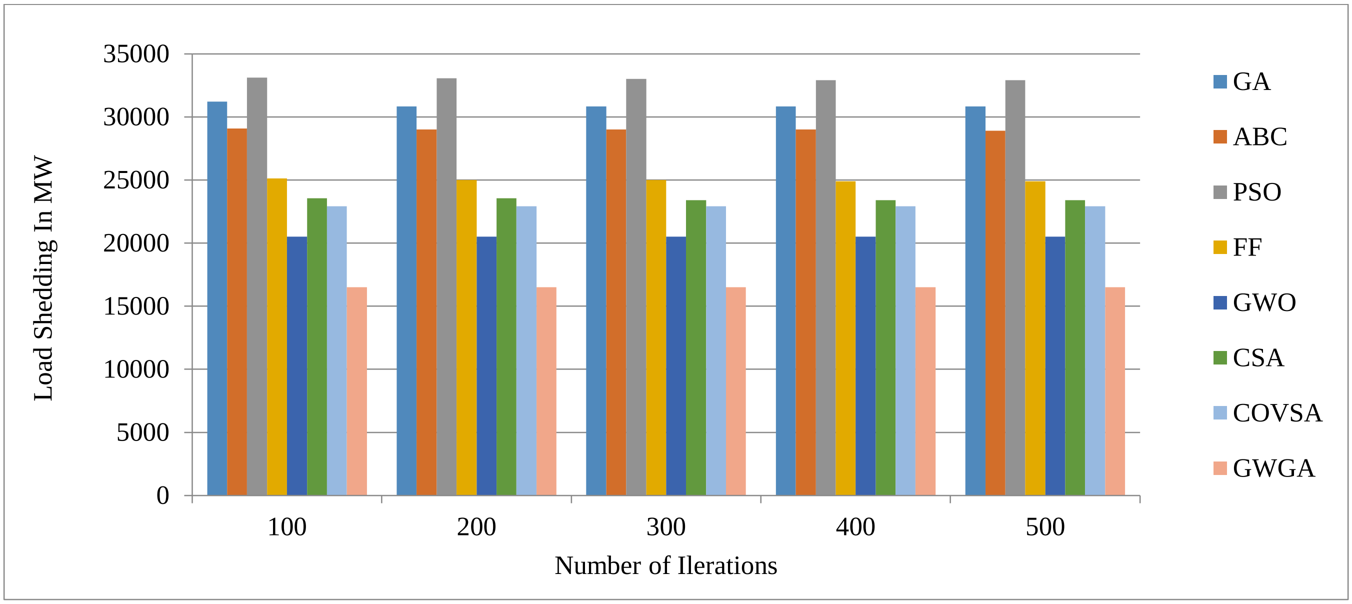

Fig. 10 Analysis of load shedding for different optimization techniques across 100 to 500 iterations

Furthermore, minimizing load shedding allows for the more efficient utilization of available resources, reducing operational disruptions and boosting the overall resilience of the power network The results from Tables 13 and 14 clearly demonstrate that the proposed GWGA algorithm achieves superior performance in both transmission cost and load shedding. The findings underscore GWGA’s effectiveness in optimizing the power system's economic and reliability aspects. The results of the performance analysis for the cost function and cost function over 200 iterations are displayed in Tables 15 and 16, respectively, for various population sizes (10, 30, 60, 80, and 100). Tables 17 and 18, respectively, show the percentage of performance improvement of the GWGA approach compared to traditional algorithms regarding the cost function and load shedding.

Table 15 highlights the performance of GWGA compared to other optimization techniques in minimizing the transmission expansion cost, a critical factor in enhancing TEP's efficiency and economic feasibility. GWGA consistently achieves the lowest costs across all population sizes, outperforming both GWO and GA when acting independently. This consistent performance across varying population sizes highlights GWGA's ability to significantly reduce transmission expansion costs, leading to substantial financial savings while ensuring reliable and efficient grid development in TEP. The performance of different optimization strategies in reducing load shedding across a range of population sizes is displayed in Table 16. When compared to all other methods, GWGA consistently produces the lowest load-shedding values, demonstrating its superior efficacy in maintaining grid reliability. End users benefit from increased grid stability, a more dependable power system with fewer disruptions, and better service quality, thanks to GWGA's reduced load shedding. Because of this, GWGA is a very effective way to maximize transmission expansion planning. Table 17 highlights the performance improvement of GWGA in the cost function compared to conventional algorithms. GWGA demonstrates significant improvement over GA, with percentage gains consistently exceeding 42%, reaching a maximum of 44.14% at population sizes of 80 and 100.

Compared to GWO, GWGA's improvement ranges from 9.15% at a population size of 30 to 13.91% at a population size of 100, showcasing steady and increasing gains as the population size grows. Table 18 illustrates the performance improvement of GWGA in reducing load shedding compared to conventional algorithms. GWGA demonstrates the highest improvement over GA, with consistent gains exceeding 46%, peaking at 46.94% for a population size of 100. GWGA also exhibits measurable gains over GWO, with improvements increasing from 19.53% at a population size of 10 to 24.02% at 80.

Table 15. Analysis of cost function using different optimization techniques with varying population size

Optimization Algorithm	Population Size				
	10	30	60	80	100
	Transmission Expansion Cost in Dollars				
GA	35802	35834	35836	36812	36819
ABC	30031	31127	31234	31345	31356
PSO	41033	41431	41520	41555	42000
FF	28051	28100	28103	28121	28232
GWO	22139	22156	22700	23412	23890
CSA	24568	25789	26641	27890	27891
COVSA	23100	23671	23689	23721	23740
GWGA	20085	20129	20456	20564	20567

Table 16. Analysis of load shedding using different optimization techniques with varying population size

Optimization Algorithm	Population Size				
	10	30	60	80	100
	Load Shedding in MW				
GA	30825	30965	31342	31467	31665
ABC	29010	29151	29672	30027	30139
PSO	33064	33174	33981	34148	34200
FF	25001	25391	25398	25412	25423
GWO	20504	21239	21684	21999	22032
CSA	23555	23709	23916	23918	24781
COVSA	22910	22994	23043	23156	23187
GWGA	16500	16512	16703	16714	16803

Table 17. Performance improvement of GWGA in cost function compared to conventional algorithms (%)

Optimization Algorithm	Population Size				
	10	**30**	**60**	**80**	**100**
GA	43.9	43.83	42.92	44.14	44.14
ABC	33.12	35.33	34.51	34.39	34.41
PSO	51.05	51.42	50.73	50.51	51.03
FF	28.4	28.37	27.21	26.87	27.15
GWO	9.28	9.15	9.89	12.16	13.91
CSA	18.25	21.95	23.22	26.27	26.26
COVSA	13.05	14.96	13.65	13.31	13.37

Table 18. Performance improvement of GWGA in load shedding compared to conventional algorithms (%)

Optimization Algorithm	Population Size				
	10	30	60	80	100
GA	46.47	46.68	46.71	46.88	46.94
ABC	43.12	43.36	43.71	44.34	44.25
PSO	50.1	50.23	50.85	51.05	50.87
FF	34	34.97	34.23	34.23	33.91
GWO	19.53	22.26	22.97	24.02	23.73
CSA	29.95	30.36	30.16	30.12	32.19
COVSA	27.98	28.19	27.51	27.82	27.53

6.2. Transmission Loss Analysis

The transmission losses obtained from the cost objective function, Equation (1). Table 19 shows the transmission losses obtained for the different optimization techniques for iterations 100, 200, 300, 400, and 500. Notably, the GWGA Algorithm consistently exhibit the lowest transmission losses throughout the iterations compared to other conventional algorithms, suggesting their efficacy in optimizing the system. Table 20 presents the final expansion plan derived from the proposed methodology. Table 21 compares the generation capacity at various nodes before and after TEP using the GWGA methodology, while Table 22 lists the nodes where renewable energy sources are connected for optimal performance in the proposed approach. Table 19 compares the transmission losses in MW for various optimization algorithms across iterations from 100 to 500 with a population size of 60. GWGA consistently achieves the lowest transmission losses, starting at 1.98 MW at 100 iterations and stabilizing at 1.45 MW from 300 iterations onward. In comparison, GWO, the next best performer, begins at 2.46 MW and reduces to 2.13 MW by 500 iterations. GA exhibits a significant reduction over iterations, starting at 5.34 MW and decreasing to 2.99 MW at 500 iterations. These results demonstrate GWGA's superior capability in minimizing transmission losses, which offers significant advantages over other optimization techniques, particularly in achieving early convergence and maintaining minimal losses as iterations progress. The number of transmission lines connected to each bus after TEP, indicating a balanced network configuration, with most buses having one or two connections, is indicated in Table 20. Bus 10 stands out with three lines, reflecting its significance as a critical node in the system. This distribution ensures efficient power flow and system reliability.

Table 19. Transmission losses for iterations from 100 to 500 for a population size of 60

Optimization Algorithm	Number of Iterations				
	100	**200**	**300**	**400**	**500**
	Transmission Loss in MW				
GA	5.34	5.32	5.33	4.04	2.99
ABC	5.76	4.09	4.04	3.87	3.79
PSO	6.3	6.23	4.45	3.45	3.44
FF	5.87	5.65	5.55	4.54	4.4
GWO	2.46	2.31	2.28	2.18	2.13
CSA	2.81	2.54	2.51	2.33	2.29
COVSA	2.58	2.38	2.31	2.2	2.18
GWGA	1.98	1.46	1.46	1.45	1.45

Table 20. Number of transmission lines connected to each bus after TEP

Bus Number	Number of Lines
1	1
2	2
3	1
4	1
5	1
6	2
7	1
8	2
9	2
10	3
11	1
12	2
13	1
14	1

Table 21. Generation capacity comparison at different nodes before and after TEP

Generator Bus Number	Generation Capacity before TEP (MW)	Generation Capacity after TEP (MW)
1	32	35.4
2	54	57.2
8	75	75.9
11	77.65	79.04

Table 22. Node numbers of buses connected to renewable energy sources

Type of Renewable Energy Source	Technique Used	Node Number
Wind Turbine	GA	3, 10, 13
	ABC	10
	PSO	9,10, 11
	FF	9,10,11
	GWO	3, 5, 10, 11
	CSA	3
	COVSA	3,10
	GWGA	3, 5, 10, 13
PV Array	GA	5, 6
	ABC	5, 6, 7
	PSO	5,6,7
	FF	6
	GWO	4, 6, 7
	CSA	6,7
	COVSA	6,7
	GWGA	5,6,7,12

Table 21 highlights that generation capacity has increased at all generator buses after TEP, with the most significant improvement at Bus 2 (from 54 MW to 57.2 MW). These upgrades demonstrate the impact of TEP in enhancing power generation to meet growing demand while improving system stability. GWGA connects renewable energy sources to the most diversified set of nodes compared to other techniques, integrating wind turbines at Nodes 3, 5, 10, and 13 and PV arrays at Nodes 5, 6, 7, and 12, as shown in Table 22. This highlights GWGA's superior capability in optimizing renewable energy integration improving system sustainability and resilience. However, the study reveals some demerits. The computational complexity of GWGA is relatively higher, demanding more resources and time for simulations, which might limit its scalability for larger systems. Moreover, the focus on a single subsystem limits the generalizability of the findings to other regions with different grid characteristics.

7. Conclusion

This research focuses on overcoming the challenges in electrical power system transmission expansion planning by optimizing the integration of reinforcement lines, generators, and renewable energy sources. The GWGA hybrid algorithm was implemented and simulated on the IEEE 24 test bus system, and the results were compared with traditional techniques, including PSO, GA, FF, ABC and GWO, demonstrating the superior performance of the GWGA algorithm. The findings demonstrate that the suggested algorithm maximizes electricity delivery to customers with lower transmission losses while minimizing transmission line investment costs. Furthermore, an analysis of a modelled transmission subsystem of the central zone of the Kerala State Electricity Board demonstrates the scalability of the suggested algorithm. The goal of this study is to provide planners and researchers working in the field with useful information. This method seeks to balance reducing transmission losses, load shedding factors, and the overall cost of expansion within the power transmission system by utilizing the advantages of both optimization techniques. GWGA can be extended to handle real-time dynamics and uncertainties in renewable generation and demand.

To improve the realism and efficacy of TEP, availability factors like land restrictions for wind farms and solar irradiance for PV can be included. The scalability of the GWGA can be tested on larger grids and multi-area systems to enhance practical applicability. As renewable energy technologies such as offshore wind, floating solar, and green hydrogen continue to advance, future TEP models should account for their distinct operational characteristics and integration challenges. Incorporating these emerging sources can significantly contribute to enhancing grid flexibility, diversity, and long-term resilience.

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