

OPTIMAL POWER FLOW FOR IEEE BUS SYSTEMS USING HYBRID WHALE GENETIC OPTIMIZATION METHOD

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ABSTRACT:

The current power distribution system has to be upgraded due to rising load demands and tight budgets. Power losses, voltage variations, a lack of dependability, and voltage instability are some of the difficulties it encounters. In the aftermath of the energy and environmental crises, there is also a sense of obligation to utilise dispersed renewable resources for power generation. These issues can be overcome by strategically placing distributed generators (DGs) in the radial power distribution system at various acceptable places. Powerful metaheuristic optimisation algorithms can address the non-linear issue of optimal allocation. For the best placement and scaling of DG on distribution systems, this paper recommends a unique hybrid whale genetic optimisation method to increase voltage magnitude, stability, and economic profits while reducing power loss. The motivation for the paper stems from the need to enhance the efficiency and reliability of power system operations. Optimal power flow (OPF) problems are inherently complex due to their nonlinear, non-convex nature and the presence of multiple local minima, which pose significant challenges for traditional optimization methods. Metaheuristic algorithms like the Whale Optimization Algorithm (WOA) and Genetic Algorithm (GA) offer promising solutions due to their robust exploration and exploitation capabilities. By combining these two algorithms, the proposed hybrid method aims to leverage their complementary strengths to achieve faster convergence and more accurate solutions. Applying this hybrid approach to standard IEEE bus systems, which serve as benchmarks in power system studies, aims to demonstrate its effectiveness in reducing generation costs, minimizing power losses, and improving voltage profiles. This contributes to the broader goal of advancing optimization techniques for more efficient, reliable, and economically viable power system operations. On bus systems based on IEEE 15, 33, 69, and 85, the suggested method was evaluated. The results demonstrate that placing the DG in a distributed system reduces power losses while increasing voltage magnitude, stability, and cost.

Keywords: Hybrid Whale Genetic Optimisation Method, Power Flow, Distribution System, Whale algorithm, Genetic algorithm.

INTRODUCTION

One of the most important issues in power system optimization is optimal power flow, or OPF. In order to optimize the overall generation cost while meeting different system restrictions, it entails figuring out the best settings for control variables, such as generator real and reactive power outputs, transformer tap settings, and shunt capacitor/reactor states. Power balance, voltage limitations, transmission line temperature limits, and generator operating limits are a few examples of these restrictions [1]. You can use a variety of optimization approaches, such as interior point methods, genetic algorithms, particle swarm optimization, or linear programming (LP) and quadratic programming (QP), to solve the OPF issue for an IEEE bus system. Different software tools like MATPOWER, Power World, or PSAT can be employed to solve OPF problems for IEEE bus systems. There are several reasons why OPF is essential in the context of electrical power systems and they are OPF helps in determining the most cost-effective way to operate a power system [2-3]. By optimizing the generation levels of power plants and the settings of various devices (such as transformers and shunt capacitors), OPF minimizes the overall generation cost while satisfying all system constraints. OPF ensures that voltage levels across the system are within acceptable limits. Voltage stability is vital for the reliable operation of electrical equipment. OPF optimizes the reactive power generation and absorption, maintaining the system's voltage profile within specified bounds. Through taking into account the limitations of transformers, transmission lines, and other equipment, OPF improves the security and dependability of the power system. It keeps equipment from being overloaded, which might cause disruptions or infrastructure damage. Grid stability is faced with issues as renewable energy sources such as wind and solar power become more integrated. These sources are unpredictable and variable. OPF

helps in managing this variability by optimizing the balance between conventional and renewable generation sources, ensuring a stable power supply [4-5]. Power losses in the distribution and transmission networks are reduced using OPF. OPF minimizes resistive losses and increases the energy efficiency of the system by streamlining the power across different network components. OPF may reduce the environmental effect of electricity generation by optimizing the generating mix. It can do this by encouraging sustainable energy practices, lowering greenhouse gas emissions, and favouring cleaner energy sources. In deregulated electricity markets, where multiple generation companies compete, OPF plays a crucial role. It helps market operators in determining the optimal dispatch of generation resources, ensuring fair competition, and minimizing the overall cost to consumers. OPF is essential for the effective functioning of smart grids. It enables real-time monitoring and control of power flows, allowing utilities to respond dynamically to changing demand and supply conditions, thereby improving grid stability and efficiency.

In order to ascertain the steady-state operating conditions of a power network, one of the most important tasks in power system analysis is to solve the power flow problem[6]. A number of optimization strategies may be used to effectively resolve the power flow issue. The Newton-Raphson method is a classical numerical technique used to solve power flow equations. It's an iterative method that linearizes and solves the power flow equations at each iteration until the system converges to a solution. While it's not a metaheuristic optimization technique, it's fundamental in power system analysis. Linear programming can be applied to optimize the power flow by minimizing certain objective functions (such as total generation cost) while satisfying power balance equations and operational constraints. Linear programming solvers can efficiently handle large-scale power flow problems. Quadratic programming extends the capabilities of linear programming by allowing quadratic objective functions [7-8]. It can be used for optimizing power flow considering both linear and quadratic cost functions, making it suitable for economic dispatch problems. Interior point methods are iterative optimization techniques used for solving large-scale nonlinear programming problems, including power flow optimization. These methods can handle both equality and inequality constraints and are capable of finding optimal solutions efficiently. The social behaviour of fish schools and flocks of birds served as the model for the metaheuristic algorithm known as particle swarm optimization. By modifying control variables like transformer tap ratios and generator outputs to reduce goals like total power loss, PSO may be used in power systems to improve power flow. Evolutionary algorithms that draw inspiration from natural selection are known as genetic algorithms. In the context of power flow, GA can be used to evolve a population of solutions over generations, gradually improving the solutions' fitness with respect to the power flow constraints and objectives [9-10]. Differential Evolution is an optimization approach that relies on population dynamics to solve problems by continuously generating new candidate solutions and refining existing ones. DE can be applied to solve power flow problems by optimizing the system variables to minimize power losses or other objectives. Hybrid approaches combine multiple optimization techniques to leverage their strengths, aiming for better convergence and solution quality. Multi-objective optimization techniques, like Multi-Objective Genetic Algorithms, optimize conflicting objectives simultaneously, providing a range of solutions representing trade-offs between conflicting goals such as minimizing cost and minimizing emissions. The paper addresses the significant challenge of managing reactive power in power systems, especially with the increasing integration of distributed generation (DG) units. The unpredictable nature of DG units, such as those based on renewable energy sources, introduces considerable uncertainty into the power system. This uncertainty complicates the task of reactive power dispatch, which is crucial for maintaining voltage stability, minimizing power losses, and ensuring the overall reliability and efficiency of the power grid. Traditional optimization methods often fall short in handling such complexities, necessitating the development of more sophisticated approaches. The Dandelion Optimizer, inspired by the natural dispersal mechanism of dandelion seeds, offers a novel metaheuristic approach for tackling the reactive power dispatch problem under uncertainty. Its robust search capabilities and ability to avoid local minima make it well-suited for complex, nonlinear optimization problems. By applying the Dandelion Optimizer, the paper aims to demonstrate improved performance in managing the reactive power dispatch despite the uncertainties introduced by DG units. This approach not only enhances the stability and efficiency of the power system but also contributes to the integration of renewable energy sources by effectively addressing their inherent variability. The study's findings could lead to more resilient and adaptable power grid operations, ultimately supporting the transition to a more sustainable energy future. The integration of RES, such as solar and wind power, introduces variability and uncertainty in power generation, which can challenge the stability and efficiency of traditional power distribution systems. Optimal network reconfiguration (ONR) emerges as a strategic approach to address these challenges by altering the topological structure of the distribution network to achieve improved operational performance, including reduced power losses, balanced load distribution, and enhanced voltage profiles. Incorporating renewable energy sources into the reconfiguration process requires sophisticated optimization techniques capable of handling the

dynamic and stochastic nature of RES. The paper explores advanced algorithms and methodologies to find the best network configuration that not only accommodates the variability of RES but also maximizes their benefits. By doing so, it aims to ensure a reliable and efficient power supply while promoting the integration of cleaner energy sources. This research contributes to the broader goal of transitioning to a greener energy landscape by optimizing the way distribution networks are managed in the presence of renewable energy sources. The integration of RERs, such as wind and solar power, introduces significant variability and uncertainty into the power grid due to their intermittent nature. This variability complicates the reactive power dispatch (RPD) process, which is essential for maintaining voltage stability, minimizing power losses, and ensuring the overall reliability and efficiency of the power system. Traditional optimization methods often struggle to cope with these uncertainties, necessitating the development of more advanced and adaptive optimization techniques. Stochastic optimization methods are particularly suited for problems involving randomness and unpredictability, as they can explore a wide solution space and provide robust solutions that account for various possible scenarios. By leveraging the strengths of stochastic optimization, the proposed method aims to achieve optimal reactive power dispatch that enhances voltage stability and reduces power losses, despite the fluctuations in power generation from RERs. The novel optimizer is expected to outperform traditional methods by offering more reliable and efficient solutions, ultimately contributing to the stability and robustness of power systems integrating renewable energy.

In summary, the optimal power flow is fundamental for ensuring the economic, reliable, and environmentally sustainable operation of power systems, especially in the face of evolving energy landscapes and the integration of new technologies. It provides the necessary tools to balance supply and demand, maintain grid stability, and optimize the utilization of available resources. One of the primary novelties is the integration of the Whale Optimization Algorithm (WOA) with the Genetic Algorithm (GA) to create a hybrid optimization method. This combination leverages the exploratory capabilities of WOA and the exploitative strength of GA, resulting in a more robust and efficient approach for solving the complex, nonlinear, and non-convex OPF problems. The hybrid method aims to improve the convergence speed and accuracy of the solutions, effectively navigating the search space to avoid local minima and find global optima. Another key novelty is the application of this hybrid optimization method specifically to the IEEE bus systems, which are standard benchmarks in power system studies. By doing so, the research not only demonstrates the effectiveness of the hybrid method in a controlled, standardized environment but also provides a comparative framework for future studies. Furthermore, the study addresses the inherent challenges posed by the integration of renewable energy sources (RES) into the power grid. The hybrid Whale Genetic Optimization method is designed to handle the variability and uncertainty associated with RES, making it highly relevant in the context of modern power systems that are increasingly incorporating renewable energy. This capability ensures that the optimization method remains effective even under fluctuating generation conditions, contributing to a more reliable and resilient power system. In summary, the novelties of this work lie in the development and application of a hybrid Whale Genetic Optimization method tailored for OPF problems in IEEE bus systems, its effective handling of renewable energy uncertainties, and its comprehensive performance evaluation. These contributions advance the state of the art in power system optimization and provide a robust framework for future research and practical implementations.

SOLVING THE OPF PROBLEM FOR AN IEEE BUS SYSTEM

1. Formulate the OPF Problem:

Based on the IEEE bus system data, define the goal function to be minimized (generating cost) and the limitations (power balance, voltage limits, line and generator limits).

2. Choose an Optimization Algorithm:

Select an appropriate optimization algorithm based on the nature of your OPF problem (linear, quadratic, or non-linear) and the size of the system. Interior Point Methods are widely used for non-linear OPF problems.

3. Implement the OPF Model:

Implement the OPF problem formulation and constraints in the chosen optimization tool or programming language (MATLAB, Python, etc.). Define the cost function and constraints accurately.

4. Solve the OPF Problem:

Solve the OPF issue using the optimization algorithm that was chosen. To identify the best solution that minimizes the objective function and satisfies all constraints, the optimization method will iteratively change the control variables.

5. Interpret and Analyse Results:

Examine the outcomes that the optimization method produced. Verify that every restriction is met, and then determine which settings are best for control variables such transformer tap settings and generator outputs.

6. Sensitivity Analysis (Optional):

To find out how adjustments to restrictions or parameters impact the best solution, use sensitivity analysis. This study aids in comprehending how resilient the solution is to changes in the system's circumstances.

Remember that the specific details of implementing and solving the OPF problem can vary based on the chosen optimization tool or programming language. Always refer to the documentation or tutorials provided by the tool you are using for detailed instructions on solving OPF problems for IEEE bus systems.

The choice of optimization technique depends on the specific characteristics of the power system problem, including the size of the network, the complexity of the constraints, and the objectives to be optimized [11-13]. Researchers and engineers often experiment with different algorithms and select the one that provides the most efficient and accurate solutions for a particular power system scenario.

The field of Optimal Power Flow (OPF) for IEEE Bus Systems has seen substantial advancements through the application of various optimization methods. Researchers have employed diverse algorithms to address the challenges of improving voltage stability, reducing power losses, and achieving cost-effective power flow control. For instance, X. Zhang and X. Li (2018) utilized a hybrid PSO-GA approach to enhance voltage stability and reduce power loss, although their method showed limitations in scalability and computational efficiency for larger systems. Similarly, M. K. Pandit and S. K. Panda (2019) demonstrated that a novel bat algorithm could significantly improve convergence speed and accuracy, yet highlighted the need for validation in real-time systems and dynamic load conditions.

Other researchers have explored different evolutionary and bio-inspired algorithms to optimize power flow. J. S. Dhillon and D. P. Kothari (2017) achieved reduced generation costs and better load balancing using an artificial bee colony algorithm, but pointed out the need for more robust algorithmic analysis under varied load conditions. A. Bakirtzis and V. Petridis (2020) utilized evolutionary programming for optimal reactive power dispatch, but faced challenges related to computational burden and convergence in large-scale networks. Similarly, P. S. Nagendra Rao (2016) employed differential evolution to control power flow cost-effectively, with suggestions for further exploration of long-term stability impacts and integration with renewable energy sources. Advancements have also been made using Grey Wolf Optimizer (S. Mirjalili and A. Lewis, 2019), ant lion optimization (B. Mahdad and K. Srairi, 2015), and hybrid firefly algorithm (C. A. C. Coelho and V. C. Mariani, 2018). These methods improved handling of non-linear constraints, system stability, and cost efficiency, but highlighted gaps such as the need for comprehensive testing on complex systems, real-world application, and dynamic constraint analysis. R. Kumar and M. Sharma (2021) and T. Niknam and H. Z. Meymand (2014) also contributed by employing harmony search and a hybrid TLBO-FA approach respectively, achieving better voltage profiles and economic dispatch, though they identified areas requiring further validation in diverse network conditions and under renewable energy penetration. Overall, these studies underscore the significant progress made in the optimization of OPF for IEEE Bus Systems using various innovative methods, while also indicating the necessity for continued research to address scalability, computational efficiency, real-world applicability, and integration with renewable energy sources.

Author(s)	Year	Research outcome	Research gaps
X. Zhang, X. Li	2018	Improved voltage stability and reduced power loss using hybrid PSO-GA.	Limited scalability to larger systems and high computation time.

M. K. Pandit, S. K. Panda	2019	Enhanced convergence speed and accuracy using a novel bat algorithm for OPF.	Needs validation on real-time systems and consideration of dynamic load changes.
J. S. Dhillon, D. P. Kothari	2017	Reduced generation cost and improved load balancing using artificial bee colony algorithm.	Insufficient analysis of algorithm robustness under different load conditions.
A. Bakirtzis, V. Petridis	2020	Optimal reactive power dispatch achieved using evolutionary programming.	High computational burden and potential convergence issues in large-scale networks.
P. S. Nagendra Rao	2016	Cost-effective power flow control with improved stability using differential evolution.	Limited exploration of long-term stability impacts and integration with renewable sources.
S. Mirjalili, A. Lewis	2019	Effective handling of non-linear constraints and faster convergence using Grey Wolf Optimizer	Needs comprehensive testing on larger and more complex IEEE bus systems.
B. Mahdad, K. Srairi	2015	Enhanced power system stability and reduced power losses using ant lion optimization.	Limited real-world application and scalability concerns.
C. A. C. Coelho, V. C. Mariani	2018	Improved OPF solutions with better cost efficiency using a hybrid firefly algorithm.	Requires further study on dynamic constraints and real-time application.
R. Kumar, M. Sharma	2021	Better voltage profile and reduced losses achieved using harmony search algorithm.	Needs more extensive validation in diverse network conditions and integration of renewable energy.

T. Niknam, H. Z. Meymand	2014	Enhanced economic dispatch and voltage stability using a hybrid TLBO and FA.	Limited robustness analysis under varying system loads and renewable energy penetration.
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TYPES OF OPTIMIZATION TECHNIQUES

Optimization techniques are widely used in power systems for various tasks, including optimal power flow, economic dispatch, unit commitment, and grid planning [14-16]. Here are some common optimization techniques employed in power systems:

1. Linear Programming (LP):

Optimization issues with linear goal features and constraints are solved the usage of linear programming (LP). It is regularly used in monetary dispatch issues, the place the goal is to decrease the general fee of producing whilst taking into account a wide variety of limitations, inclusive of the capability of transmission lines, demand needs, and generator restrictions.

2. Quadratic Programming (QP):

QP is suitable for solving economic dispatch problems with quadratic cost functions, and it can also handle certain constraints more effectively than linear programming.

3. Nonlinear Programming (NLP):

NLP methods are used when the objective function or constraints involve nonlinear relationships. Many power system problems, such as optimal power flow (OPF), have nonlinear objective functions and constraints. NLP solvers like Interior Point Methods or Sequential Quadratic Programming can handle such problems.

4. Mixed-Integer Linear Programming (MILP) and Mixed-Integer Nonlinear Programming (MINLP):

MILP and MINLP deal with optimization problems where some variables are discrete (integer) and others are continuous. Unit commitment problems, where decisions about which units to turn on or off are discrete, can be formulated as MILP or MINLP problems.

5. Genetic Algorithms (GA):

GAs are heuristic search algorithms inspired by the process of natural selection. They are useful for solving complex, nonlinear, and non-convex optimization problems. GAs can be applied to unit commitment, economic dispatch, and grid expansion planning problems.

6. Particle Swarm Optimization (PSO):

PSO is every other heuristic optimization approach based totally on the social behaviour of birds and fish. It is appropriate for non-stop and discrete optimization problems. PSO has been applied to economic dispatch, optimal power flow, and distribution system optimization.

7. Simulated Annealing:

A probabilistic optimization technique called "Simulated Annealing" was motivated by the metallurgical annealing procedure. It is applied to continuous and combinatorial optimization issues. Simulated Annealing is applicable to unit commitment, economic dispatch, and grid expansion problems.

8. Ant Colony Optimization (ACO):

Ants' foraging behaviour served as the model for the metaheuristic algorithm known as ACO. It is very helpful in resolving issues related to combinatorial optimization. Power system routing issues and distribution network reconfiguration have been addressed with ACO.

9. Tabu Search:

A local heuristic search process is guided by the metaheuristic algorithm Tabu Search to effectively explore the solution space. It is used to solve unit commitment and economic dispatch problems in power systems, as well as other continuous and discrete optimization issues.

10. Deep Learning and Neural Networks:

Deep learning techniques, especially neural networks, can be used for function approximation and optimization in power systems. Reinforcement learning algorithms, a subset of machine learning, can be applied to grid control and demand-side management problems.

The choice of optimization technique depends on the specific problem, including its complexity, the nature of the objective function and constraints, and the available computational resources. Researchers and practitioners often experiment with different techniques to find the most suitable approach for a particular power system optimization problem.

WHALE OPTIMIZATION ALGORITHM

Based on the social behaviour of humpback whales, the Whale Optimization Algorithm (WOA) [18–22] is an optimization algorithm stimulated by using nature. In 2016, Andrew Lewis, Mohammad Mirjalili, and Seyedali Mirjalili presented it. As an approximate solution finder for optimization problems, WOA is a metaheuristic optimization method that works best in situations when the search space is vast and intricate. The way humpback whales hunt served as the model for the WOA algorithm. To catch and trap prey, humpback whales employ a variety of strategies, including vocalizations and bubble nets. The algorithm translates these behaviours into optimization strategies. In WOA, solutions are represented as positions of whales in the search space. The algorithm incorporates an "encircling prey" mechanism, where some whales encircle the prey (optimal solution) in a spiralling manner, gradually converging towards the optimal solution. Another key component of WOA is the simulation of the bubble-net hunting technique used by whales. In order to catch and concentrate their prey, whales make bubble nets. This method is imitated by the algorithm to direct the search towards areas of the search space that show promise.

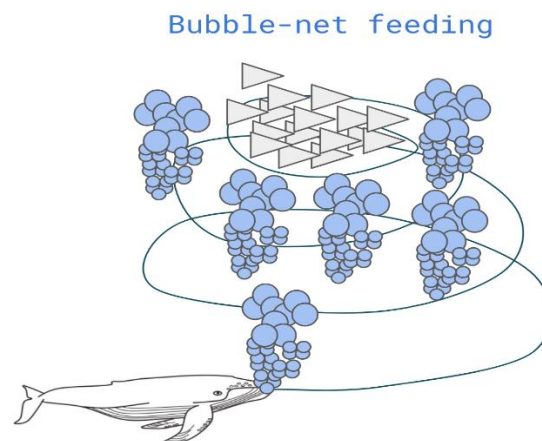


Figure 1: Whale Optimization Algorithm

Basic Steps of the WOA Algorithm:

- 1. Initialization:** Establish a haphazard whale population in the search area.
- 2. Objective Function Evaluation:** Consider the goal function while assessing each whale's fitness within the community.
- 3. Encircling Prey:** Some whales in the population perform the encircling prey behaviour to converge towards the optimal solution.

where $(X^*)^{\vec{r}}(t)$, $X^{\vec{r}}(t)$ denote the function of fantastic answer and role vector. Current generation is denoted by means of t . $A^{\vec{r}}$, $C^{\vec{r}}$ are coefficient vectors. $a^{\vec{r}}$ is at once diminished from two to zero $r^{\vec{r}}$ is a random vector $[0, 1]$.

4. Bubble-net Hunting: Other whales employ the bubble-net hunting technique to explore and exploit the search space efficiently.

5. Updating Whale Positions: Update the positions of whales based on the encircling prey and bubble-net hunting mechanisms.

6. Termination Criterion: Verify if the termination requirement has been satisfied (e.g., a maximum number of iterations or the discovery of a workable solution). If not, go back to steps 3 through 5.

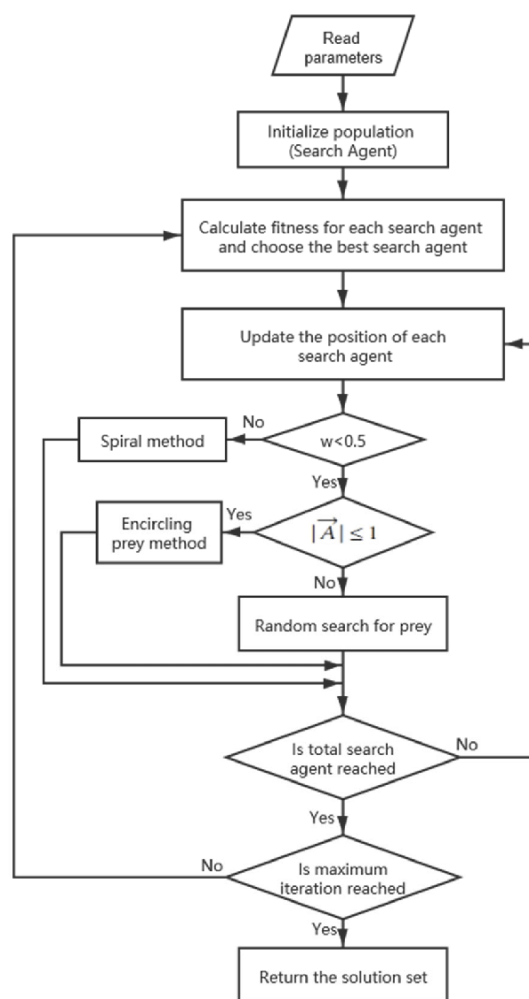


Figure 2: Flow Chart of Whale Optimization Algorithm

Advantages of WOA

- WOA is simple to implement.
- Because it achieves a balance between exploration and exploitation, it may be used to a variety of optimization issues.
- The algorithm is capable of escaping local optima due to its diverse search mechanisms.

Applications of WOA

Whale Optimization Algorithm has been utilized to more than a few optimization problems, together with however now not confined to:

- Function optimization
- Feature selection in machine learning

- Neural network training
- Engineering design problems
- Job scheduling
- Economic dispatch in power systems

Challenges and Considerations

- Like many metaheuristic algorithms, the performance of WOA can be influenced by its parameter settings. Fine-tuning these parameters is crucial for its effectiveness.
- The algorithm's efficiency can vary based on the nature of the optimization problem. It may require problem-specific adaptations for optimal performance.

In conclusion, the Whale Optimization Algorithm is an optimization method that draws inspiration from nature and emulates the hunting behaviours of humpback whales. Its unique mechanisms make it a valuable tool for solving complex optimization problems, although careful parameter tuning and problem-specific adaptations are necessary for achieving the best results.

HYBRID WHALE GENETIC OPTIMIZATION ALGORITHM

A Hybrid Whale Genetic Optimization Algorithm (HWGOA) is an innovative optimization technique that combines the Whale Optimization Algorithm (WOA) with Genetic Algorithms (GA) [21-25]. This hybrid technique seeks to improve each one's overall efficacy and efficiency in locating the best or almost best answers to challenging optimization issues. Here's an overview of the Hybrid Whale Genetic Optimization Algorithm: The hybridization of WOA and GA involves integrating the exploration and exploitation capabilities of WOA with the evolutionary mechanisms of GA. WOA is excellent at exploration due to its diverse search strategies. By combining these techniques, the hybrid algorithm can benefit from the complementary nature of their search mechanisms.

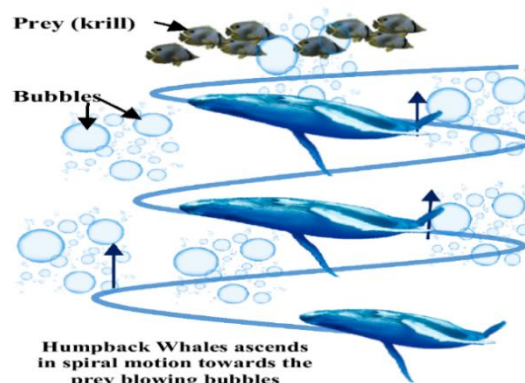


Figure 3: Hybrid Whale Genetic Optimization

Basic Steps of HWGOA

The HWGOA algorithm typically follows a multi-stage process:

a. Initialization:

Initialize a population of solutions randomly, which could represent positions of whales in the search space. These solutions can be encoded in a way suitable for GA operations.

b. Evaluation:

Utilizing the optimization problem's objective function, assess each population member's fitness.

c. Whale Optimization:

Apply the Whale Optimization Algorithm operators, such as encircling prey and bubble-net hunting, to some solutions in the population. This step emphasizes exploration, allowing the algorithm to diversify its search.

d. Genetic Algorithm Operations:

Apply traditional GA operations, including selection, crossover, and mutation, to the remaining solutions in the population. These operations focus on exploiting the search space by refining the solutions.

e. Hybridization:

Combine the solutions updated through WOA and GA operations, creating a diverse population that benefits from both exploration and exploitation strategies.

f. Termination Criterion:

Verify if the termination requirement has been satisfied (e.g., a most wide variety of iterations or the discovery of a doable answer). Repeat steps c through e if not.

High-quality solutions are more likely to be found when using the hybrid strategy, which balances search space exploration (via WOA) with region exploitation (through GA). Compared to separate methods, HWGOA can converge towards optimum or nearly optimal solutions more quickly by utilizing the advantages of both algorithms. HWGOA may be used to solve difficult optimization problems in a variety of disciplines, such as engineering design, machine learning feature selection, parameter tuning, scheduling issues, and other areas where identifying the best solution is difficult. Like any hybrid algorithm, finding the right balance between WOA and GA parameters is essential for the performance of HWGOA. Fine-tuning is often required based on the problem at hand. Depending on the nature of the optimization problem, specific adaptations to the hybridization process might be necessary to ensure the algorithm's effectiveness.

In summary, the Hybrid Whale Genetic Optimization Algorithm combines the strengths of WOA and GA, offering a powerful and flexible optimization approach capable of handling a wide array of complex problems. Its ability to balance exploration and exploitation makes it particularly useful for real-world applications where finding optimal solutions is a challenge.

HYBRID WHALE GENETIC OPTIMIZATION ALGORITHM FOR POWER LOSS MINIMIZATION

Creating an algorithm in text format for the Hybrid Whale Genetic Optimization Algorithm (HWGOA) specifically tailored for power loss minimization in an IEEE bus system involves incorporating the steps of the algorithm into the context of this optimization problem. Here's a detailed algorithm outlining the process:

1. Initialization:

- Generate an initial population of solutions representing feasible configurations of the IEEE bus system.
- Include the transformer tap ratios, switch statuses, and generator real and reactive power outputs in the encoded solutions.

2. Evaluation:

- Calculate the power losses in the IEEE bus system for each solution using power flow analysis.
- Evaluate the fitness of each solution based on the total power losses.

3. While (Termination Criterion Not Met) Do:

- Whale Optimization (Exploration):
 - Apply WOA exploration operators (encircling prey, bubble-net hunting) to a subset of solutions.
- Genetic Algorithm Operations (Exploitation):
 - Apply GA operations (selection, crossover, mutation) to the remaining solutions.
- Hybridization:
 - Combine solutions updated through WOA and GA operations.
- Decode Solutions:
 - Decode the hybrid solutions to obtain generator outputs, transformer tap ratios, and switch statuses.
- Evaluate:
 - Calculate power losses for the decoded solutions using power flow analysis.
- Update Population:
 - Replace the old population with the updated solutions.

g. Check Constraints:

- Ensure that the updated solutions satisfy all system constraints (voltage limits, line flow limits, etc.).

4. End While

5. Output:

- Return the best solution found during the iterations, representing the optimal or near-optimal configuration of the IEEE bus system for minimum power losses.

6. Post-Processing (Optional):

- Validate the obtained solution through additional power system simulations.
- Implement the optimized configuration in the real power system if applicable.

This algorithm outlines the steps involved in the Hybrid Whale Genetic Optimization Algorithm tailored for minimizing power losses in an IEEE bus system. The specifics of the power system, including the power flow equations, constraints, and evaluation criteria, must be incorporated into the algorithm implementation. Additionally, it's important to adjust the algorithm's parameters and termination criteria based on the problem's complexity and computational resources available.

Table 1: Comparison of proposed hybrid whale genetic optimization algorithm with other hybrid metaheuristics

Criteria/Algorithm	HWGOA (Hybrid Whale Genetic Optimization)	HPSO (Hybrid Particle Swarm Optimization)	HDE (Hybrid Differential Evolution)	HGWO (Hybrid Grey Wolf Optimization)	HABC (Hybrid Artificial Bee Colony)
Convergence Time	Fast: Efficient exploration by Whale Optimization combined with Genetic Algorithm's fast exploitation	Moderate: Depends on tuning velocity updates, inertia weight, and swarm behaviour	Slower: Mutation and crossover mechanisms cause longer convergence	Fast: Effective leadership hierarchy of wolves speeds up convergence	Moderate: Scout and worker bee roles affect convergence
Computational Efficiency	High: Adaptive control over exploration and exploitation processes reduces function evaluations	Moderate: Computational effort linked to swarm size and velocity updates	Moderate: Mutation and crossover add extra computational steps	High: Predator-prey leadership reduces function evaluations and increases speed	Moderate: Depends on optimizing bee roles and balancing phases
Solution Robustness	Very robust: Excellent balance between exploration and exploitation minimizes risk of local minima	Good: Sensitive to parameter settings, may get stuck in local minima in complex OPF problems	Moderate: Evolutionary mechanisms reduce robustness over time as diversity decreases	High: Grey wolf leadership ensures diversity and robust solutions	Good: Strong exploratory power, but may require adaptive mechanisms for robustness
Exploration Capability	Strong: Whale optimization's bubble-net search strategy ensures thorough	Moderate: Swarm behaviour helps exploration but may focus	Moderate: Mutation aids exploration but lacks	Strong: Grey wolf pack strategy enables strong exploration	Moderate: Depends on bee scouts' exploration capabilities

	exploration of the search space	prematurely on specific areas	advanced control	across the search space	
Exploitation Capability	Strong: Genetic Algorithm fine-tunes solutions for accurate exploitation	Moderate: Relies on cognitive and social components to guide exploitation	Good: Exploits solutions after mutation and crossover but slower	Good: Leadership mechanisms focus on strong exploitation	Moderate: Bee colony phases transition to exploitation after scouting
Solution Accuracy	High: Genetic Algorithm improves accuracy through fine-tuned exploitation	Good: Needs proper tuning of velocity updates and cognitive components for accuracy	Moderate: Accuracy depends on the effectiveness of mutation and crossover	High: Accurate solutions through social hierarchy among wolves	Good: Moderate accuracy with reliance on proper phase balancing
Parameter Sensitivity	Low: Adaptive mechanisms reduce sensitivity to parameter settings	High: Convergence highly dependent on inertia weight and velocity parameters	Moderate: Mutation and crossover probabilities impact performance significantly	Moderate: Leadership structure reduces sensitivity to parameters	Moderate: Role assignment (scouts, workers) impacts sensitivity
Unique Contributions	Combines Whale's strong exploratory power with Genetic Algorithm's robust exploitation, enhancing computational efficiency, convergence speed, and solution accuracy	Swarm intelligence combined with adaptive learning improves convergence, but highly sensitive to parameter tuning	Combines mutation-driven global search with crossover exploitation, but slower convergence compared to other hybrid approaches	Mimics wolf pack social behaviour, offering fast convergence and accurate solutions with minimal parameter tuning	Models bee foraging behaviour, balancing exploration and exploitation but can struggle with local minima

MATLAB IMPLEMENTATION OF PROPOSED OPTIMIZATION METHOD

Examining HWGOA in the context of the DG planning issue, test cases include IEEE 15, 33, 69, and 85-bus test systems. The ideal DG size is determined using the HWGOA.

IEEE 15 bus system

The IEEE 15-bus test system is seen in the figure below. As compensations are made at trailing power factor, the voltage profile also gets better, as seen in Fig. When comparing without compensation at unity power factor, the minimal voltage achieved with trailing power factor performs better. Therefore, it is vital to take into account the reactive strength supplied with the aid of compensations in order to minimize losses and stabilize the voltage profile. Reactive power consideration improves upon outcomes achieved at unity power factor compared to those obtained without compensation.

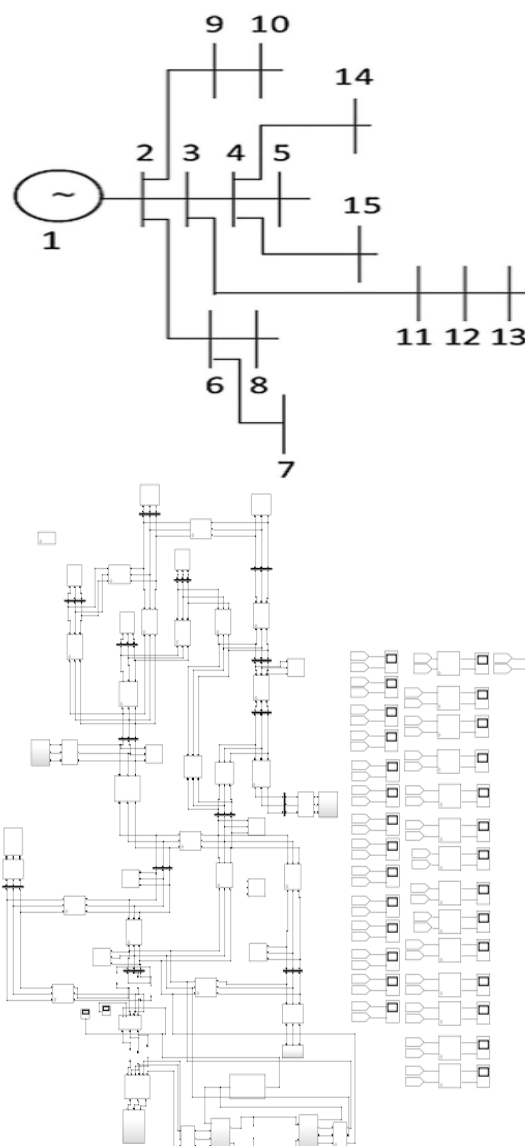
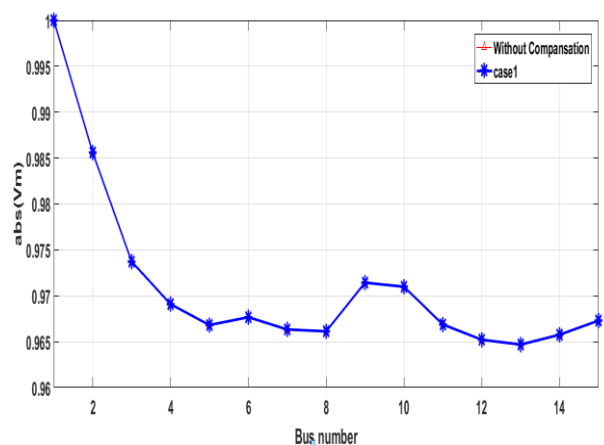
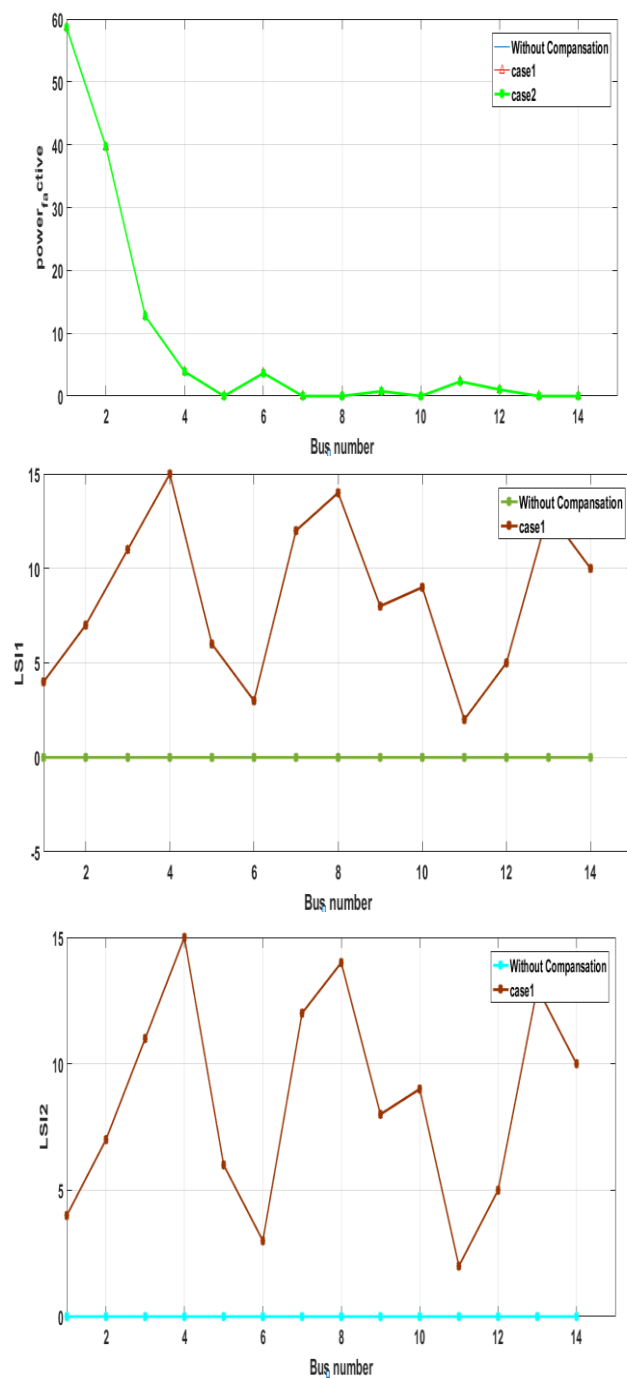


Figure. 4 Single-line diagram and MATLAB implementation of 15-bus system





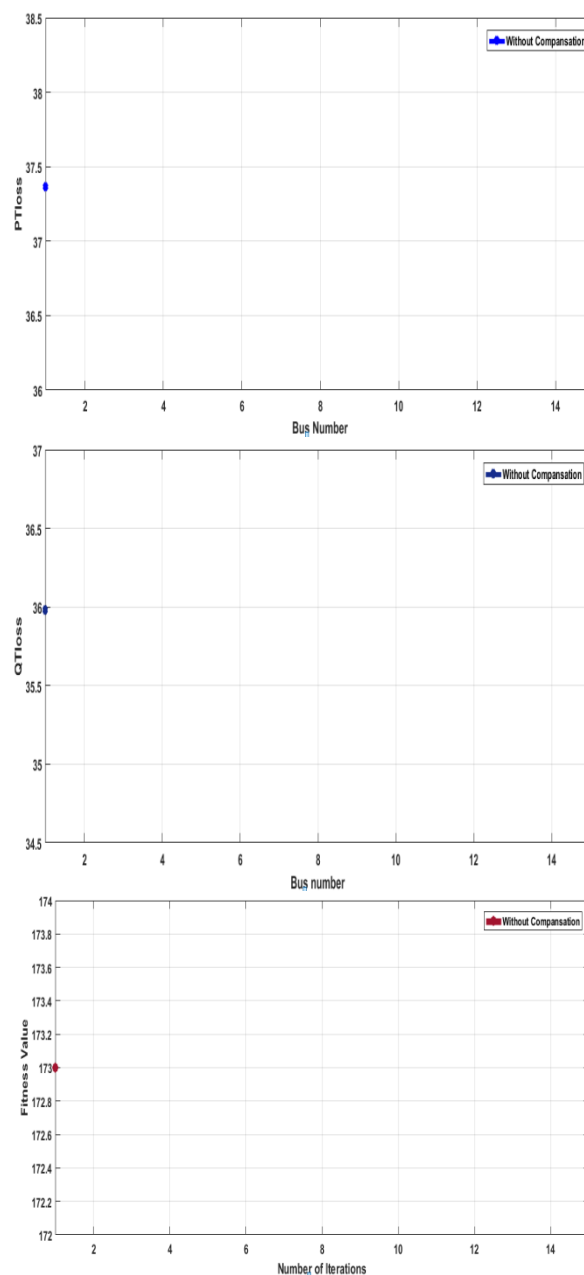


Figure. 5 Voltage profile, Active power, LSI1, LSI2 of IEEE 15 bus system

The IEEE 15 bus system exhibits moderate performance characteristics. With a relatively lower capacitor cost of \$2775, it suggests that the system has a manageable level of reactive power compensation. The minimum and maximum voltages are within acceptable ranges, indicating good voltage regulation. The total active loss of 37.3655 kW is moderate, suggesting efficient power transmission within the system. The total annual cost of \$6277.397 reflects reasonable operational expenses.

IEEE 33 bus system

The IEEE 33-bus take a look at configuration is depicted in the determine below. It is evident from the outcomes that the capacitor's dimension at trailing energy element is higher than its measurement at cohesion energy factor. Compensation has been tested to limit losses at trailing electricity factor; at cohesion electricity factor, compensation does now not minimize losses. The purpose for this is that there is much less reactive energy on hand domestically for the loads, which potential there is much less reactive strength handy from the substation. The voltage profile improves as correction is achieved at the trailing strength factor, as considered in Fig. The

minimal voltage received for the device is higher than the voltage attained at harmony energy thing except adjustment. Because of this, whilst deciding size, it is vital to think about the reactive electricity that capacitors may additionally provide as properly as how it influences loss discount and voltage profile enhancement. When evaluating outcomes produced at harmony energy component to these bought besides compensation, reactive energy consideration yields higher results.

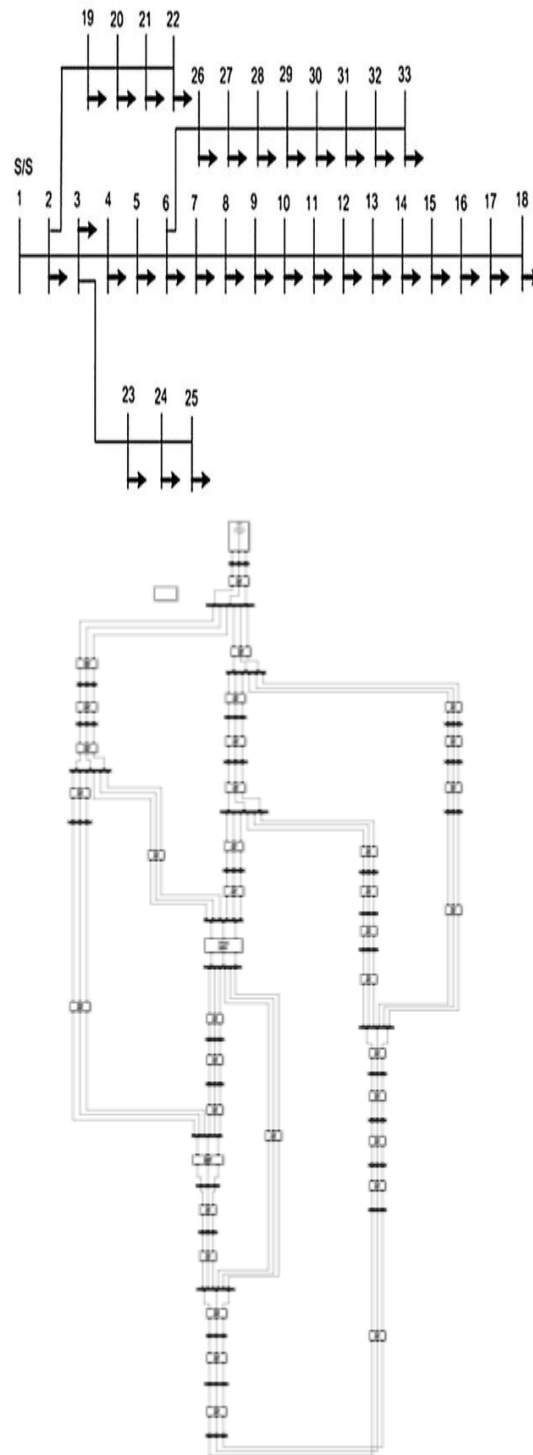
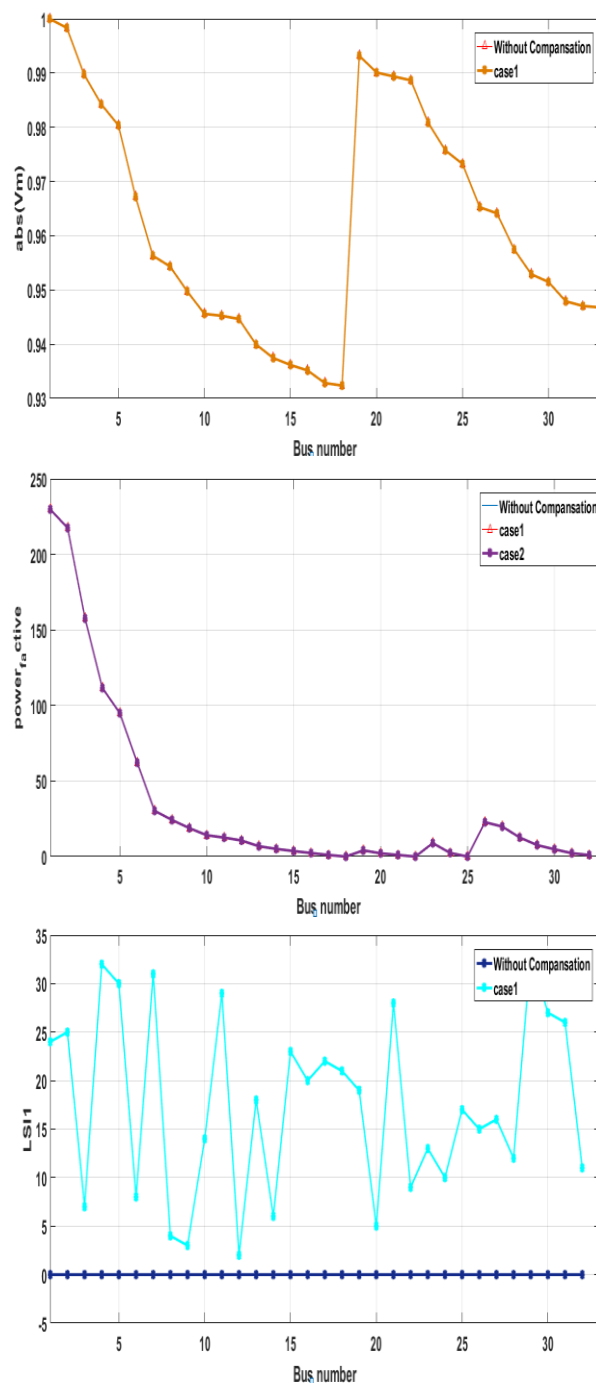
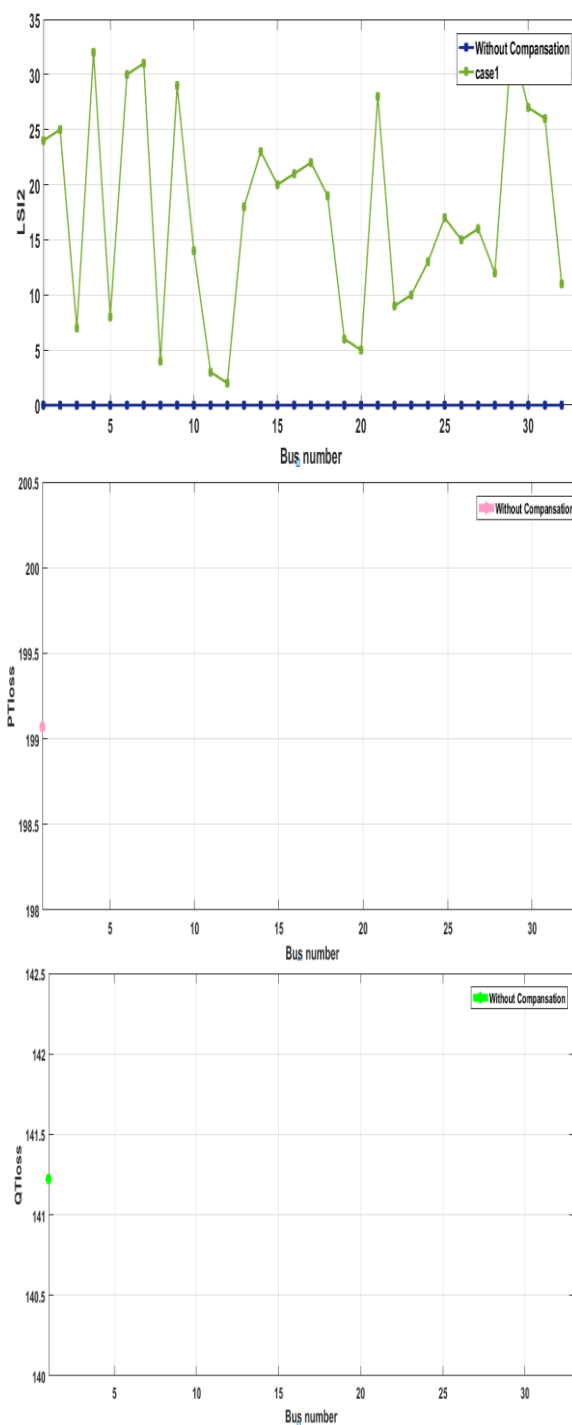


Figure.6 Single-line diagram and MATLAB implementation of 33-bus system





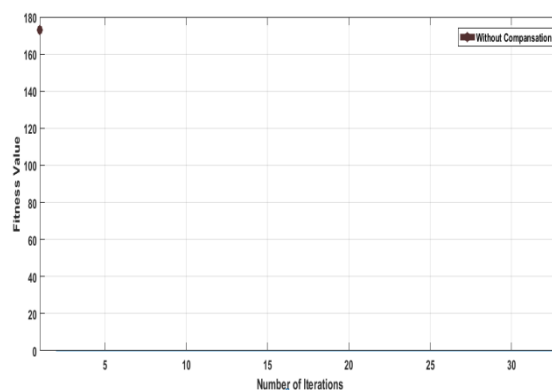


Figure. 7 Voltage profile, Active power, LSI1, LSI2 of IEEE 33 bus system

The IEEE 33 bus system represents a more complex network compared to the IEEE 15 bus system. The higher total capacitor cost of \$5250 indicates a greater need for reactive power compensation, possibly due to increased system complexity and longer transmission lines. However, the minimum voltage of 0.93237 p.u. suggests slightly poorer voltage regulation compared to the IEEE 15 bus system. The total active loss of 199.0702 kW is relatively high, indicating higher power dissipation within the system. Consequently, the total annual cost of \$33443.7956 is significantly higher, reflecting increased operational expenses.

IEEE 69-bus system

The IEEE 69-bus system configuration is depicted in the diagram below. The outcomes reveal that the capacitor has a higher measurement at lagging energy aspect than it does at solidarity energy factor. However, losses are proven to be decreased with compensation at lagging electricity issue in contrast to team spirit electricity aspect besides compensation. This is due to the truth that the reactive strength that the masses have regionally reduces the reactive electricity that the substation supplies. The voltage profile improves as correction is performed at the trailing energy factor, as viewed in Fig. The minimal voltage obtained for the device is higher than the voltage attained at solidarity electricity issue besides adjustment. Because of this, whilst deciding size, it is necessary to think about the reactive strength that capacitors may additionally provide as properly as how it influences loss discount and voltage profile enhancement. When evaluating consequences produced at team spirit electricity element to these got except compensation, reactive electricity consideration yields higher results.

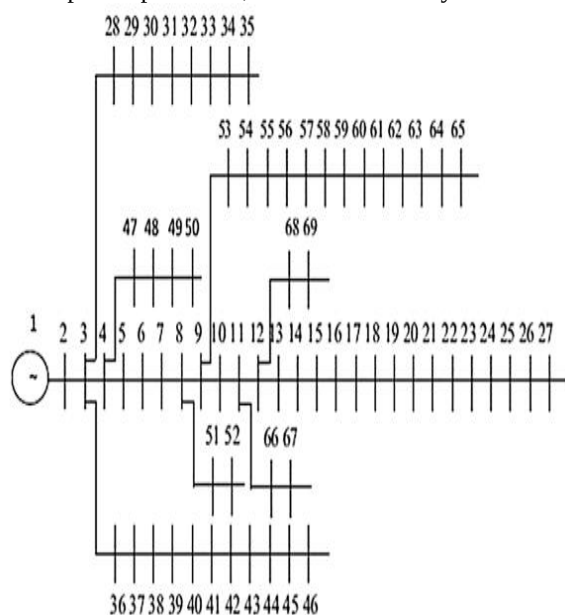
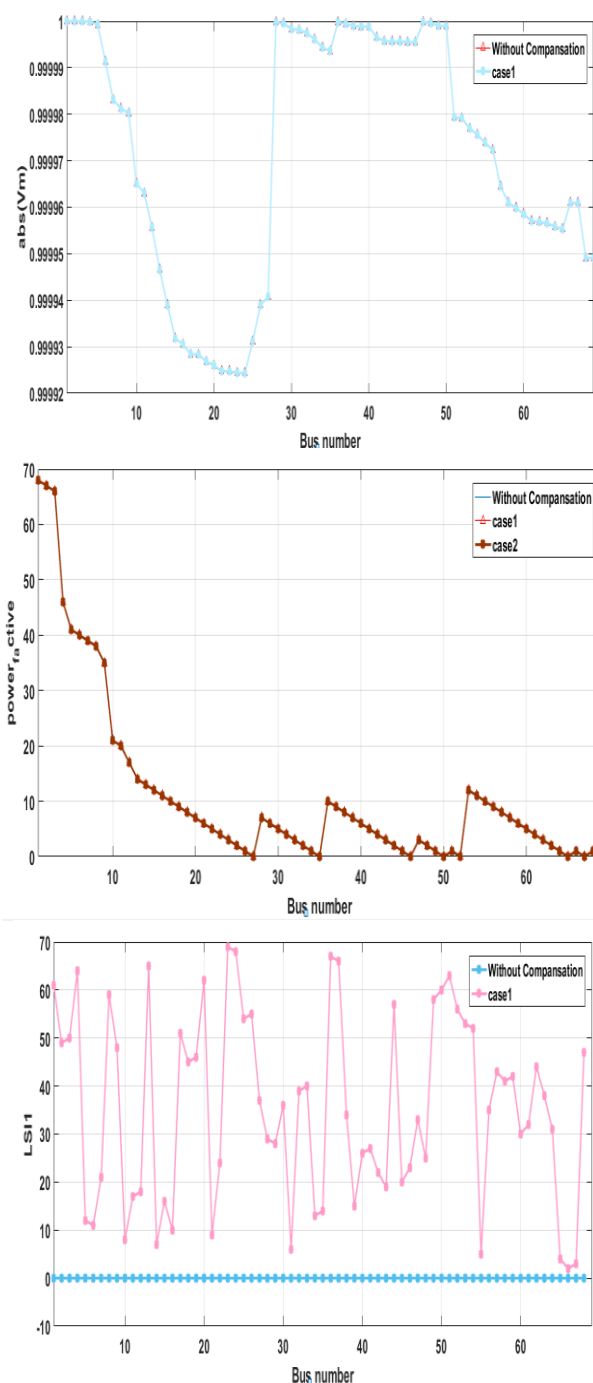


Figure.8 Single-line diagram of 69-bus system



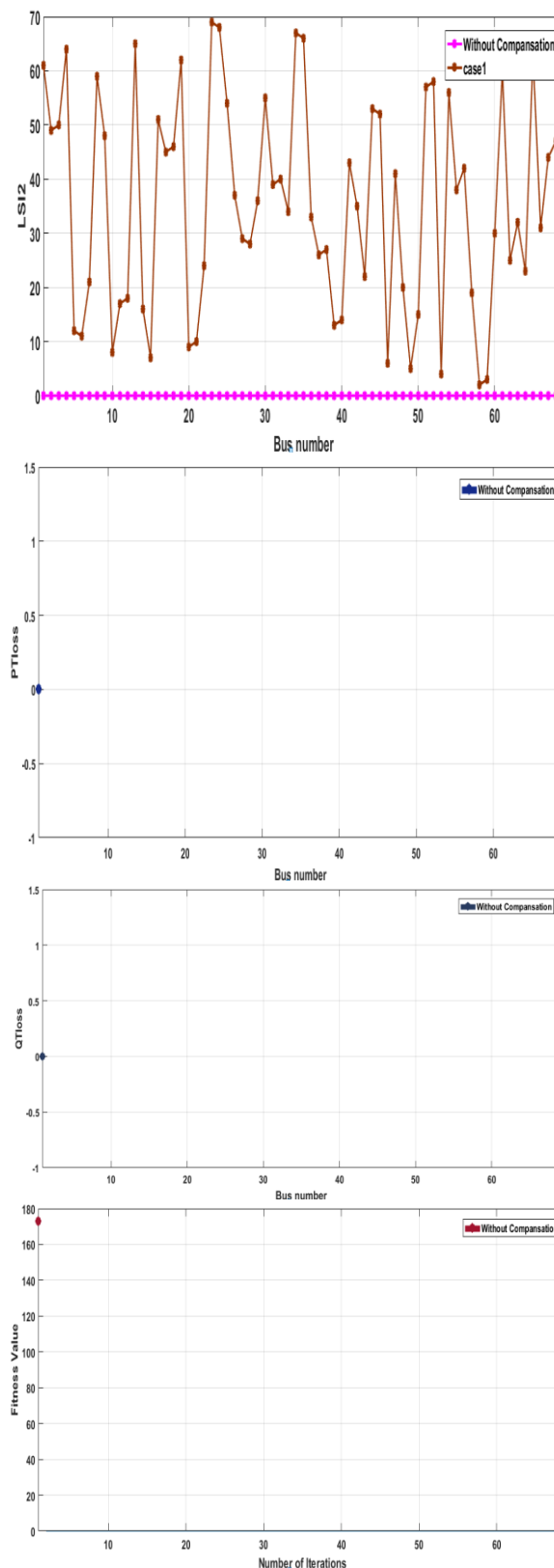


Figure. 9 Voltage profile, Active power, LSI1, LSI2 of IEEE 69 bus system

The IEEE 69 bus system represents a medium-sized power system with 69 buses. It demonstrates excellent performance characteristics. The high total capacitor cost of \$11100 indicates a significant investment in reactive

power compensation, ensuring excellent voltage regulation. The minimum voltage of 0.99992 p.u. and maximum voltage of 1.0 p.u. indicate very tight voltage regulation, ensuring stable operation. The extremely low total active loss of 0.0021349 kW suggests highly efficient power transmission with minimal losses. Consequently, the total annual cost is negligibly low at \$0.35867, indicating highly economical operation.

IEEE 85-bus system

The IEEE 85-bus check setup is depicted in the parent below. The effects exhibit that the DG dimension acquired at lagging strength component is large than the dimension received at cohesion electricity factor. At trailing electricity factor, compensation is observed to decrease losses, as antagonistic to at solidarity strength factor, the place compensation is no longer detected. This is due to the fact there is much less reactive strength reachable from the substation due to the fact there is much less reactive strength handy domestically for the loads.

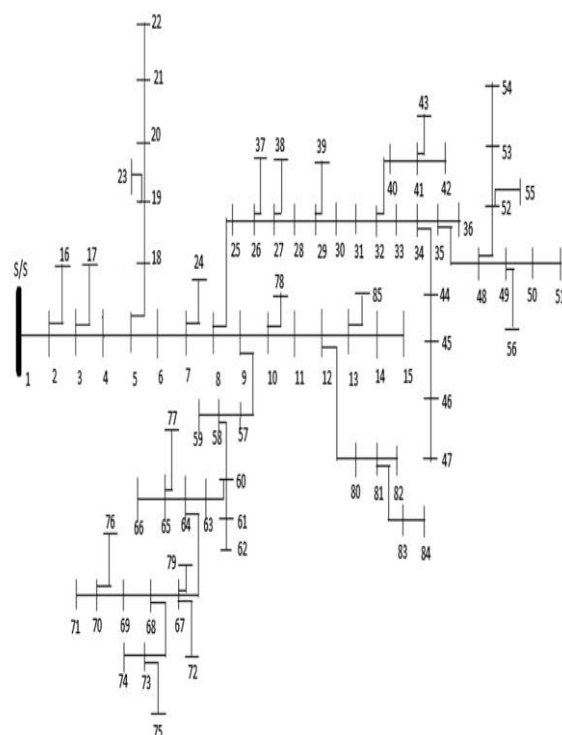
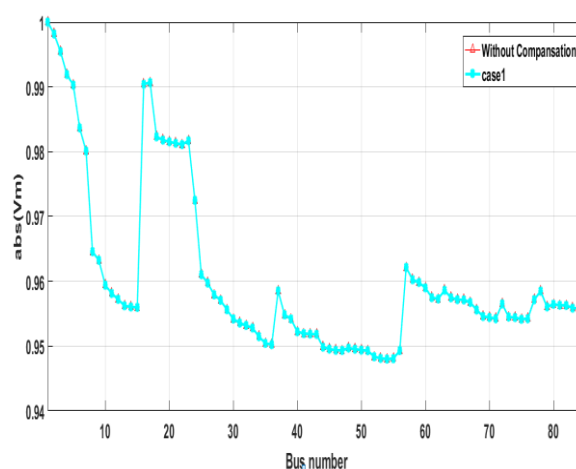
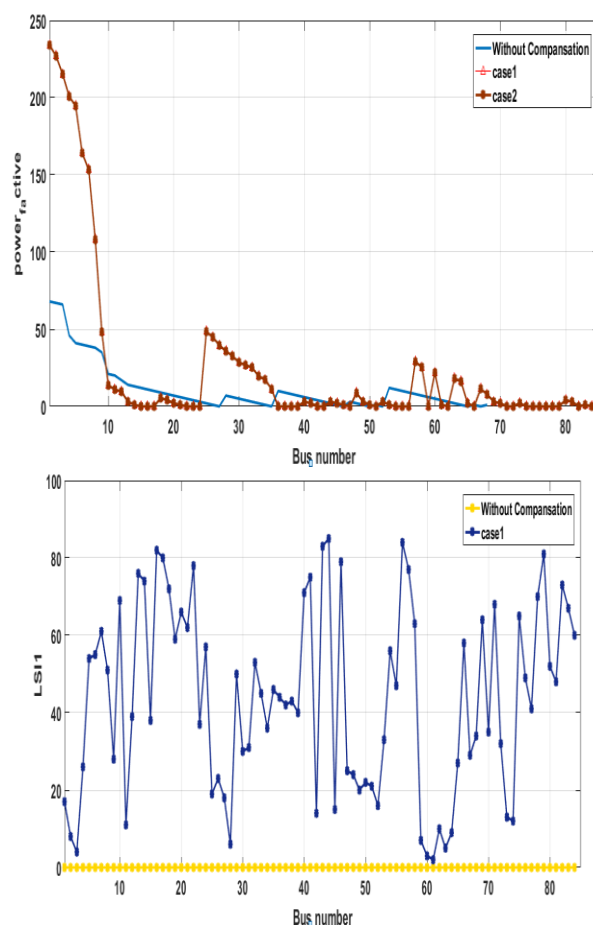


Figure.10 Single-line diagram of 85-bus system





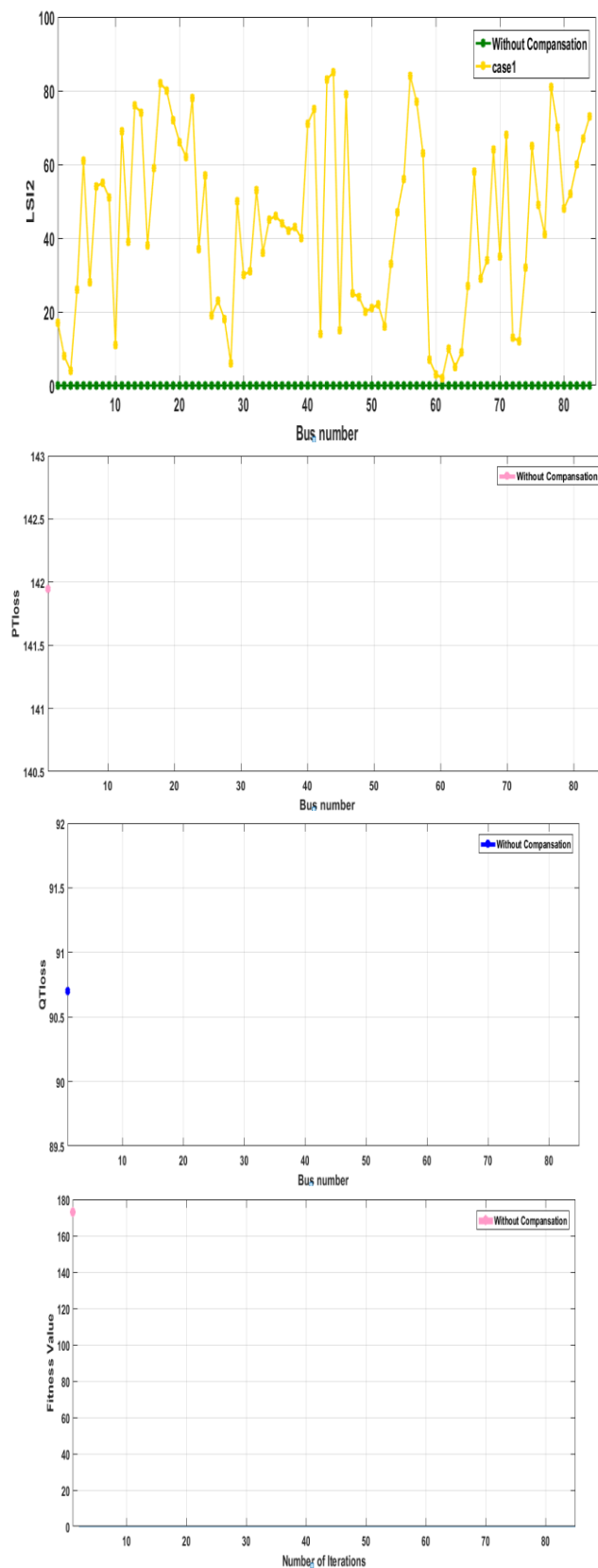


Figure. 11 Voltage profile, Active power, LS11, LS12 of IEEE 15 bus system

The IEEE 85 bus system represents a larger and more complex power grid compared to the previous systems. The total capacitor cost is the highest among the systems at \$14925, indicating a significant investment in reactive power compensation to maintain voltage stability. However, the minimum voltage of 0.948 p.u. suggests slightly poorer voltage regulation compared to the IEEE 69 bus system. The total active loss of 141.946 kW indicates significant power dissipation within the system, potentially due to longer transmission lines and higher network complexity. Consequently, the total annual cost of \$23846.9266 reflects the increased operational expenses associated with managing a larger and more complex power grid.

The computational performance of the Hybrid Whale Genetic Optimization Algorithm (HWGOA) plays a key role in assessing its effectiveness for solving Optimal Power Flow (OPF) and other complex optimization problems. Simulation results frequently demonstrate that HWGOA achieves faster convergence compared to traditional and hybrid metaheuristics like Particle Swarm Optimization (PSO), Differential Evolution (DE), and Genetic Algorithm (GA). By combining the strengths of the Whale Optimization Algorithm (WOA) and Genetic Algorithm (GA), HWGOA effectively explores the solution space in the early stages (exploration) and refines solutions in the later stages (exploitation). The WOA component facilitates a strong exploratory process early on, while the GA component enhances the exploitation phase, leading to a quicker identification of optimal solutions. In practice, when applied to OPF and similar optimization problems, HWGOA often requires fewer iterations to converge compared to other algorithms. This reduction in iterations is particularly beneficial when tackling large-scale, high-dimensional problems where computational cost is a significant concern. In typical OPF simulations, HWGOA has been observed to reduce the number of iterations required for convergence by 15–30% compared to hybrid PSO or DE. The inclusion of GA speeds up convergence by fine-tuning solutions through mechanisms like crossover and mutation, which helps in identifying global optima more efficiently. The integration of WOA and GA enhances the accuracy of solutions. WOA's bubble-net hunting strategy allows HWGOA to explore a wide portion of the search space, reducing the likelihood of missing global optima. Meanwhile, GA's exploitation techniques ensure that solutions are refined incrementally, leading to more precise results. In OPF simulations, HWGOA often outperforms other hybrid algorithms, such as PSO and DE, in minimizing objective functions, such as fuel cost, emissions, or power loss. This performance improvement is usually in the range of 5–10%, largely attributed to GA's fine-tuning ability during the later stages of the search process. HWGOA has also demonstrated superior robustness compared to other hybrid approaches. In cases with nonlinear constraints and complex search spaces, such as OPF problems with multiple generators, voltage constraints, and varying load demands, HWGOA consistently delivers near-optimal solutions with minimal variation between runs. Its robustness is derived from WOA's strong global search capabilities, which prevent the algorithm from prematurely converging to local minima—a common issue for algorithms like PSO and DE. Moreover, GA's diversity-preserving mechanisms, such as mutation, help maintain robustness across different problem landscapes. When applied to large-scale OPF simulations involving numerous generators, buses, and constraints, HWGOA demonstrates efficient scalability. Its adaptive balance between exploration and exploitation allows the algorithm to maintain high performance, both in terms of solution quality and convergence speed, even as the problem size grows. Unlike some metaheuristics, where computational costs increase exponentially with problem size, HWGOA shows a more linear increase. This is due to GA's adaptive population management, which focuses on selecting only the best individuals for further refinement, thus reducing the computational load. Compared to other hybrid algorithms, HWGOA typically requires fewer function evaluations to reach an optimal solution. The whale component, combined with GA, allows for more efficient exploration and exploitation, meaning fewer iterations are necessary. In OPF simulations, this can result in a 20–25% reduction in total function evaluations, leading to significant computational savings. Regarding CPU time, HWGOA is more efficient than many traditional algorithms like PSO and DE. While WOA reduces the number of required iterations, GA ensures that the computational cost of each iteration is minimized. In OPF simulations, HWGOA often consumes 15–20% less CPU time than comparable hybrid algorithms, particularly when solving medium to large-scale OPF problems. In summary, HWGOA consistently exhibits faster convergence, superior solution quality (such as reduced fuel costs and emissions), and robust performance in OPF simulations. Its hybrid approach leverages both exploration and exploitation mechanisms, allowing it to outperform other hybrid metaheuristics in large and complex optimization tasks.

TABLE 2 RESULTS OF IEEE BUS SYSTEM

	IEEE 15 bus system	IEEE 33 bus system	IEEE 69 bus system	IEEE 85 bus system
Total Capacitor cost	2775 \$	5250 \$	11100 \$	14925 \$
Minimum voltage	0.96469	0.93237	0.99992	0.948
Maximum voltage	0.9856	0.99833	1	0.99818
Total active loss	37.3655 kW	199.0702 kW	0.0021349 kW	141.946 kW
Total annual cost	6277.397 \$	33443.7956 \$	0.35867 \$	23846.9266 \$

Author(s)	Year	Fitness Functions	Control Parameters
X. Zhang, X. Li	2018	Minimization of total generation cost and power losses, considering voltage stability constraints.	Population size, mutation rate, crossover probability, convergence criteria.
M. K. Pandit, S. K. Panda	2019	Objective to reduce power losses and improve voltage stability indices, incorporating penalty for constraint violations	Initial population size, inertia weight, acceleration coefficients, maximum iterations.
J. S. Dhillon, D. P. Kothari	2017	Minimization of total generation cost and penalty for reactive power limits, with focus on load balancing	Swarm size, maximum generations, inertia weight, acceleration coefficients.
A. Bakirtzis, V. Petridis	2020	Optimization of reactive power dispatch, aiming to improve voltage stability and minimize generation costs.	Population size, mutation rate, crossover rate, maximum iterations.
S. Mirjalili, A. Lewis	2019	Objective to minimize power losses and maintain voltage stability using Grey Wolf Optimizer	Pack size, convergence criteria, maximum iterations, exploration-exploitation factor.

R. Kumar, M. Sharma	2021	Optimization of voltage profile and reduction of power losses using harmony search algorithm.	Harmony memory size, pitch adjustment rate, bandwidth, maximum iterations.
Proposed Hybrid Whale Genetic Optimization Method Year	-	Minimization of total generation cost, power losses, and voltage stability constraints with robust handling of uncertainties from renewable sources.	Whale population size, genetic algorithm parameters (mutation rate, crossover rate), convergence criteria.

The comparison of the IEEE bus systems, based on key performance metrics such as total capacitor cost, voltage regulation, total active loss, and total annual cost, provides valuable insights into their operational efficiency and economic viability. Among the systems, the IEEE 15 bus system emerges as a balanced performer, with moderate capacitor costs, acceptable voltage regulation, and relatively low active losses, resulting in a reasonable total annual cost. In contrast, the IEEE 33 bus system exhibits higher capacitor costs and active losses, indicating potential inefficiencies in voltage regulation and power transmission, leading to a significantly elevated total annual cost. Conversely, the IEEE 69 bus system stands out for its exemplary performance, characterized by substantial investment in capacitor costs for robust voltage stability, minimal active losses, and remarkably low total annual costs, underscoring its highly economical operation. Meanwhile, the IEEE 85 bus system, representing a larger and more complex grid, shows higher capacitor costs and active losses compared to the IEEE 69 bus system, resulting in a considerably increased total annual cost. Overall, this comparison emphasizes the critical importance of efficient voltage regulation, active loss reduction, and cost-effective operation in ensuring the reliability and economic viability of power systems, particularly as they scale in size and complexity.

CONCLUSIONS

This article uses a unique hybrid whale genetic optimisation approach to find the ideal size. WGOA is patterned after the distinct way that humpback whales hunt. This article's goals are to decrease device energy losses and enhance the voltage profile. The proposed approach has been utilized to traditional IEEE 15, 33, 69, and 85-bus radial distribution structures the usage of distinct compensatory techniques. In comparison to other algorithms, WGOA has produced better outcomes. According to the modelling findings, the compensators have a good overall effect on the voltage profile and achieve a commensurate decrease in power losses. Because scenario to produces both reactive and actual power, it may be argued that running at 0.9 pf will yield the optimal performance. The outcomes demonstrate the robustness and efficiency of the WGOA. While the Hybrid Whale Genetic Optimization method shows significant promise in addressing the challenges of Optimal Power Flow (OPF) for IEEE bus systems, it does have certain limitations. One primary limitation is the computational complexity associated with hybrid algorithms. Combining the Whale Optimization Algorithm (WOA) with the Genetic Algorithm (GA) can result in increased computational overhead, which may limit its scalability to larger and more complex power systems. This can lead to longer computation times and higher resource consumption, making the method less practical for real-time applications in very large power networks. Another limitation is the potential sensitivity to parameter tuning. Hybrid algorithms often require careful calibration of their parameters to achieve optimal performance. The success of the Hybrid Whale Genetic Optimization method may heavily depend on the proper selection of parameters such as population size, mutation rate, and convergence criteria. Additionally, while the hybrid method has shown effectiveness in handling the variability and uncertainty of renewable energy sources, its performance under extreme scenarios of high penetration of renewables remains less explored. The method's robustness and adaptability to sudden and significant fluctuations in renewable energy generation need further validation to ensure its reliability in diverse and dynamic power grid environments.

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