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Enhancing Economic Operation and Planning of Power Systems through Artificial Intelligence: Implementation of Optimal Power Flow in Chennai Utility Bus System

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Abstract: The aim of this paper is to integrate Artificial Intelligence (AI) into Economic Operation and Planning (EOP) methodologies of power systems, specifically by implementing an Optimal Power Flow (OPF) optimization method in the Chennai Utility Bus System. Many traditional approaches to optimize power generation and planning are inherently limited and many of these limitations can be overcome by the use of Artificial Intelligence (AI) techniques. Herein, we have used the AI powered optimization algorithms such as Multi Objective Particle Swarm Optimization (MOPSO) and Multi Objective Genetic Algorithm (MOGA) to increase the efficiency in economical ranking and also grid planning. Implementation of AI techniques in Chennai utility bus system and also evaluating it in real time using Multi Objective Particle Swarm Optimization, Multi Objective Genetic Algorithm, Newton Raphson method and their results are compared. These AI-based methods aim to reduce operation costs, minimize power loss and improve voltage stability as well as minimizing deviation of voltages in order to increase the efficiency. Future work will expand the use of these techniques to more intricate systems, such as the Indian utility 146-bus system to validate their effectiveness, in real world applications.

Keywords: Artificial Intelligence (AI), Economic Operation and Planning (EOP), Multi Objective Particle Swarm Optimization (MOPSO), Multi Objective Genetic Algorithm (MOGA), Chennai utility bus system, Optimal power flow (OPF).

1. Introduction

Economic Operation and Planning (EOP) of the power system is one of the critical components of modern electrical energy and grid management. It offers opportunities for the generation of electrical energy in the most effective manner to meet the demand stably, economically, and reliably. More specifically, EOP is the optimization of the resources of power generation and their allotment to improve generation efficiently, economically and reliably. The purpose of this paper is to explore the potential implementation of the optimal power flow using multi objective particle swarm optimization and multi objective genetic algorithm methodologies in Chennai Utility Bus System, while also addressing the limitations of the traditional method. EOP necessarily incorporates the challenging trade-offs of from minimizing generation cost and environmental impacts while maximizing generation efficiency and stability. Additionally, EOP must consider the growing contribution of non-conventional sources of energy, e.g. solar energy, bio energy, tidal energy, wind energy and hydroelectric energy. Artificial Intelligence application in power systems presents an opportunity to foment developments in grid efficiency and reliability. It is impossible to address today's issues of load forecast, fault diagnosis and real time control of the power system without artificial intelligence integration. Due to their ability in providing quick, precise, and self-adjustable solutions to some of the most challenging problems in power systems, AI solutions outperform conventional methods in many aspects [1]. Researchers have extensively documented and studied the applications of Artificial intelligence in power system operation, control and planning. These have laid a firm basis and presented new methods to solve complex optimization problems [2]. More recent research and technologies have come up more technologies and methods are used in the power sector. The existing research approaches are rapidly becoming irrelevant as a result of their inability to stay up to date on worldwide issues that data scientists and other researchers need to be aware of and to provide any valuable knowledge from the billions of data points scattered across power systems. On the distribution level, AI has been used to optimize distribution power system operation through the implementation of AI techniques. Of note, AI has been found to enhance the grid's resilience and performance [3]. AI has also been utilized in multi-object power flow, where the AI-driven enhanced genetic algorithm has been used to find optimal solutions [4]. Recent development of the PSO and GA algorithms in AI-based optimization have been identified as an effective way to improve the grid's efficiency and stability. They present a new way in optimizing energy flow in the Chennai Utility Bus System, free of traditional method limitations [5, 6]. The study expounds the benefits of using AI for preventive and fault diagnosis and real-time operational management [7]. Using a advanced big data processing, AI can track the real-time activity occurring within today's complex power systems to identify areas that need improvement and possible failures [8]. Moreover, some studies have analysed the possibility of adding energy storage systems to micro grids for power flow management which shows changing AI landscape in terms of current grid challenges [9]. The significance of optimal power flow in controlling the operating conditions of power systems in relation to real-time requirements for demand and supply, thus boosting the system efficiency and reliability [10]. Additionally, the research background has also highlighted the developments in voltage stability constrained OPF modelling and solutions as an indication of what AI techniques can offer to facilitate a smooth transition toward sustainable energy systems [11, 12]. AI's worth in enhancing the credibility of the stability assessment tools that are crucial for the efficient functioning of present day scale power systems [13]. The advantages of using the AI-based method over the traditional methods are the enhanced fault detection accuracy, time reaction, and adaptability to variations in systems characteristics [14]. The multiple objective AI algorithm that weigh for instance cost, reliability, and the impacts on the environment for a better balance for system planning as well as operation [15]. In summary, this paper seeks to contribute to the existing body of knowledge by applying PSO and GA algorithms for OPF in the Chennai Utility Bus System, while critically evaluating the limitations of traditional methods [16]. This study aims to advance the understanding of AI enabled solutions in power system optimization and planning, ultimately enhancing the economic operation and planning of electrical grids [17]. The Table 1 outlines the different facets of power system operation and planning.

India is a Country which holds third position for producing electricity worldwide [18]. According to March 2024, the installed grid capacity of India is 442.0 GW. Chennai, a metropolitan city, hosts several power station including Ennore Thermal Power Station (ETPS), North Chennai Thermal Power Station (NTPS), Madras Atomic Power Station (MAPS), GMR Vasavi Diesel Power Plant, Basin Bridge Gas (BBGAS) Turbine Power Station. In this Paper, Chennai utility bus system is utilized for addressing the Optimal Power Flow (OPF) problem through Artificial Intelligence computational methods. Future work will focus on implementing these methods on the Indian utility 146-bus system to tackle more complex transmission challenges [19].

2. Experimental Methods

2.1 Optimal Power Flow (OPF)

The Optimal Power Flow is the optimization problem aimed at economic operation of power system [20]. In this paper, OPF is selected from various Power system operation areas, for the implementation AI techniques to enhance Power system operation. There are numerous methods available to solve OPF. The traditional methods can compute only one optimized solution in a single execution. So for more optimized solution, the more execution is required. Also, the computational time is time consuming and poor convergence. In AI methods, it can optimize many problems in a single execution and giving good convergence in quick time. The table 2 outlines the various methods used to solve OPF problems [21].

2.1.1 System Description

Chennai, formerly named Madras, serves as the capital city of Tamil Nadu, a state situated in India. Figure 1 illustrates the power transmission across the Tamil Nadu, which is a southern State of India. Figure 2 displays the power map of Chennai, highlighting various power transmission network.

Table 1. Power System Operation and Planning Areas

Operation	Planning
Optimal Power Flow	Generation Scheduling
Unit Commitment	Maintenance Scheduling
Constrained load Flow	Hydro Scheduling
Fault diagnosis	Long term load forecasting
Transient Stability	Power mix planning
Voltage/Var loss reduction	Generation and Distribution
Static and dynamic security assessment	Generation Expansion Planning
Dynamic load modelling	Reactive Power Planning
Market operation	

Table 2. OPF Solution Methods

Traditional Methods	Artificial Intelligence Methods
Linear Programming	Particle Swarm Optimization
Non-Linear Programming	Genetic Algorithm
Quadratic Programming	Bacterial foraging optimization
Newton-Raphson	Fuzzy logic
Interior point	Tabu search
Gradient Method	Greedy randomized adaptive search procedure
	Simulated Annealing
	Ant colony optimization

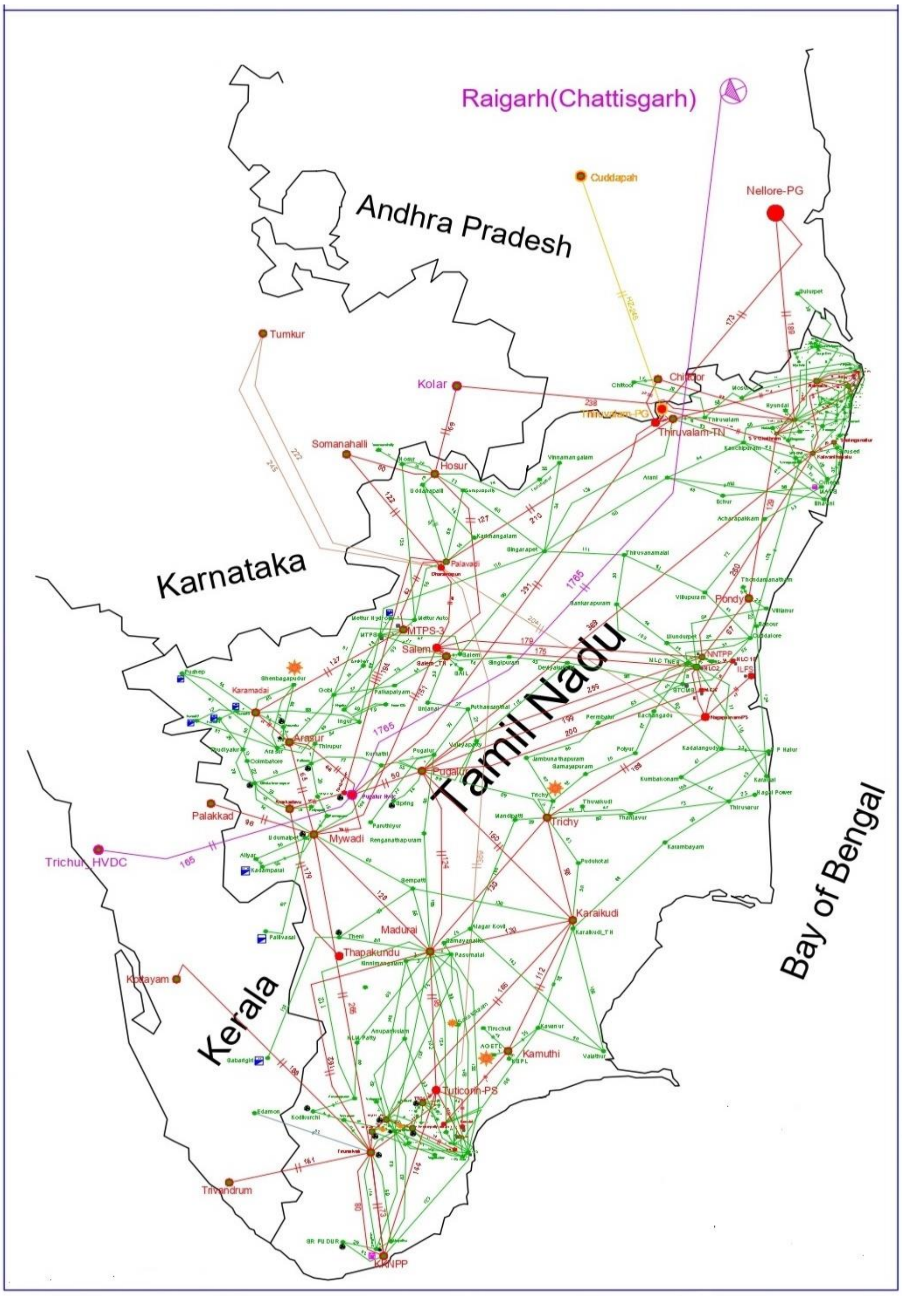

Figure 1. Power Network of Tamil Nadu State

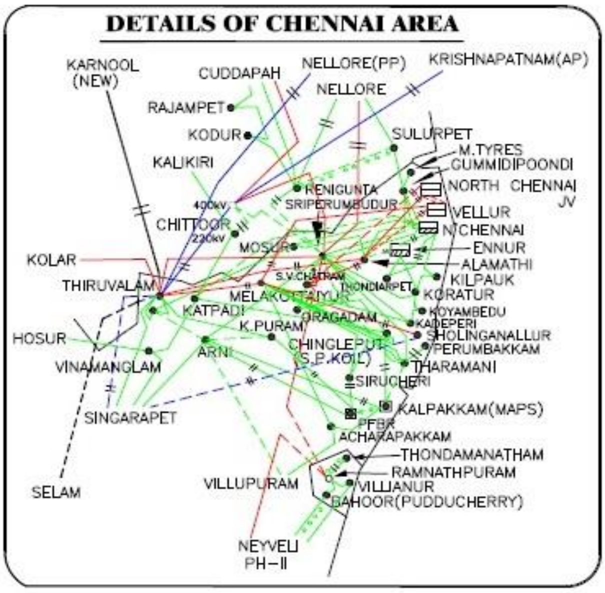

Figure 2. Power Network of Chennai City

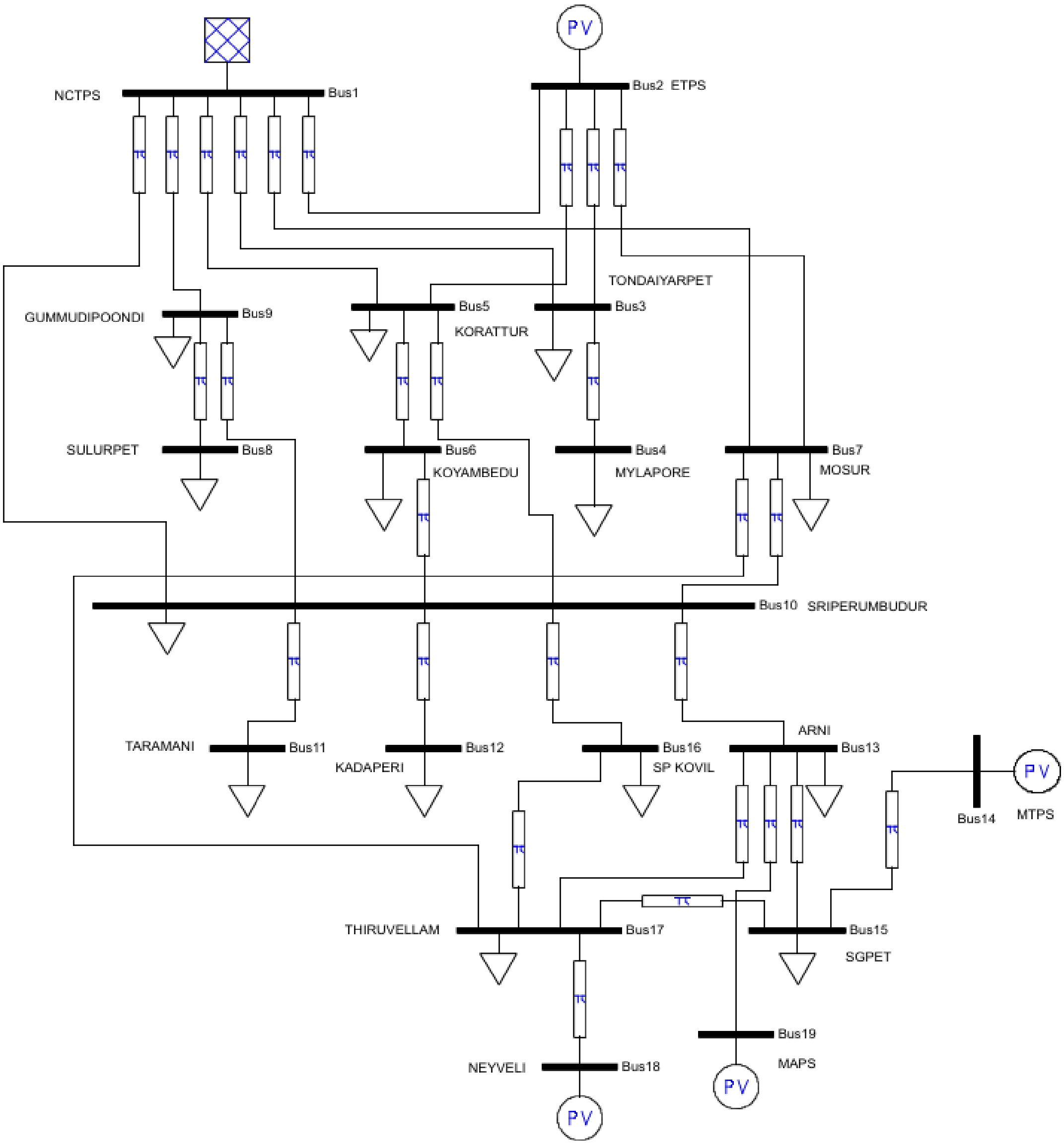

Figure 3. Single line diagram of Chennai utility bus system

Figure 3 presents the single line diagram of Chennai utility power system which includes 29 transmission lines and 19 nodes. In this Paper, Chennai Utility Power System is taken for real time computation of optimal power flow by Artificial Intelligence Techniques.

2.1.2 Problem Formulation

Objective I:

The objective F_1 is to minimize the generation cost.

Objective Function for obtaining optimal generating cost,

$$\text{Min} : F(m,n) \quad (1)$$

with respect toEquality constraint

$$G(m,n) = 0 \quad (2)$$

Inequality constraint

$$H(m,n) \leq 0 \quad (3)$$

Where, m and n are the controllable and dependable variables respectively. The objective function for total system cost minimization is defined as,

$$F = (ai + b_i (PG_i) + c_i (PG_i)^2) \quad (4)$$

Where, PG_i represents the Power generation and a_i, b_i and c_i are the cost coefficients for the generator. To minimize the entire power system's cost, the objective function becomes,

$$Fc = \sum_{i=1}^{N} (ai + bi\,(PGi) + ci(PGi)2) \quad (5)$$

$$F_1 = \min (Fc) \quad (6)$$

where, N is the number of generation.

Objective II:

The objective F_2 is to minimize the total active power losses in the transmission lines of the network.

Objective function for the reduction of power loss:

$$P_{loss,ij} = g_{ij} \left(V_i^2 + V_j^2 - 2 V_i V_j \cos(\theta_i - \theta_j)\right) \quad (7)$$

where,

$P_{loss,ij}$ is the active power dissipation in transmission line between bus i and bus j

g_{ij} represents the conductance of transmission line between bus i and bus j

V_i and V_j indicates the voltage magnitude at bus i and bus j respectively

θ_i and θ_j denotes the voltage angle at bus i and bus j respectively

Total active power loss in the system is calculated as cumulative loss across all transmission lines and it is formulated as,

$$P_{loss} = \sum_{(i,j \in L)} \text{Ploss}_{\,i,j} \quad (8)$$

Where, L represents the collection of all transmission lines within the power systems.

$$F_2 = \min (P_{loss}) \quad (9)$$

Objective III

The objective F_3 is to minimize the voltage deviation for efficient transmission and it is formulated as,

$$V_{dev} = \sum_{i=1}^{Nl} |\, Vnom - Vact \,| \quad (10)$$

Where, Vnom is the nominal voltage

Vact is the voltage at the i^{th} bus

Nl is the number of load buses.

$$F_3 = \min (V_{dev}) \quad (11)$$

Objective IV:

The objective F_4 is to maximize the Voltage Stability Index (VSI), in order to improve the system stability, and system resilience.

It is formulated as,

$$VSI = (|V_m^4| - 4(P_i X_{rij} - Q_t R_{tij})^2 - 4(P_i R_{tij} + Q_t X_{rij}) |V_m|^2) \quad (12)$$

$$F_4 = \max (VSI) \quad (13)$$

Constraints

1. Generator limits

Active Power limits

$$P_{Gi}^{\ min} \leq P_{Gi} \leq P_{Gi}^{max} \quad (14)$$

Reactive Power limits

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{\ max} \quad (15)$$

2. Voltage limits

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

3. The Phase angle of bus voltage limits

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

4. Apparent power flow(MVA) limit should be

$$S_{Aij} \leq S^{max}\, Aij \quad (18)$$

5. Power Balance Constraints:

The difference between the total generated power and total load must equal the total power loss in the system.

$$\sum_{i=g} PGi - \sum_{j=d} PGj = P_{loss} \quad (19)$$

Where, g denotes the collection of all generator buses.

d denoted the collection of of all load buses

PGi is the generated real power at bus i

PGj is the real power demand at bus j

6. Transformer Tap Setting limits

$T_{fi}^{\,min} \leq T_{fi} \leq T_{fi}^{\,max}$ (20)

7. Reactive Power injection limits

8. $Q_{ci}^{\,min} \leq Q_{ci} \leq Q_{ci}^{\,max}$ (21)

9. Transmission line limits

$S_{ij} \leq S_{ij}^{\,max}$ (22)

2.2 Artificial Intelligence Methods Implementation

2.2.1 Multiple Objective Particle Swarm Optimization (MOPSO) method

Multi Objective Particle Swarm Optimization (MOPSO) is an extended version of the Particle Swarm Optimization (PSO) algorithm, designed to address optimization challenges involving multiple conflicting objectives [22]. Unlike the PSO, which focuses on optimizing a single fitness function MOPSO aims to identify a range of optimal solutions that strike a balance among different objectives forming what is known as the Pareto front.

In MOPSO each particle represents a solution within the dimensional search space. These particles navigate the space by adjusting their positions based on their own experiences and those of neighbouring particles. The algorithm maintains a collection of dominated solutions (Pareto front) that evolves as the particles explore the search space [23].

Key aspects of MOPSO encompass,

1. Objective Functions: Multiple functions to be optimized simultaneously.
2. Pareto Dominance: A concept where a solution is deemed superior if it is not worse in any objective and is strictly better in at least one.
3. Pareto Front; A set of non-dominated solutions demonstrating the trade-offs among objectives.
4. Leader Selection; A mechanism for choosing leaders from the Pareto front to steer the particles.
5. Diversity Preservation; Techniques employed to sustain diversity, in solutions preventing convergence and ensuring a distributed Pareto front.

MOPSO Algorithm:

Step1: Initialization

- Define the objective functions:
  1. Minimize Generation Cost
  2. Minimize Power Loss
  3. Minimum Voltage Deviation
  4. Optimize Voltage Stability Index
- Define constraints: Power balance, generator limits, voltage limits, transformer tap setting limits and line flow limits
- Initialize the swarm of particle with random position and velocities within the search space.
- Initialize the number of particles to $N_p = 40$
- Set the maximum number of iterations to $t_{max} = 100$
- Initialize inertia weight u= 0.5, cognitive coefficient b_1= 1.5 and social coefficient $b_2 = 2.0$
- Initialize the repository to store non dominated values.

Step 2: For each particle's new position, calculate the fitness value for all objective functions.

Step 3: Update personal best position P_{best} : For each particle, update the P_{best}, if current fitness value is better than any previous objective values

Step 4: Update global best position g_{best} : using a Crowding distance strategy, select g_{best} from the non-dominated values in the repository.

Step 5: Update velocity

$V_N = (u^*V_{old} + b_1 * r_1 *(P_{best} - x) + b_2 * r_2 *(g_{best} - x))$

Where V_N is the new velocity of the particle

u is the inertia weight

V_{old} is the previous position of the particle

r_1 and r_2 are the random numbers 1 and 0

Step 6: Check all the constraints if its satisfied, otherwise apply repair mechanism.

Step 7: Update Repository: Add Non-dominated values to the repository and maintain its diversity by removing dominated values.

Step 8: Stop if convergence criteria is met and print the Pareto front from the repository, otherwise go to Step 2 and repeat the process.

2.2.2 Multi Objective Genetic Algorithm (MOGA)

Multi Objective Genetic Algorithm (MOGA) is an extended version of Genetic Algorithm (GA) approach that is designed to tackle optimization challenges, with multiple conflicting objectives [24]. While single-objective Genetic Algorithm (GA) are confined to seeking out an ideal solution for only one fitness function, MOGAs focus on generating a complete set of solutions whose convergence corresponds to the Pareto optimal front [25].

Key aspects of MOPSO encompass,

1. Population: Individuals or Chromosomes are the collection of potential solutions to the optimization problem.
2. Objective Functions: Multiple fitness function measures the quality of every solution based on certain factors.
3. Selection: Based on the fitness value, process of choosing a current individual from the existing population.
4. Crossover (Recombination): To explore the new region in the search space, the parts of two parent's solution are combined by genetic operator to produce offspring.
5. Mutation: Introducing changes to each individual solution, diversity is proposed within the population.
6. Pareto Dominance: A solution is considered superior if it is not inferior to another solution in any objective and is strictly better in at least one objective.
7. Pareto Front: A collection of non-dominated solutions which swap among all objections which provides an optimal solution.
8. Fitness Assignment: Approaches to help in arriving at fitness values for the individuals, which is particularly important for selection.
9. Diversity Preservation: Using Tournament technique, maintaining a various set of solution for well distributed parent front and to avoid premature convergence.

MOGA Algorithm

Step 1: Set the objective function for F and read all the active and reactive power data

Step 2: Initialize the parameters:

Population size pop_size = 40

Number of generators N_g = 6

Cross over probability p_c = 0.95

Number of Tap Position N_{tp}= 8

String Length l =155

Elitism Probability e = 0.15

Mutation Probability p_m = 0.001

Step 3: Generate the Chromosome in a random manner

Step 4: Compute the fitness value of all objective functions for each individual chromosome.

Step 5: Based on fitness value, select the individuals using tournament technique.

Step 6: Apply crossover to the selected individuals to create offspring using the crossover probability p_c.

Step 7: Introduce diversity by applying mutation to the offspring using the mutation probability p_m.

Step 8: Ensure offspring satisfies all the constraints, otherwise apply the repair mechanism.

Step 9: Replace the existing population with the new generation.

Step 10: Based on new population, update the collection of non-dominated values.

Step 11: Stop if convergence criteria is met and print the final Pareto front as the collection of optimal solutions, otherwise go to Step 3 and repeat the process.

3. Results and Discussion

The implementation of AI-based optimization techniques such as Multi-Objective Particle Swarm Optimization (MOPSO) and Multi-Objective Genetic Algorithm (MOGA) and traditional technique which is Newton Raphson method have been successfully implemented in the Chennai Utility Bus System. The results of the AI-based techniques show significant enhancement in economic operation and planning of power system. The results of the AI-based techniques were compared with the conventional Newton Raphson technique, demonstrates the superior performance of AI-based techniques in several key aspects such as optimal generating cost, computation time, power loss, voltage deviation, voltage stability index and voltage magnitude.

3.1 Optimal Generating Cost and its Computation Time Results

The Table 3 provides a comparative analysis of results obtained by AI-based techniques with the traditional method. The table list the optimum generating cost and its computation time. The results are computed sequentially and plotted using Python 3.12

3.1.1. Optimum Generating Cost

The Figure 4 illustrates the convergence cost curve obtainted by MOPSO and MOGA techniques and it is evident that the generating cost decreases with respect to each iteration for both MOPSO and MOGA techniques. The optimal generating cost achieved by MOPSO is the lowest which is $7117.032/hr, followed by MOGA of $8046.721/hr and the Newton Raphson method is the highest at $13136.55/hr. The results suggest the potential for reducing costs using MOPSO which are necessary for the cost-effective operation of power systems. The convergence cost curves demonstrates how the generating cost decreases with each iteration for both AI techniques, MOPSO outperformed MOGA in cost-effectiveness. Although, MOPSO was found to have better optimization ability in power systems as was observed in other studies.

This indicates the MOPSO is superior cost-effective in this context. By comparing both MOPSO and MOGA results with the Newton Raphson, there is much difference in optimal generating cost. So it is clearly evident that AI-based techniques how far better than the traditional method.

3.1.2. Computation Time

The Figure 5 demonstrates the Computation time of optimum generating cost obtained by both MOPSO and MOGA techniques. MOPSO took computation time of 6 ms for optimization which is slightly shorter than MOGA of 7 ms and more significantly better than the Newton Raphson method of 40 ms. MOPSO and MOGA consume less computation time indicates they can be real-time implemented on the modern power system for disruption free optimum solution. This confirms previous literature that underscores the importance of fast computation in real-time power system operation.

3.2 Power Loss and Voltage Stabilization Profile Results

The Table 4 provides a comparative analysis of results obtained by AI-based techniques with the traditional method. The table list the power loss, voltage deviation, voltage stability index for both AI based Optimization techniques and Traditional method. The results are computed sequentially and plotted using Python 3.12.

Table 3. Optimum Generating Cost and its Computation Time Results

Optimization Techniques	Optimum Generating Cost ($/hr)	Computation Time (ms)
Newton Raphson Method	13136.55	40
MOPSO	7117.032	6
MOGA	8046.721	7

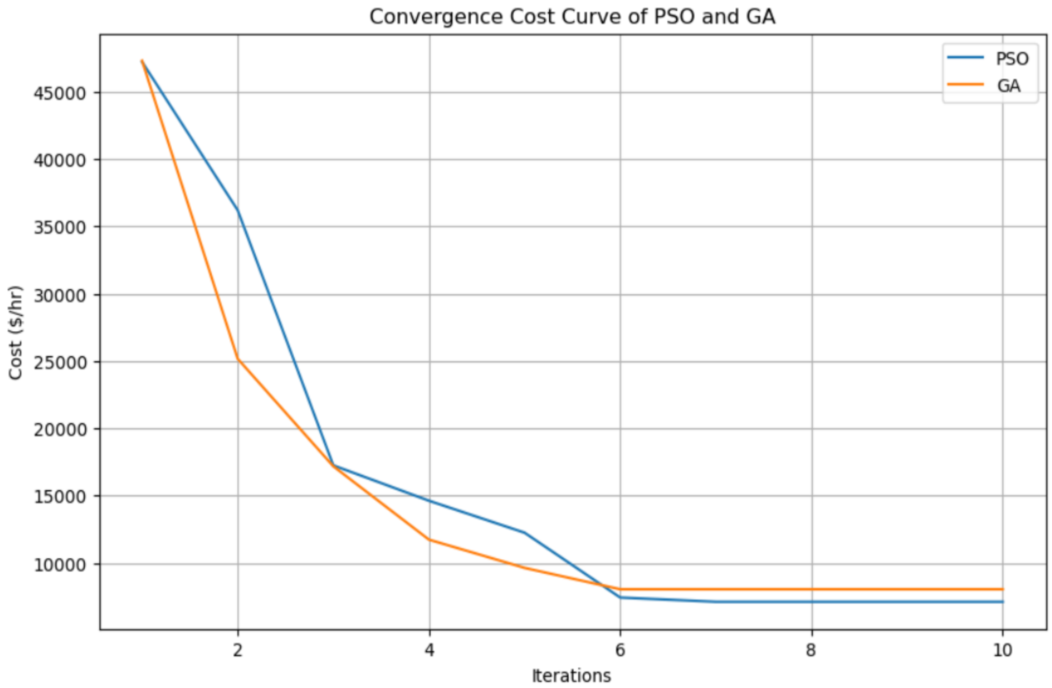

Figure 4. Convergence cost curve of MOPSO and MOGA

3.2.1 Power Loss

The Figure 6 illustrates the optimal power loss achieved by MOPSO and MOGO algorithms. The MOPSO achieves a lower power loss (301.573 MW) compared to MOGA (306.94 MW), which is useful for overall efficiency of the power system. The Power loss obtained by Newton Raphson method is higher than the MOPSA and MOGA.

3.2.2. Voltage Deviation

The Figure 7 shows a voltage deviation curve with respect to iterations obtained by Newton Raphson method. The Figure 8 depicts a voltage deviation convergence curve obtained by the optimization techniques MOPSO and MOGA and it is concluded that, it converged to minimal value which improves the voltage profiles. MOGA obtains a marginally lower voltage deviation (0.0317 p.u) compared to MOPSO (0.0350 p.u), suggesting that MOGA might provide a better voltage regulation. The voltage deviation obtained from Newton Raphson method (1.2586 p. u) is higher than the MOPSO and MOGA.

Figure 9 illustrates the Voltage stability index of Newton Raphson method. Figure 10 depicts a nature of voltage stability index before the optimization techniques. After optimization achieved by MOPSO and MOGA, the voltage stability index converged to stabilized values with respect to the iteration and it can shown from the Figure 11. MOGA optimized a better voltage stability index(0.00010 p.u) than MOPSO (0.00035), so MOPSO can hold a better voltage profile. By comparing voltage stability index of Newton Rapshon with MOPSO and MOGA, it is concluded that voltage profile is much better in AI-based techniques.

3.2.4 Voltage Magnitude

Figure 12. depicts the voltage magnitude with respect to bus number of Newton Raphson method. Figure 13. presents a comparision of voltage magnitudes before and after AI-based techniques optimization. It is evident friom the MOPSO and MOGA optimization results, it converged to a stabilized value indicating enhanced voltage stability. This convergence graph highlights the efficiency of optimization techniques to achieve a stable power system operation. By comparing Figure 12 and 13, it can observed that, AI-based technique effectivess in maintaining a stable voltage profile.

3.2.5 Robustness and Flexibility

AI-based methods like MOPSO and MOGA provides a more robustness and flexibility in dealing with multiple objectives and constraints simultaneously. The consistence with which these techniques can be applied to various power system conditions since they are able to optimize many factors of interest like cost, power loss, voltage stability. This flexibility has well emphasized by other researchers while identifying the role of AI techniques in solving other real optimization challenges in power systems.

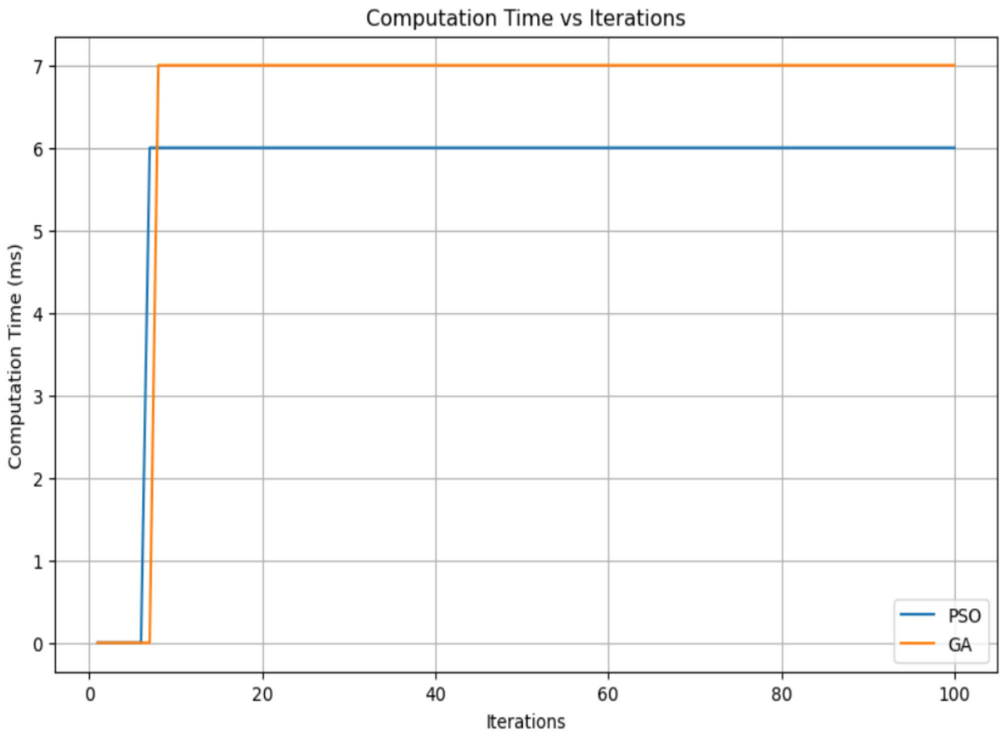

Figure 5. Computation Time of MOPSO and MOGA

Table 4. Optimum Power Loss and Voltage Stabilization Profile Results

Optimization Technique	Optimal Power loss (MW)	Voltage Deviation (p.u)	Voltage Stability Index (p.u)
Newton Raphson	693.632	1.2586	2.50220
MOPSO	301.573	0.0350	0.00035
MOGA	306.949	0.0317	0.00010

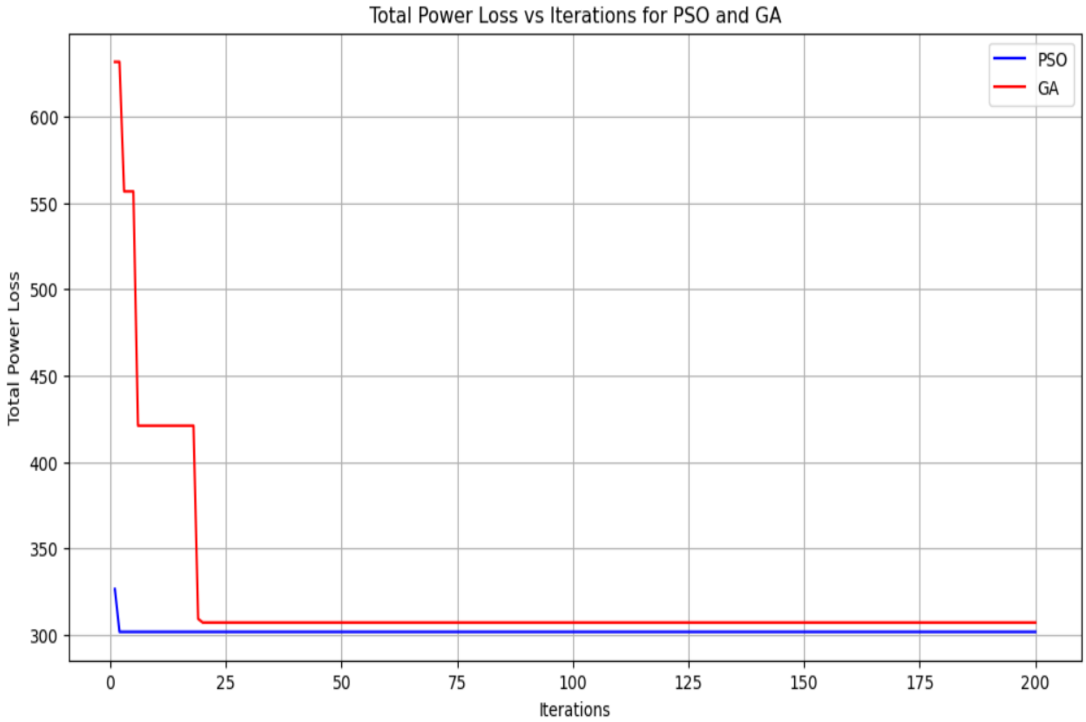

Figure 6. Power Loss Convergence obtained by AI-based Optimization techniques

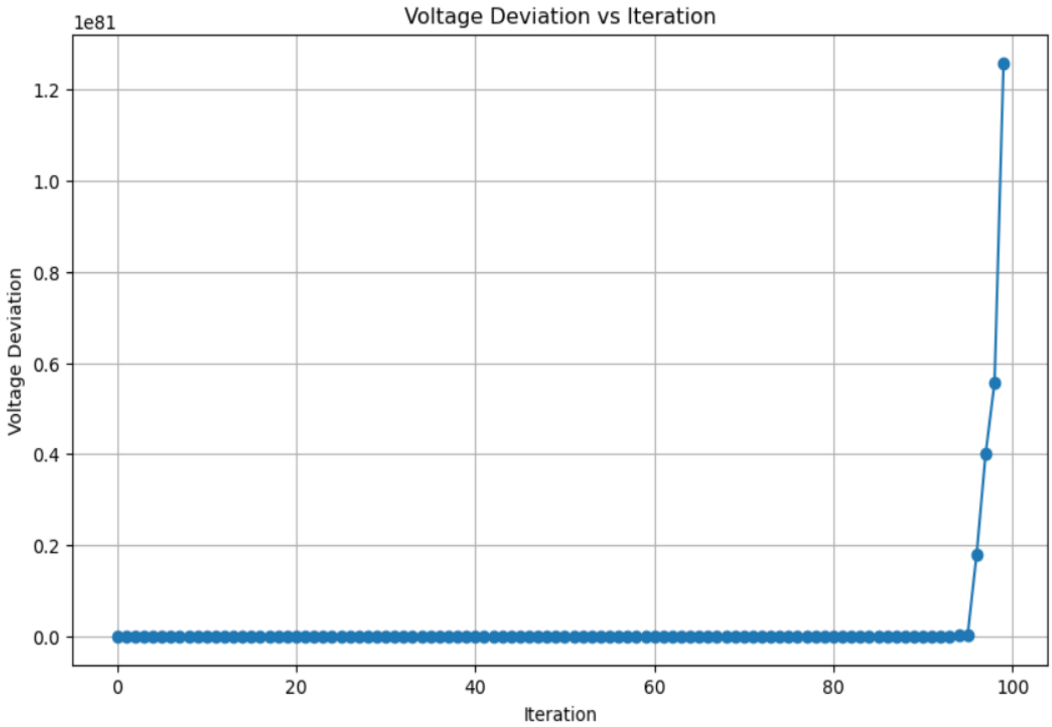

Figure 7. Voltage Deviation for Newton Raphson

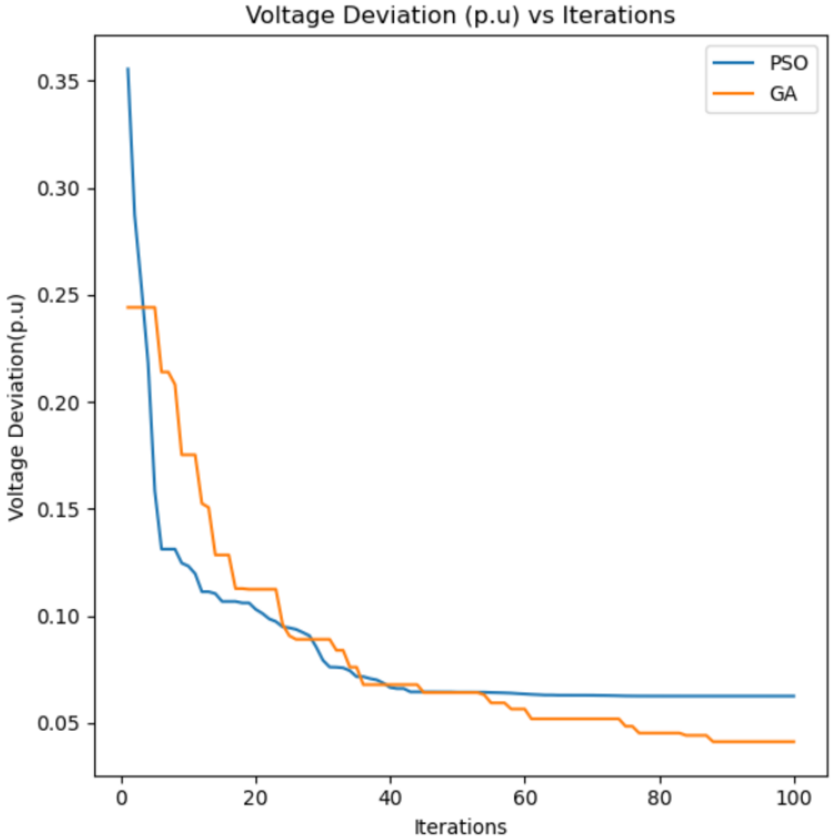

Figure 8. Voltage Deviation convergence curve obtained by AI-based Optimization

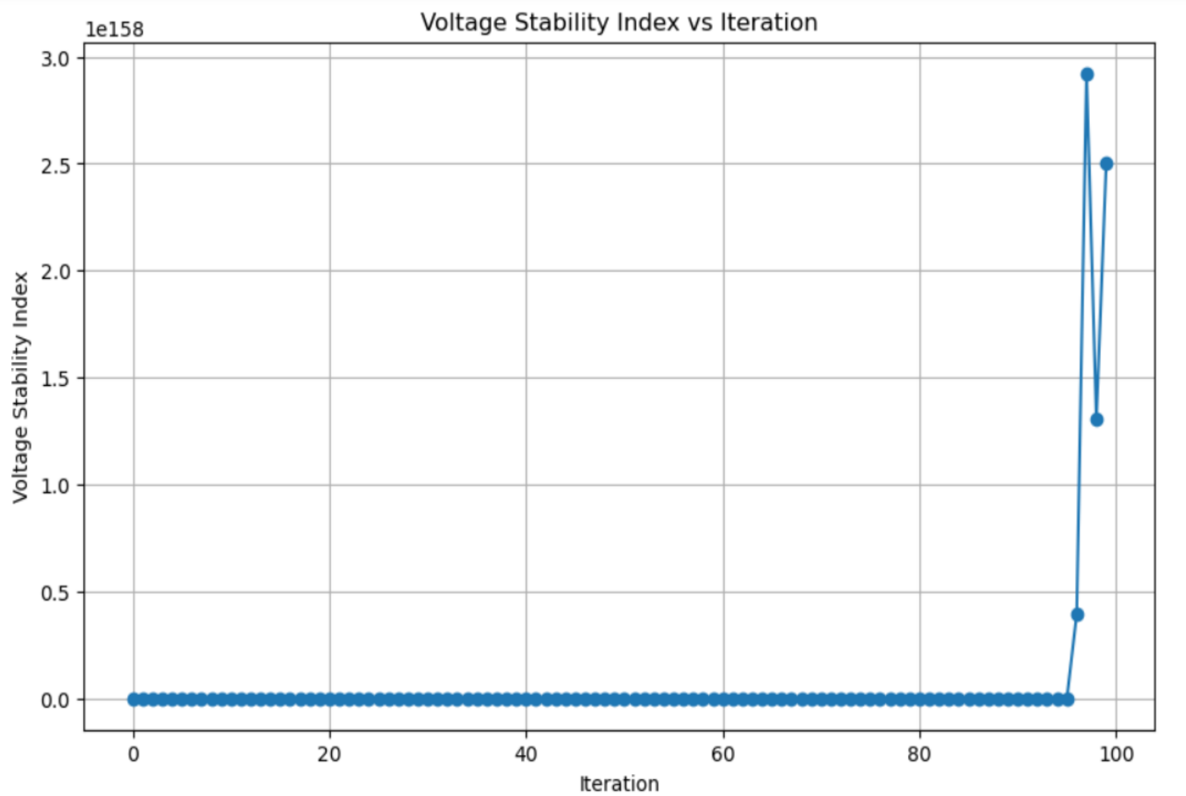

Figure 9. Voltage Stability Index convergence curve obtained by Newton Raphson

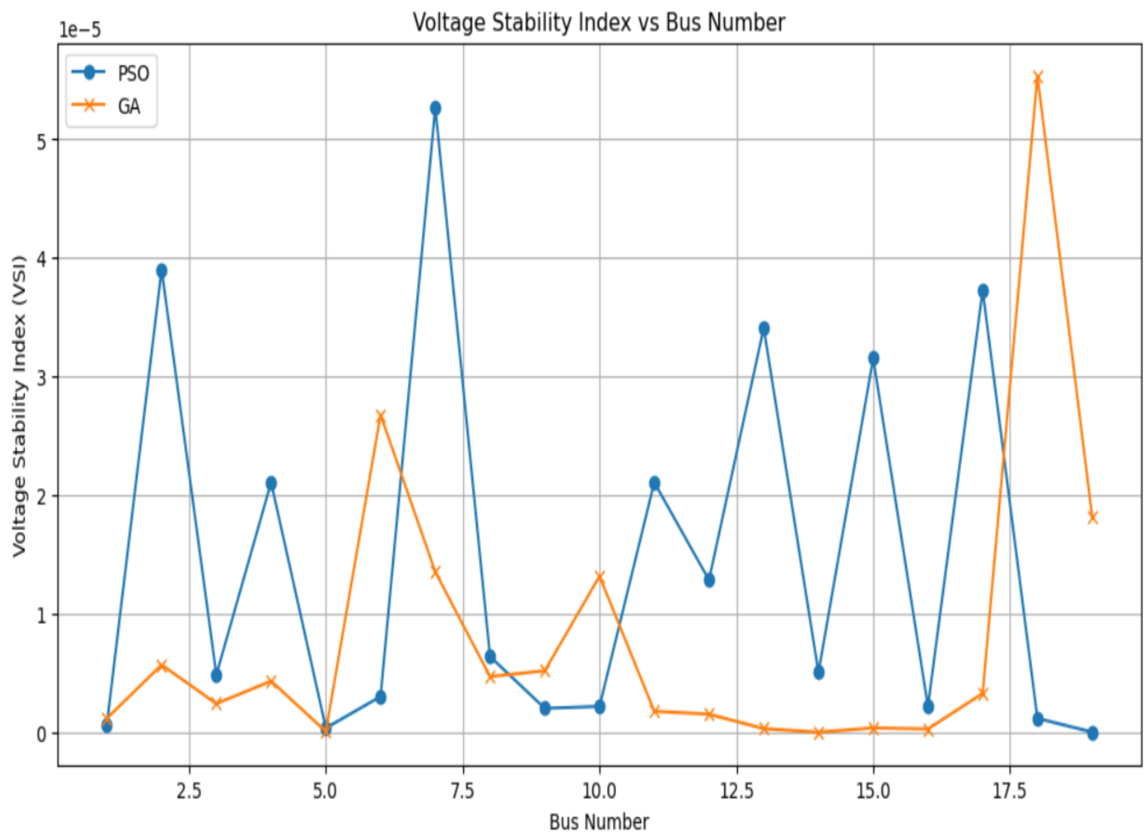

Figure 10. Voltage Stabilty Index (VSI) with respect to the Bus Number obtained by AI-based Optimization techniques Method

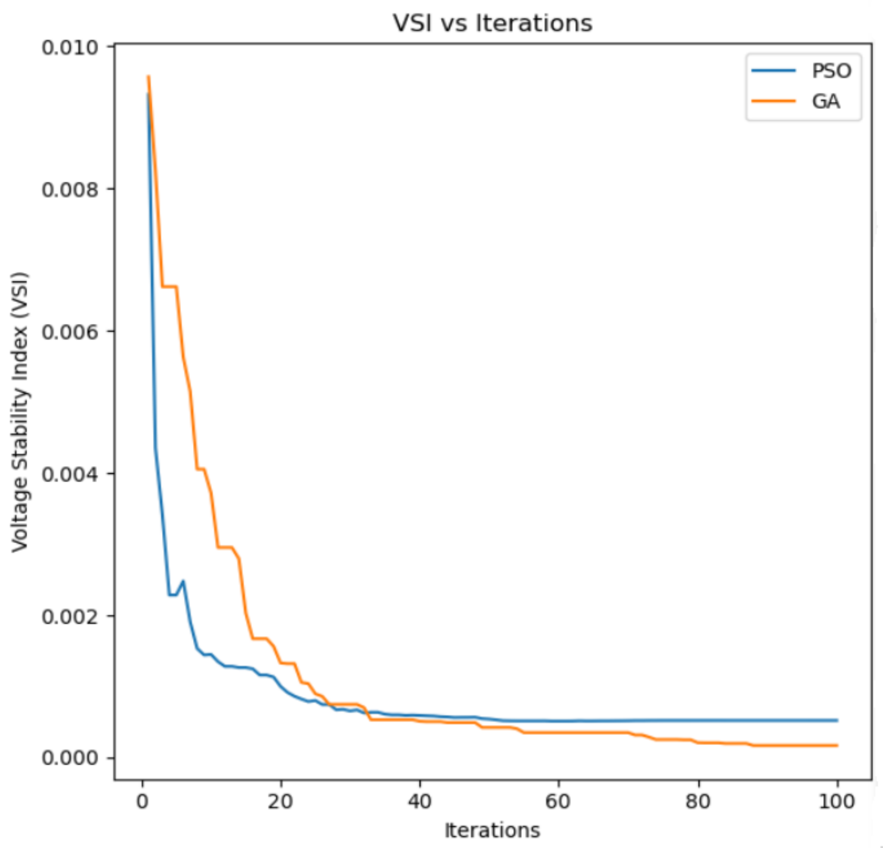

Figure 11. Convergence curve of VSI obtained by AI-based Optimization techniques

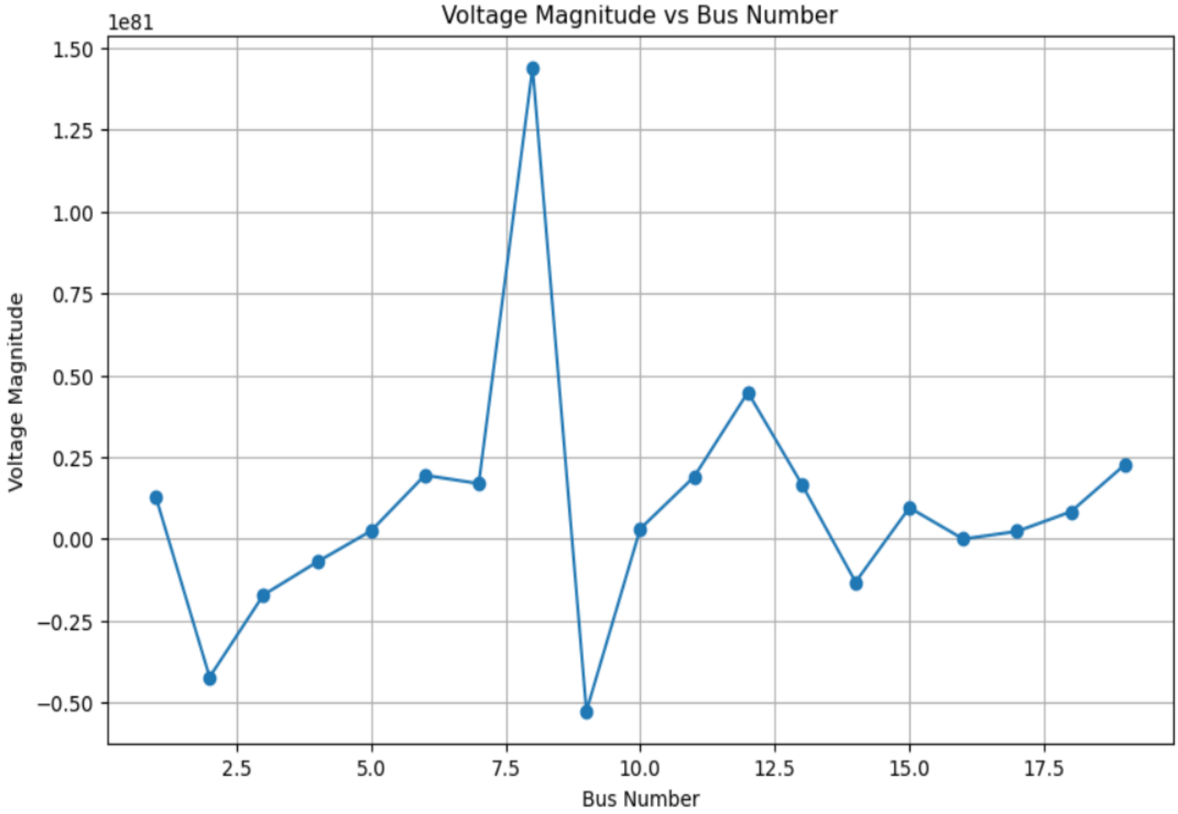

Figure 12. Voltage Magnitude of Newton Raphson Method

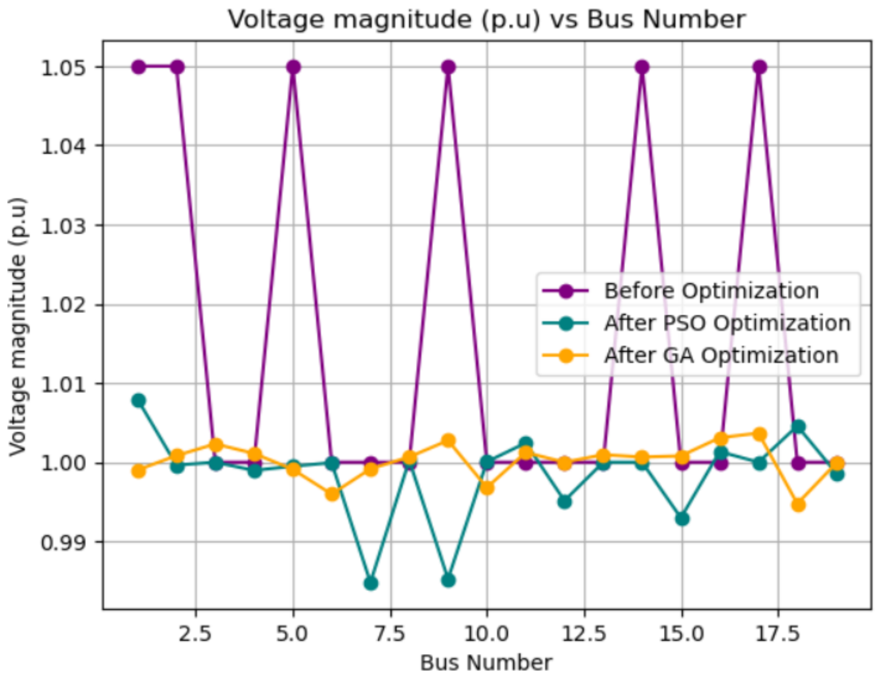

Figure 13. Voltage Magnitude before and after AI-based optimization

4. Conclusion

This paper successfully implements both Artificial Intelligence (AI) method and traditional method such as Multi Objective Particle Swarm Optimization (MOPSO), Multi Objective Genetic Algorithm (MOGA). Newton Raphson Method and have been applied to tackle the Optimal Power Flow (OPF) challenge within the Chennai Utility Bus System. The outcomes demonstrate that AI-driven approaches optimization methods significantly impact generating cost, computation time, power loss, voltage deviation, voltage magnitude and voltage stability index. By comparing with Newton Raphson results, it is truly evident that performance of AI-based techniques is much superior than traditional method and also overcomes the limitations of traditional method. Specifically, MOPSO exhibited the generation cost, quickest convergence time, optimal power loss making it an efficient choice compared to MOGA. Also, MOGA demonstrates a better performance in enhancing a voltage stability. By incorporating these AI strategies there has been a decrease in generating cost, power losses and voltage instabilities while enhancing power system operation. These results demonstrate the potential of AI-based optimization techniques to enhance the Economic Operation and Planning of power systems, providing solutions to the intricate issues present in the modern power grids.

5. Future Scope

On successful implementation of the AI-based OPF methods in the Chennai Utility Bus System, future work will focus on extending these techniques to the overall Indian transmission network, Indian Utility 146-Bus System(IUBS). This larger and more intricate system will serve as a testing platform to further validate the effectiveness of AI optimization methods in real-world scenarios. Additionally, the exploration of other AI optimization techniques beyond MOPSO and MOGA such as Bacterial foraging optimization, Fuzzy logic, Tabu Search, Greedy randomized adaptive search procedure, Simulated annealing etc., will be undertaken to enhance real-time decision-making capabilities and overall system performance. These advancements are targeted at managing the expanding complexity and scale of power systems, ultimately resulting in energy management solutions that are more, efficient, reliable and sustainable.

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S.D. Saranya- Conceptualization, Data Collection, Methodology, Writing- Original draft, Algorithm formulation, Software development- Python Scripts and Visualization. M.Balasingh Moses- Conceptualization, Methodology, Data Analysis, Writing- Review & Editing, Validation and Supervision.

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

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