Enhancing Energy Efficiency in Power Systems: Particle Swarm Optimization for Minimizing Power Losses in the IEEE 14-Bus System

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Abstract – *The Particle Swarm Optimization (PSO) algorithm, renowned for its expeditious attainment of optimal solutions, demonstrates exceptional efficacy when utilized in the context of the IEEE 14-bus system. Importantly, the algorithm's remarkable effectiveness in the reduction of power losses is clearly evidenced by its rapid convergence within a restricted number of iterations. This serves to underscore its capacity to significantly augment energy efficiency within power systems. The findings accentuate PSO's invaluable status as a versatile optimization tool with multifaceted applications, even in the intricate scenarios encountered within power systems. The ability of PSO to adeptly navigate complex problem spaces situates it as a potent instrument for addressing challenges pertaining to energy loss, thereby showcasing its adaptability and usefulness across a diverse range of contexts within the domain of power system optimization. The demonstrated triumph of PSO within the IEEE 14-bus system underscores its importance as a pragmatic and efficient solution for optimizing power system performance and minimizing energy dissipation.*

***Keywords**: energy efficiency, IEEE 14-bus system, particle swarm optimization (PSO)*

Article History
Received 9 November 2024
Received in revised form 6 February 2025
Accepted 12 February 2025

I. Introduction

The notion of the smart grid symbolizes a transformative shift in the traditional electrical grid, as it encompasses a comprehensive and profound metamorphosis. By leveraging state-of-the-art technologies, advanced data analytics, and two-way communication, the smart grid aspires to establish a highly optimized, resilient, and environmentally conscious energy distribution system. This ground-breaking system not only enhances the overall efficiency of energy transmission but also plays a significant role in mitigating the environmental impact. Furthermore, the smart grid serves as a platform for the seamless integration and utilization of renewable energy sources, thereby paving the way for a more sustainable and ecologically friendly energy future [1]. The emergence of the smart grid heralds a new era in the realm of energy management, as it opens a plethora of possibilities for the advancement of both technological and environmental frontiers. It represents a paradigm shift that transcends the conventional boundaries of energy distribution and management, revolutionizing the way we conceptualize and utilize electricity. By embracing cutting-edge technologies and innovative approaches, the smart grid not only optimizes the allocation of energy resources but also fosters a more resilient and reliable electrical infrastructure. It embodies a holistic and transformative vision for the future of energy, encompassing not only efficiency and reliability but also sustainability and environmental stewardship. Through its sophisticated data analytics capabilities, the smart grid empowers energy providers and consumers alike to make informed decisions and optimize their energy usage patterns, leading to substantial cost savings and reduced carbon footprints [2].

The planning and operation of smart grids require the utilization of intricate simulation and modeling techniques, which serve a crucial purpose in the advancement and upkeep of effective and astute power grids. The researchers and grid operators, in their tireless pursuit of enhancing the functionality and resilience of smart grids, rely heavily on the IEEE bus systems as a fundamental framework for simulating and emulating real-world scenarios. By leveraging these meticulously crafted models, they are able to gain valuable insights into the potential issues that may arise in the complex web of interconnected power systems. In addition to that, these simulations empower individuals to refine and perfect the employed control strategies in intelligent networks, guaranteeing the regulation and optimization of electricity flow. As a result, this elevates the general performance and dependability of the grid to unparalleled heights [3]. The process of creating and refining algorithms and control strategies for the smart grid commonly commences by conducting thorough testing and validation procedures, which involve the utilization of IEEE bus systems. By employing these systems, researchers can effectively implement and fine-tune the control algorithms within simplified power systems, thereby providing a preliminary evaluation of their efficacy and reliability before they are eventually applied to real world smart grids. This sequential approach allows for a controlled and methodical progression towards the goal of optimizing the performance and functionality of the smart grid, ensuring its seamless integration and operation within the existing power infrastructure [4].

The IEEE 14-bus system is widely utilized as a benchmark to assess the efficacy of power system optimization techniques, a practice that is commonly employed within the field. Among the various approaches that are utilized for the objective of optimization, particle swarm optimization (PSO) has attracted substantial interest and fascination due to its exceptional capability in conducting a highly effective exploration and its straightforwardness in relation to incorporation and utilization. Numerous studies have shown the efficacy of PSO in addressing diverse optimization problems within the 14-bus system, such as optimal power flow (OPF) [5]-[6]. By minimizing transmission losses while adhering to power balance constraints, PSO can obtain nearly optimal solutions within reasonable computational durations, thus presenting itself as a practical option for real-time power system optimization. Nevertheless, additional investigations are necessary to explore the performance of PSO under different operational scenarios and incorporate advanced techniques to handle intricate constraints and uncertainties.

The fundamental purpose of the paper is to analyze the effectiveness of particle swarm optimization in the context of IEEE 14-bus system. The primary focus is on comparing the performance of PSO with other traditional optimization techniques for OPF, while considering various factors including the solution quality, the rate at which convergence is attained and the computational efficiency. Additionally, the aim is to investigate how well PSO can handle different operating conditions and constraints within the 14-bus systems. The objective is to minimize real power losses within the system while ensuring power balance constraints are met at all buses, thus ensuring the secure operation of the system by respecting transmission line capacity limits. The study also intends to investigate how different PSO parameters affect the speed at which convergence occurs and the quality of the solutions. Ultimately, the objective is to create a reliable and effective PSO algorithm that is specifically tailored for OPF in the IEEE 14-bus system.

II. Literature Review

Optimal solution of IEEE 14-bus system could be based on fundamental of PSO, economic dispatch with line losses minimization, optimal sizing and placement of FACTS devices, multi-objective PSO for line losses minimization and can be explained as below.

Particle Swarm Optimization (PSO) explores the domain of collaborative optimization by simulating the communal foraging conduct exhibited by avian or aquatic organisms, thereby delving into the intricate intricacies of their collective behavior and the fascinating dynamics that unfold within their social structures. In order to comprehend how PSO addresses power system challenges such as minimizing line losses, it is imperative to first grasp its fundamental principles. Each particle can be envisioned as a prospective solution, fluttering through the exploration space, steered by its own velocity and influenced by the knowledge of its fellow swarm members. Their individual best positions and the collective's global optimum serve as guides for their velocity updates, propelling them towards achieving efficient solutions. Fitness functions, serving as objective metrics, assess the performance of each particle within the problem's context, such as the reduction of line losses. By delving further into these mechanisms, as explored in references [7]-[8], we unlock the genuine potential of PSO in optimizing the operation of power systems.

Integrating PSO into economic dispatch (ED) presents a promising pathway for achieving optimal schedules for power generation, all the while endeavoring to minimize line losses. PSO effectively emulates the collective foraging behavior observed in swarms, artfully maneuvering individual particles that represent potential solutions throughout the expansive search space. These particles are skillfully guided by both personal best solutions and the overall optimum of the swarm, propelling them towards cost-effective generation plans that are accompanied by significantly reduced transmission losses. By cleverly integrating line loss penalty terms into the fitness function, PSO can effectively strike a balance between economic goals and grid efficiency, as effectively demonstrated in the work presented by reference [9]. This innovative and integrated approach serves as a constructive and forward-thinking method for facilitating power generation that is both cost conscious and mindful of reducing energy wastage in the realm of transmission.

Particle swarm optimization is mandatory to reduce the line losses, increase the voltage stability and optimize load flow of IEEE 14-bus system and in this way improving the efficiency of power system. By employing PSO, researchers can precisely size and strategically place FACTS devices, thereby paving the way for significant improvements in power system performance [10]. This optimization methodology not only aids in minimizing line losses but also contributes to enhancing system reliability and ensuring efficient energy transmission within the power grid. The utilization of advanced optimization techniques, such as PSO, offers a promising avenue for researchers and industry professionals to explore in their quest for enhanced power system efficiency and reliability through optimal sizing and placement of FACTS devices, due to its ability to optimize their operation and achieve superior system performance and improved energy management [11].

Researchers seek to attain sustainable and efficient operation of the IEEE 14-bus system by employing a multi-objective Particle swarm optimization technique, where a swarm of particles explores the search space to maximize system reliability, stability, and overall performance while considering conflicting objectives, thereby enhancing sustainability. The works conducted in [12], as well as in [13] have dedicated its efforts to investigating the application and efficacy of multi-objective PSO in addressing and resolving the conflicts that arise from competing objectives within the IEEE 14-bus system. These objectives include but are not limited to economic cost, emission reduction, and line loss minimization. Using a multi-objective PSO approach, these investigations strive to optimize and discover the optimal solutions for multiple objectives in power system optimization.

Particle Swarm Optimization (PSO) emulates the collective foraging behavior seen in nature to tackle power system issues like minimizing line losses, where particles act as potential solutions and move through the search space by adjusting their velocity using individual and global information. By integrating PSO into the economic dispatch process, it becomes possible to optimize generation schedules with the aim of minimizing line losses while also considering the balance between economic goals and grid efficiency. PSO plays a crucial role in achieving optimal sizing and placement of FACTS devices, ensuring precise positioning and dimensions that result in reduced line losses and improved system reliability. Moreover, the application of multi-objective PSO allows for the resolution of conflicting objectives in the IEEE 14-bus system, optimizing system reliability, stability, and performance while considering economic cost, emission reduction, and line loss minimization. This foundational work establishes the basis for the forthcoming paper, which will delve into the utilization of PSO for optimizing line losses in the IEEE 14-bus system, thereby contributing to the effectiveness of power system optimization techniques.

A. Motivation

The impetus for undertaking this study stems from the pressing need to address and tackle the formidable and crucial challenges that arise in the functioning and management of power systems, with a specific and distinct emphasis placed on the intricate and well-known IEEE 14-bus system. Issues such as line losses, economic dispatch, optimal sizing of FACTS devices and multi-objective optimization present complex and intricate problems. The innate abilities of Particle Swarm Optimization (PSO) to simulate collective behavior and navigate intricate search spaces serve as a compelling driving force. This paper analyzes the use of PSO for minimizing the line losses of IEEE 14-bus system and making the power system more effective and efficient.

B. Contribution

This paper contributes by delving into the theoretical underpinnings of Particle Swarm Optimization (PSO) and its various applications in optimizing power systems. The focus of this paper is to utilize PSO in minimizing line losses in the IEEE 14-bus system, thereby providing fresh insights into the practical implementation of this optimization technique. Furthermore, this study explores the role of PSO in multi-objective optimization, resulting in a comprehensive understanding of its potential in addressing diverse challenges. This research is important because it adds to our understanding of how to make power systems better by reducing energy loss during transmission and improving overall performance.

III. System Modelling

Particle Swarm Optimization (PSO) is an optimization technique that draws inspiration from the captivating social dynamics of birds and fish. This ingenious algorithm was ingeniously conceived by the brilliant minds of James Kennedy and Russell Eberhart back in the year 1995. PSO, renowned for its potency, is frequently employed in the pursuit of optimal solutions to a wide array of complex optimization problems, particularly those that inhabit multidimensional search spaces. The fundamental principle behind this algorithm lies in its ability to emulate the cohesive social behavior exhibited by a collective of individuals, aptly referred to as particles, as they gracefully traverse the expansive solution space in their relentless quest to unearth the most optimal solution. The working of PSO is based on the following steps.

i. Initialization: it is the first step of PSO. A group of unique entities is haphazardly initiated within the realm of potential solutions. Each entity possesses a distinct location and motion.

ii. Evaluation: It is the second step of PSO, and the efficacy of each entity's placement is appraised by means of the objective function pertaining to the optimization predicament. This function measures the proficiency of a solution.

iii. Updating particle velocity and position: It is the third step of PSO, and the velocity and position of each particle are progressively updated based on its individual best-known position (personal-best) and the best-known position of its neighboring entities (global best).

iv. Reiteration: It is the last step of PSO and in this step, steps 2 and 3 are reiterated for a predetermined number of cycles or until a convergence criterion is fulfilled.

The (PSO) is widely witnessed across diverse domains, encompassing power systems, with the primary objective of refining parameters and configurations to enhance overall functionality. In the realm of the IEEE 14-bus system, PSO can be effectively employed to accomplish a multitude of tasks, including but not limited to optimal power flow, economic dispatch, and voltage control. As IEEE 14-bus system comprised of generator bus, PV bus, PQ bus, Load bus and slack bus. Therefore, it is mandatory to write the mathematical modeling of the aforementioned buses using PSO. The mathematical modeling IEEE 14-bus system can be explained as follows.

Generator Bus of IEEE 14-bus system and PSO: in the context of PSO, generator bus can be divided into particle position, particle velocity and updated position and velocity of generator bus.

Particle position for generator bus: in the context of Particle Swarm Optimization, a particle's three-dimensional coordinates represent an underlying solution to the problem of optimization. Each component within the three-dimensional vector corresponds to a distinct variable within the optimization puzzle. In the case of a generator bus, these variables may entail attributes such as active power, and magnitude of voltage, or any other pertinent factor that shapes the generator's current state.

Mathematically the particle position for generator bus is shown as below:

$$\mathbf{X_{GB}} = [\mathbf{P_{GB}} \quad \mathbf{V_{GB}}] \tag{1}$$

Particle velocity for generator bus: The parameter known as velocity is intricately linked to every particle in the realm of PSO. It serves as the ultimate decision-maker, dictating both the path and motion through which the particle traverses the vast search space. In the realm of a generator bus, the velocity vector serves as the compass that guides the dynamic changes in values for parameters such as power output or voltage, revealing the intensity and direction of their fluctuations.

$$\mathbf{V_{GB}} = [\Delta\mathbf{P_{GB}} \quad \Delta\mathbf{V_{GB}}] \tag{2}$$

The operating efficacy and use of the PSO algorithm are convolutedly secured to the application and assimilation of the mathematical equations denoted as in the following (3) and (4). These equations play a pivotal role in establishing the fundamental structure and functioning framework that underlies the algorithm's operations. Within this algorithm, each generator bus is responsible for adjusting its position and velocity. These adjustments are based on two important factors: the bus' own best-known position (referred to as PGBbest) and the globally best-known position (known as PGBglobal_best). With help of an iterative method, the positions and velocities are constantly refined to find the optimum effective conditions for the generator buses within the power system. To strike a balance between exploration and exploitation during the optimization process, the inertia weight ω and acceleration constants c_1 and c_2 hold utmost significance. These constants play a crucial role in ensuring that the algorithm effectively searches for the most favorable operating conditions.

$$\mathbf{V_{GB}^{(k+1)}} = \boldsymbol{\omega}\mathbf{V_{GB}^{(k)}} + \mathbf{c_1 r_1}\left(\mathbf{P_{GB}^{best}} - \mathbf{P_{GB}^{(k)}}\right) + \mathbf{c_2 r_2}\left(\mathbf{P_{GB}^{global\_best}} - \mathbf{P_{GB}^{(k)}}\right) \tag{3}$$

$$\mathbf{X_{GB}^{(k+1)}} = \mathbf{X_{GB}^{(k)}} + \mathbf{V_{GB}^{(k+1)}} \tag{4}$$

Where $V_{GB}^{(k+1)}$ is the updated velocity of generator bus at k+1 iteration, $X_{GB}^{(k+1)}$ is the updated position of generator bus at k+1 iteration, ω is the inertial weight and it is used to control the impact of previous velocity, c_1 and c_2 are the acceleration coefficients which is used to determine the influence of personal and global best positions of the particle, r_1 and r_2 are the random number between zero and one, P_{GB}^{best} is the personal best position for generator bus and $P_{GB}^{global\_best}$ is global best position of the generator bus.

PQ Bus of IEEE 14-bus system and PSO: in the context of PSO, PQ bus can be divided into particle position, particle velocity and updated position and velocity of IEEE 14-bus system. A particle's three-dimensional coordinates in Particle Swarm Optimization correspond to an underlying solution for optimization, with each component representing a distinct variable within the puzzle, such as active power or reactive power for a PQ bus. Mathematically, the position of PQ bus is given in (5).

$$\mathbf{X_{PQ}} = \left[\mathbf{P_{PQ}} \quad \mathbf{Q_{PQ}}\right] \tag{5}$$

The parameter called velocity is crucially interconnected with each individual particle in the realm of PSO, acting as the determining factor for the trajectory and movement within the extensive search space; similarly, in a PQ bus, the velocity vector functions as a compass, directing the dynamic variations in parameters like real power and quadrature power, thereby indicating the magnitude and direction of their fluctuations. Mathematically, the velocity for PQ bus is given by (6).

$$\mathbf{V_{PQ}} = [\Delta \mathbf{P_{PQ}} \quad \Delta \mathbf{Q_{PQ}}] \tag{6}$$

The operational effectiveness and utilization of the Particle Swarm Optimization (PSO) algorithm are intricately linked to the implementation and integration of mathematical equations in (7) and (8), which form the foundation of the algorithm's operations. Within this algorithm, each PQ bus updates its position and velocity based on its own best-known position (PGBbest) and the globally best-known position (PGBglobal_best), with the aim of finding the optimal operating conditions for the power system. The inertia weight ω and acceleration constants c_1 and c_2 are of utmost importance in balancing exploration and exploitation during the optimization process.

$$\boldsymbol{V_{PQ}^{(k+1)} = \omega V_{PQ}^{(k)} + c_1 r_1 (P_{PQ}^{best} - P_{PQ}^{(k)}) + c_2 r_2 (P_{PQ}^{global\_best} - P_{PQ}^{(k)})} \tag{7}$$

$$\mathbf{X_{PQ}^{(k+1)} = X_{PQ}^{(k)} + V_{PQ}^{(k+1)}} \tag{8}$$

Where, $V_{PQ}^{(k+1)}$ is the updated velocity of generator bus at k+1 iteration, $X_{PQ}^{(k+1)}$ is the updated position of generator bus at k+1 iteration, ω is the inertial weight and it is used to control the impact of previous velocity, c_1 and c_2 are the acceleration coefficients which is used to determine the influence of personal and global best positions of the particle, r_1 and r_2 are the random number between zero and one, P_{PQ}^{best} is the personal best position for generator bus and $P_{PQ}^{global\_best}$ is global best position of the generator bus.

Similar interpretation is also used for PV buses and Slack buses of IEEE 14-bus system. The mathematical equations for PV bus position, velocity and updated position and updated velocity are shown in (9), (10), (11) and (12) respectively. Furthermore, the position, velocity, updated position and updated velocity for slack buses of IEEE 14-bus system are given by (13), (14), (15) and (16) respectively.

$$\boldsymbol{X_{PV} = [P_{PV} \quad V_{PV}]} \tag{9}$$

$$\boldsymbol{V_{PV} = [\Delta P_{PV} \quad \Delta V_{PV}]} \tag{10}$$

$$\boldsymbol{V_{PV}^{(k+1)} = \omega V_{PV}^{(k)} + c_1 r_1 (P_{PV}^{best} - P_{PV}^{(k)}) + c_2 r_2 (P_{PV}^{global\_best} - P_{PV}^{(k)})} \tag{11}$$

$$\boldsymbol{X_{PV}^{(k+1)} = X_{PV}^{(k)} + V_{PV}^{(k+1)}} \tag{12}$$

$$\boldsymbol{X_{PQ} = [V_{slack} \quad Q_{slack}]} \tag{13}$$

$$\boldsymbol{V_{PQ} = [\Delta V_{slack} \quad \Delta Q_{Slack}]} \tag{14}$$

$$\boldsymbol{V_{slack}^{(k+1)} = \omega V_{slack}^{(k)} + c_1 r_1 (P_{slack}^{best} - P_{slack}^{(k)}) + c_2 r_2 (P_{slack}^{global\_best} - P_{slack}^{(k)})} \tag{15}$$

$$\boldsymbol{X_{slack}^{(k+1)} = X_{slack}^{(k)} + V_{slack}^{(k+1)}} \tag{16}$$

The process of mathematically modeling line losses in the IEEE 14-bus system includes creating an objective function that accurately represents power system losses and utilizing Particle Swarm Optimization (PSO) to discover the most optimal solutions. The total line losses in the system, denoted as P_L, can be calculated by adding up the losses in each transmission line. The objective function, which aims to minimize these losses, can be precisely defined as follows.

$$\mathbf{f}(\boldsymbol{X}) = \sum_{i=1}^{20} \boldsymbol{I_i^2 R_i} \tag{17}$$

Where I_i is the current in the i^th^ line of the IEEE 14-bus system and R_i is the resistance of the line of i^{th} line of the power system. In order to express the line current in term of decision variable of particle swarm X, we have to write the current in term of voltage at sending and voltage at receiving end along with reactance of the line of power system. where V_{si} is the sending end voltage of i^{th} bus and V_{ri} is the receiving end voltage of the i^{th} bus of the IEEE 14-bus system and X_{Li} is the reactance of the IEEE 14-bus system. Equation (18) shows the mathematical form of the line current I_i.

$$\boldsymbol{I_i = \frac{V_{si} - V_{ri}}{X_i}} \tag{18}$$

By putting (18) in (17), the final form of objective function of IEEE 14-bus system is given in (19).

$$\boldsymbol{f(X) = \sum_{i=1}^{20} \left(\frac{V_{si} - V_{ri}}{X_i}\right)^2 R_i} \tag{19}$$

Minimizing the deviation in voltage is a widely pursued aim in the realm of power system optimization quandaries. Voltage deviation denotes the disparity that arises between the actual voltage present at a given bus and the voltage value that is deemed desirable for that specific bus. The primary intention is to diminish these deviations across the entirety of the buses that comprise the system.

According to the power balance constraints, it becomes crucial to guarantee that the cumulative amount of active power being infused at every bus station remains equivalent to the cumulative quantity of active power being retrieved, thereby maintaining a harmonious equilibrium between the two opposing actions of power injection and withdrawal. Correspondingly, the aggregate amount of reactive power being injected at every bus must be equivalent to the aggregate amount of reactive power being drawn. Power balance constraints for real and reactive power at each bus "*j*" are given in (20) and (21) respectively.

$$\sum_{k\in N(i)}\left(P_{jk}-P_{kj}\right)+P_{dj}=P_{gj} \tag{20}$$

$$\sum_{k\in N(i)}\left(Q_{jk}-Q_{kj}\right)+Q_{dj}=Q_{gj} \tag{21}$$

Where, P_{jk} and Q_{jk} are the real and reactive power flow from bus j to bus k. Similarly, P_{kj} and Q_{kj} are the real and reactive power flow from bus k to j. P_{dj} and Q_{dj} are the demand power at bus j and P_{gi} and Q_{gi} are the real and reactive power generated at bus j. k ε $N(j)$ is used to represent the neighboring buses of bus j.

Line flow constraints are utilized to impose certain limitations on the active and reactive power flows that occur within each transmission line, thereby effectively averting the possibility of overloading. Mathematically line flow constraints for active and reactive line flow for line "*j*" are shown in (22) and (23) respectively.

$$\left(S_j\right)^2 \leq \left(S_{(max)j}\right)^2 \tag{22}$$

$$\left(Q_j\right)^2 \leq \left(Q_{(max)j}\right)^2 \tag{23}$$

Where, S_j is the complex power flow in line "*j*" and Q_j is the reactive power flow in line "*j*". On the other hand, S_{maxj} is the maximum complex power at line "*j*" and Q_{maxj} is the maximum reactive power flow at line "*j*".

The range of equations, specifically from (1) to (23), effectively illustrate the manner in which the positions and velocities of each bus type are iteratively updated, thereby facilitating the convergence of particles towards optimal solutions for the Optimal Power Flow (OPF) problem in IEEE bus system. For the IEEE 14-bus system, which serves as a benchmark in the realm of power systems research, the utilization of PSO presents a promising avenue for determining the optimal values for generator parameters. These parameters encompass vital aspects such as power output, and their optimal settings can play a pivotal role in the cost minimization or attainment of a desired state within the overall system. In order to effectively capture the essence of the specific optimization problem at hand, the formulation of an objective function is of paramount importance. This objective function essentially acts as a mathematical representation that encapsulates the goals and requirements of the optimization problem, thus enabling the optimization process to be driven towards minimizing power losses, maximizing system reliability, or achieving a harmonious balance between competing objectives.

IV. Methodology

The methodology provides a comprehensive and practical framework for carrying out optimal power flow solution of IEEE 14-bus system using particle swarm optimization to minimize line losses. It is comprised of detail explanation of implementation of particle swarm optimization using MATLAB along with table of algorithm for implementation of PSO.

i. In order to initialize IEEE 14-bus system, MATLAB is selected for software base analysis. Bus data and line data for IEEE 14-bus system has been imported into the MATLAB for software base analysis.

ii. For power flow studies, bus admittance matrix (Y matrix) has been formulated and equation of power flow has been solved in order to achieve bus voltage and angle, active and reactive power for each bus of IEEE 14-bus system.

iii. Implement particle swarm optimization algorithm in order to find optimal solution of IEEE 14-bus system and to minimize the line losses.

iv. Define PSO parameters that are swarm size, inertial weight, and acceleration coefficients.

v. Formulate the objective function for particle swarm optimization algorithm.

vi. Randomly initialize the particle positions and velocities.

vii. Update the particle positions and velocities based on particle swarm optimization.

viii. Evaluate the fitness of particles using objective function.

ix. Repeat the optimization until convergence and best objective function value is not achieved.

The overall methodology of IEEE 14-bus system using particle swarm optimization to reduce the line losses has been shown in Table I.

TABLE I
ALGORITHM FOR OPTIMAL SOLUTION OF IEEE 14-BUS SYSTEM USING PARTICLE SWARM OPTIMIZATION

Summary of the algorithm for optimal solution of IEEE 14-bus system using particle swarm optimization
1. Start
2. Initialization of IEEE 14-bus system:
- Opening MATLAB for software based analysis.
- Import bus data and line data of the IEEE 14-bus system for analyzing particle swarm optimization.
3. Power flow analysis:
3.1. Use the MATLAB code for power flow study:
- Formulate Y-bus matrix.
- Solve power flow equations to obtain bus voltages, angles, and power values.
4. Particle swarm Optimization:
- Implement a PSO algorithm to optimize power system parameters
- Define parameters of PSO (e.g., swarm size, inertial weight, and acceleration coefficients).
- Formulate the objective function based on the IEEE 14-bus system characteristics.
- initialize particle positions and velocities randomly.
- Update the particle position and velocities based on PSO.
- Evaluate the fitness of particles using the objective function.
- Repeat until convergence and best objective function value is not achieved.
5. End

V. Results and Discussions

The result and discussion of the paper has been divided into two subsections, in which one dealing with single line diagram of IEEE 14-bus system and other is dealing with implementation of particle swarm optimization algorithm.

A. Single Line Diagram of IEEE 14-bus System

The single line diagram of IEEE 14-bus system to analyze the line losses is comprised of 14-buses that are connected with each other through 20 transmission lines. The single line diagram consist of one slack bus, four PV buses, four PQ buses, three generator buses and two load buses. Bus 1 is slack bus, bus 3, bus 4, bus 10 and bus 13 are considered to be PV buses, bus 6, bus 7, bus 11 and bus 14 are PQ buses, bus 2, bus 8 and bus 12 are considered to be generator buses and bus 5 and bus 9 are the load buses of IEEE 14-bus system. Bus 1 is connected with bus 2 and bus 5, bus 2 is connected with three buses that are bus 3, bus 4 and bus 5. Bus 3 is connected with bus 4 only. Bus 4 is also connected with three buses that are bus 5, bus 7 and bus 9. Bus 5 is connected with bus 6. Bus 6 is connected with bus 11, bus 12 and bus 13. Bus 7 is connected with bus 8 and bus 9. Bus 9 is connected with bus 10 and bus 14. Bus 10 is only connected with bus 11 and bus 12 is connected with 13 and bus 13 is connected with bus 14. The aforementioned buses are labeled with their name and lines and shown in Fig. 1.

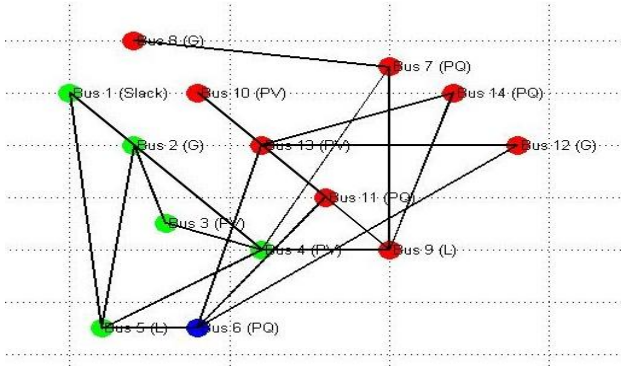

Fig. 1. Single line diagram of IEEE 14-bus System

In Fig. 1, PV represents PV bus, PQ represents PQ bus, G represents generator bus, L represents load bus and slack represents slack bus. The slack bus, which is also referred to as Bus 1, stands out as the solitary bus within the power system that possesses the unique ability to regulate both the voltage and angle. Notably, this distinctive characteristic of the slack bus renders it an indispensable reference point for the entire system, effectively enabling it to serve as a benchmark against which the remaining buses can be measured. Thus, the slack bus plays a pivotal role in maintaining the stability and reliability of the power system, as it ensures that all other buses adhere to a predetermined standard set by its controlled voltage and angle. The PV buses namely bus 3, 4, 10, and 13, have their operations regulated to uphold a predetermined voltage level. The primary function of these PV buses is to offer electrical potential assistance to the remaining components of the system. The generator bus, which includes bus numbers 2, 8, and 12, is skillfully manipulated to generate a predetermined quantity of actual power within the system. It is crucial to note that the generator bus serves as the primary supplier of power within the entire system. The single line diagram exhibits that bus 5 and bus 9 function as load buses, indicating that their voltage is determined by the load of the system and their reactive power consumption is predetermined. It is imperative to closely monitor the system load. When the system experiences a significant load change, it is crucial to thoroughly assess the voltages and power flows to maintain its stability and reliability.

B. Implementation of Particle Swarm Optimization

The initialization of the Particle Swarm Optimization (PSO) algorithm involves the creation of a population consisting of numerous particles; each particle representing a potential solution to the problem at hand is shown in Fig 2.

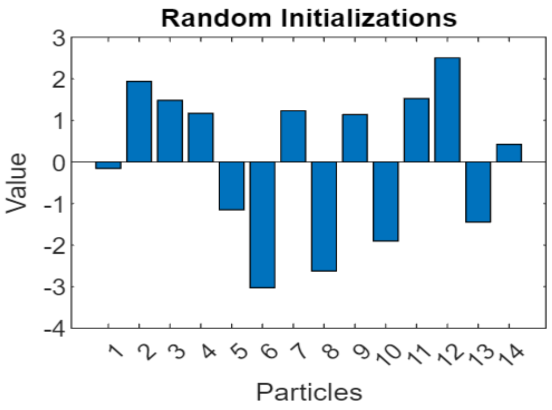

Fig. 2. Random initialization of PSO algorithm

In order to assess the quality of these solutions, the fitness of each particle is evaluated. This evaluation is performed by considering the total power losses occurring within the system, which are determined by utilizing the objective function provided for this purpose. As the algorithm progresses, it continuously updates various important elements. Firstly, it keeps track of the best solution discovered thus far, also known as the optimal solution. Moreover, it modifies the positions and velocities of the particles to explore the search space more effectively. In order to better understand the behavior of the algorithm during its execution, it is often helpful to visualize the convergence pattern. This can be achieved by monitoring the power losses and best objectives as they evolve over the iterations. Finally, once the algorithm has completed its execution, the best solution and optimal solution, along with their respective objective values, can be presented for further analysis and interpretation.

The particle that demonstrates the minimal accumulation of power losses across the duration of the comprehensive optimization procedure is deemed the optimal solution. Consequently, the global optimal total power losses are represented by the optimal objective value. By identifying the particle that exhibits the lowest overall power losses, the optimization process successfully determines the optimal solution and quantifies it in terms of the objective value. Table II shows the optimal solution for IEEE 14-bus system along with optimal solution found at iteration number, and optimal objective value. Bus 13 possesses the most superior solution among all the buses, while bus 7 exhibits the most substandard optimal solution and the minus indicates the power flow out of the bus. Bus 6, 8, 9,10 and 11 have the flow of power into the lines rather than from lines into the buses. The attainment of the optimal solution occurred during the 45th iteration number, with a total of 100 iterations and a particle swarm size of 50. Furthermore, according to Table II, it is evident that the application of genetic algorithm has resulted in optimal objective values reaching 1.7494 MW. Fig. 3 shows the optimal solution of PSO algorithm. The vertical axis represents the power losses in MW whereas horizontal axis represents the bus index.

TABLE II
OPTIMAL SOLUTION OF IEEE 14-BUS SYSTEM USING PSO ALGORITHM

Bus No.	Optimal solution Real power in (MW)
1	1.0793
2	0.5378
3	0.3715
4	1.2408
5	0.8276
6	-1.1423
7	0.0835
8	-1.4737
9	-0.9053
10	-0.3196
11	-1.4414
12	0.3518
13	1.7494
14	0.1380
Generation at which optimal solution found	45
Optimal objective value	1.7494

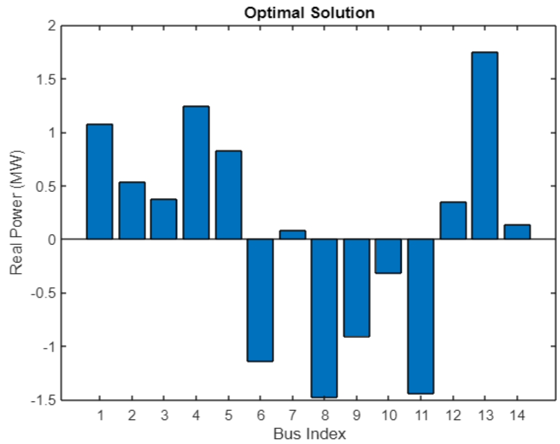

Fig. 3. Optimal solution of IEEE 14-bus system using Particle swarm optimization

Fig. 3 shows a graphical representation of the outcomes derived from a comprehensive investigation into power loss, which was meticulously executed employing a particle swarm optimization (PSO) algorithm. By scrutinizing the graph, one can discern the portrayal of the actual power output of a given system, juxtaposed against the bus index. Based on this visual depiction, it becomes evident that the PSO algorithm has successfully ascertained an optimal solution that effectively minimizes the overall power losses within the system. The findings derived from this meticulous power loss study undeniably highlight the remarkable ability of the PSO algorithm to successfully identify and implement a solution that significantly mitigates the power losses sustained by the system. Consequently, this compelling evidence strongly suggests that PSO serves as a highly efficient and effective tool for the optimization of power systems.

The primary goal of the objective function is to reduce the discrepancy between the designated real power values for every individual bus and the overall real power within the system. In order to ascertain the fitness of each particle, the total power losses are taken into consideration, with the lower values being indicative of superior solutions. By minimizing the difference between the specified real power values and the total real power, the objective function endeavors to optimize the performance of the system and enhance its efficiency. Fitness evaluation based on total power losses serves as a means of assessing the effectiveness of the solutions generated by the objective function, ultimately leading to the identification of the most optimal solution.

The objective function of the particle swarm optimization (PSO) algorithm can be observed on Fig. 4. It is evident that the objective function exhibits a downward trend with an increase in the number of iterations. This trend suggests that the PSO algorithm is making progress towards an optimal solution. Nevertheless, it is worth noting that at 45th iteration, the power losses experienced during the optimization process decreased to a value of 0.8 x 10^5MW. Subsequently, beyond the 45th iteration, the power losses seem to stabilize and remain relatively constant.

The PSO algorithm has seemingly reached a state of convergence on a solution that is considered optimal, a notable achievement that occurred after approximately 45 iterations. This conclusion is supported by the observation that the curve representing the objective function consistently declines and ultimately converges towards a minimum value. Moreover, the final value obtained for the objective function is estimated to be in the vicinity of 0.8 x 10^5, indicating a substantial decrease in power losses when compared to the initial state. This outcome demonstrates a significant improvement in the system's performance as shown in Fig. 5.

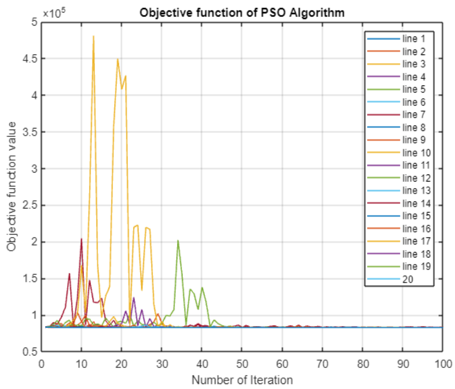

Fig. 4. Objective function value of IEEE 14-bus system using PSO algorithm

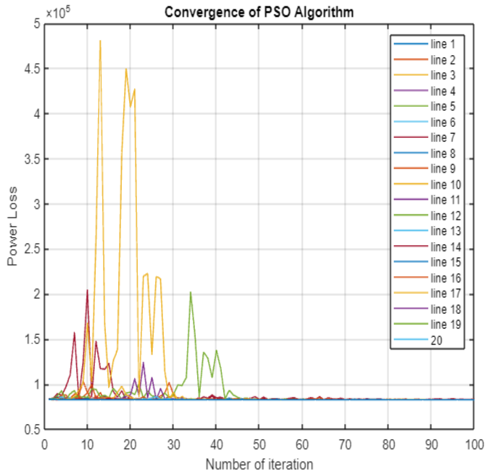

Fig. 5. Convergence of IEEE 14-bus system using PSO algorithm

This implementation of the PSO algorithm appears to be highly efficient in its ability to minimize power losses for the IEEE 14-bus system. The fact that it achieves convergence within a mere 45 iterations is a clear indication of its remarkable efficiency in swiftly locating the optimal solution. The effectiveness of this PSO implementation in reducing power losses for the electrical system is truly noteworthy, as it showcases the algorithm's potential in enhancing overall energy efficiency and thus contributing to the sustainable development of power systems.

VI. Conclusion and Future Works

The Particle Swarm Optimization (PSO) algorithm, renowned for its expeditious identification of optimal solutions, has exhibited immense efficacy when applied to the IEEE 14-bus system. It is worth noting that the algorithm's remarkable capacity to efficiently minimize power losses is exemplified by its convergence within a limited number of iterations, thereby accentuating its potential to significantly augment energy efficiency within power systems. These findings serve to underscore PSO as an invaluable optimization instrument, boasting a vast array of applications that extend even to the most intricate and convoluted scenarios encountered in power systems.

Future work on optimal solutions of the IEEE 14-bus system using particle swarm optimization involves minimization of line losses and thereby enhancing grid efficiency and reliability through various approaches. These approaches include:

i. Dynamic optimization, where algorithms need to adapt to changes in the power system over time by considering time-varying parameters and evolving system conditions.

ii. Distributed optimization techniques, such as decentralized GA and PSO algorithms, can improve scalability and handle large-scale power networks.

iii. Sensitivity analysis is important to identify critical parameters in GA and PSO and optimize them for robustness.

iv. Incorporating models of renewable energy sources and storage systems into the optimization process helps accommodate variability and uncertainty.

v. Implementing parallel processing techniques can accelerate convergence, while real-time monitoring and control systems based on optimized solutions enhance decision-making.

Acknowledgements

The authors greatly acknowledge the support and facilities provided by Southeast University, Nanjing, China, that was necessary to complete this study. We are also grateful to our colleagues for their excellent technical assistance and stimulating discussions. The authors would like to thank anonymous reviewers for valuable comments that improved the quality and readability of this article. Lastly, we would like to thank our family for their constant support and encouragement during the research.

Conflict of Interest

The authors declare no conflict of interest in the publication process of the research article.

Author Contributions

Awais Khan directed the PSO algorithm research design and development. Performed the simulations and created the early draft of the manuscript along with the math modeling.

Muhammad Sajjad supported the analysis of data, support of implementation, and verification of simulation outcomes. Helped in the review of the literature and fine-tuning the discussion.

Yan Wang offered oversight and guidance throughout the project. Contributed to the theoretical framework, reviewed the methodology, and critically revised the manuscript.

Muhammad Ikram provided assistance in setting up the simulation, PSO parameter adjustment, and preparing visual materials such as figures and tables.

Irfan Khan provided technical implementation support in MATLAB, assisted in the collection of the literature, and read the manuscript for technical correctness.

All the authors reviewed, edited, and approved the final manuscript, contributed towards discussions and interpretation of the results.

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