An Approach for Power Flow Analysis Based on Particle Swarm Optimization

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Abstract:- Power flow solution is the ultimate solution for determining the unknown parameters of a power system. The suitable operation of the system depends on knowing the losses in the system, like those of loads and transmission lines, before they are installed. This paper presents a load flow analysis approach that uses particle swarm optimization algorithm. The method introduced helps to find the best solution for improving the bus voltage of the network and minimize corresponding losses. To find the optimal solution to the problem, an IEEE 6 bus is used to present the case.

Keywords:- *Voltage; Global Best; Position Best; Velocity; Fitness Function; Etc.*

I. INTRODUCTION

Load flow is an important tool used by power engineers for planning the best operation of a power system [1]. The power system consists of an electric circuit that includes generators, transmission network, and distribution network, where power flows from the generating station to the load through different branches of the network. Power flow studies provide a systematic mathematical approach to determine various bus voltages, phase angles, active and reactive power flows through different branches, generators, transformers, and loads under steady-state conditions [1]. In the present scenario, load-flow analysis faces several challenges that need to be addressed. Firstly, modern power systems are becoming more complex with the integration of renewable energy sources, distributed generation, and advanced control technologies [2]. This complexity poses challenges in accurately modeling the system components, capturing their dynamic behavior, and ensuring accurate load-flow solutions. Secondly, voltage stability and reactive power management are critical to the operation of power systems. Inadequate reactive power support or voltage control can lead to voltage violations and even voltage collapse. Load-flow analysis needs to consider reactive power sources, such as capacitor banks, voltage regulators, and accurately model their impact on system voltage stability [3]. Thirdly, high penetration of nonlinear loads, such as electronic devices and power electronic converters, is becoming more prevalent in modern bus systems. These loads introduce harmonic distortions, voltage fluctuations, and power factor issues, which can impact load-flow calculations and require specialized modeling techniques.

To solve the challenges mentioned above, computational intelligence methods such as Particle swarm optimization (PSO) can be implemented for the voltage stability assessment to solve the complexity of active and reactive power. This paper analyzes the load flow problem in power system planning studies to stabilize system bus voltage and minimize the corrosponding possible losses.

II. LOAD FLOW ANALYSIS

In a power system, power flows from the generating station to the load through different branches of the network [1]. Power flow analysis is a fundamental technique used in electrical power systems to determine steady-state operating conditions by calculating parameters such as voltages, currents, active power and reactive power. The load flow equations include power balance equations for both active and reactive powers at each bus [5].The load flow problem can be formulated as an optimization problem with the objective to find the voltage magnitudes and angles that minimize the difference between the input and the output power at each bus.

A. Voltage Stabilization

Voltage stabilization refers to minimizing the difference in voltage level from a flat voltage profile in an electrical system. The voltage stability problem refers to the voltage drop that occurs when the power system experiences a heavy load. There are a few tools that can be used to simulate the load flow of the system. In the static voltage stability study, optimization methods are the main analysis techniques, and they are used to find the voltage stability margin or loading margin of the system [4],[5]. This is important for various reasons, including the improvement of the efficiency of the system. By minimizing voltage drop, the voltage level can be maintained closer to the desired value. Therefore, an approach considering an evolutionary computational technique such as PSO may be interesting to analyze.

B. Loss Minimization

In an electrical power system, losses occur due to various factors, such as resistance in conductors, transformer losses, reactive power consumption, system inefficiencies, and losses in transmission and distribution networks [23]. Due to the rapid increase in demand for electricity, environmental constraints, and competitive energy market scenarios, transmission and distribution systems are often operated under heavily loaded conditions. This causes concern about distribution system losses. Traditionally, loss minimization focuses on optimizing network

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configuration or reactive power support through capacitor placement [21]. Possible remedies to reduce these losses include the implementation of reactive power compensation devices such as static capacitors or synchronous condensers that can compensate for reactive power and reduce associatedlosses. Improving the system voltage profile not only reduces reactive power requirements but also demotesassociated losses [24].

C. Optimization

Optimization can be defined as a mechanism through which the maximum or minimum value of a given function can be found. There are numerous optimization techniques available across various domains. Optimization using constraints in terms of reliability is found to be the best option for optimizing structures withdiscrete parameters [9]. Fig.1 shows a few examples of optimization techniques, as described below.

- Particle swarm optimization (PSO): It is a computational algorithm that simulates the social behavior of individuals in a swarm to optimize solutions to various problems.
- Ant Colony Optimization (ACO): The ant colony optimization algorithm (ACO) is an evolutionary meta-heuristic algorithm based on a graph representation that has been applied successfully to solve various hard combinatorial optimization problems. Initially proposed by Marco Dorigo in 1992 [6], the main idea of ACO is to model the problem as the search for a minimum cost path in a graph. Artificial ants walk through this graph, looking for good paths. Each ant has rather simple behavior, so it will typically only find rather poor-quality paths on its own. Better paths are found as the emergent result of the global cooperation among ants in the colony [7],[8].
- Genetic Algorithm (GA): A genetic algorithm (GA) is a search heuristic that mimics the process of natural selection to find optimal solutions to problems. GAs are an example of mathematical technology transfer. By simulating evolution, one can solve optimization problems from a variety of sources. The principle of GAs is to simply imitate genetics and natural selection using a computer program. A genetic algorithm is a problem-solving method that uses genetics as its model of problem solving [9], [10], [11].
- Artificial Bee Colony Optimization (ABCO): Artificial bee colony optimization (ABC) is a swarm intelligence algorithm inspired by the intelligent foraging behavior of honey bees. It is a metaheuristic algorithm, which means that it does not guarantee to find the optimal solution to a problem, but it is often able to find good solutions in a reasonable amount of time. ABC works by maintaining a population of artificial bees, which represent potential solutions to the problem. The bees are divided into three groups: employed bees, onlooker bees, and scout bees [12],[13]. It is efficient to hybridize ABC with other techniques to increase its performance**.**

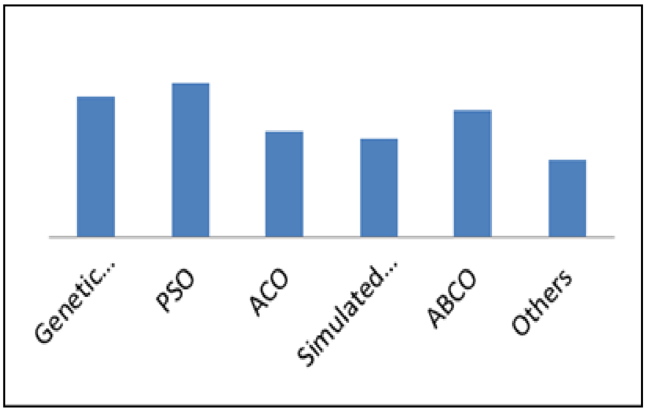

Fig. 1: Optimization Techniques

Studies show that particle swarm optimization is the most commonly used optimization technique.

D. System Design and Analysis

An IEEE 6 bus system is used in this paper to analyze the presented load flow analysis method. A simplified graphical representation of an IEEE 6 bus power system is shown in Fig. 2. The bus data of the IEEE 6 bus system is shown in Table 1 below.

Table 1: Bus Data of the IEEE 6 Bus System

BusNo.	**Bustype**	**Voltage Magnitude(p.u.)**	**VoltageAngle (degrees)**
1	SB	1.05	0
2	PV	1.05	0
3	PV	1.07	0
4	PQ	1	0
5	PQ	1	0
6	PQ	1	0

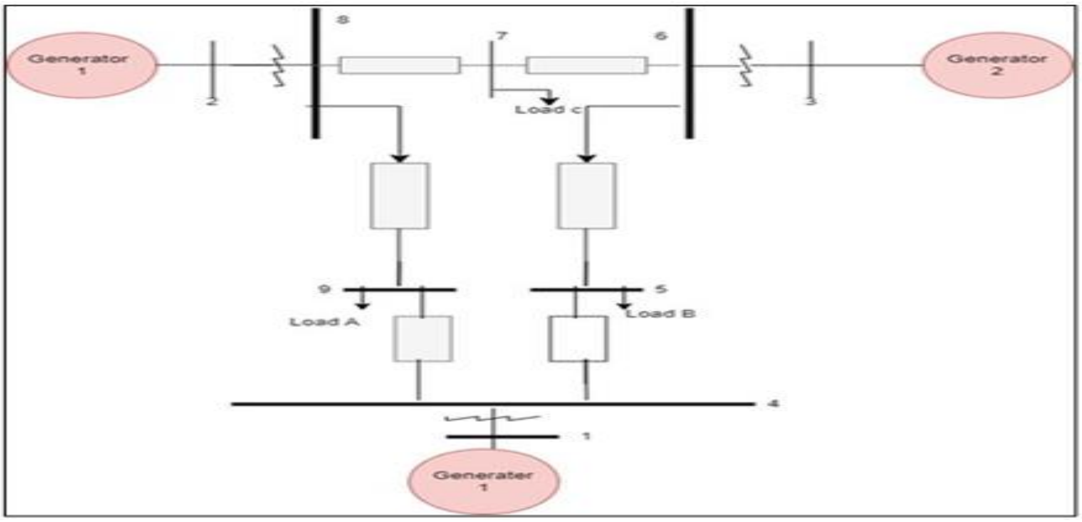

Fig. 2: IEEE 6 Bus System Layout

III. PARTICLE SWARM OPTIMIZATION CONCEPTS AND FORMULATION

Many areas in power systems require solving one or more indirect optimization problems. While systematic methods might suffer from slow convergence and the curse of amplitude, heuristic-based swarm intelligence can be an efficient alternative. Particle swarm optimization (PSO), is known to effectively solve large- scale nonlinear optimization problems. PSO (Particle Swarm Optimization) was first introduced by Eberhart and Kennedy (1995) and used for the optimization of continuous nonlinear functions. This paper presents a detailed overview of the basic concepts of PSO. Also, it provides an inclusive review of the power system applications that have benefited from the powerful nature of PSO as an optimization technique. For each application, technical details that are required for applying PSO, such as its type, particle formulation (solution representation), and the most efficient fitness functions, are also discussed [13]. It is discovered through the simulation of the social behavior of bird blocks. The swarm is composed of some volume-less particles with velocities, each of which represents a feasible solution in the solution space. The algorithm finds the optimal solution by moving the particles in the solution space because of the convenience of realization[14].

The basic elements of the PSO [11] technique are briefly stated and defined as follows:

- Particle: These are the interacting elements for the solutions that are potentially possible in the problem space. These agents (particles) constitute a swarm moving around in the search space looking for the best solution. In standard PSO, each member of the population is called a particle. Each particle contains its position and a velocity [2].
- Swarm: It is apparently not a properly planned and controlled population of moving particles that seems to move in a random direction in the problem space.
- Position: The position of each particle is updated by adding the updated velocity to the current position of the individual in the swarm. The position of the i^{th} individual at $(k + 1)^{th}$ iteration is found in the equation of position.
- Velocity: The velocity is updated by considering the current velocity of the particle, the best fitness function value of that particle, and the best fitness function value among the particles in the swarm. The velocity of each particle is modified in each iteration [4].
- Inertia: It makes the particle move in the same direction and with the same velocity. The greater the inertia of the particle, the more force is required to change its motion.
- Personal Influence: Improves individual particle position by making them return to a position that is better than the current one.
- Social Influence: Makes the particle follow the best-neighbor direction.
- Position best: The best individual position of a particle is defined as position best, which is the best position giving the particle.
- Global best: The best position of all the particles is defined as the global best. The position of the best particle among all the particles in the population is called the global best.
- Applications of PSO: PSO is a method of evolutionary computation that can be realized conveniently [24]. It uses primary math operators and receives good results in static, noisy, and continuously changing environments. All these advantages make PSO applicable to more and more fields. Classification based on diverse categories of PSO applications in selected research studies is shown in Fig. 3.

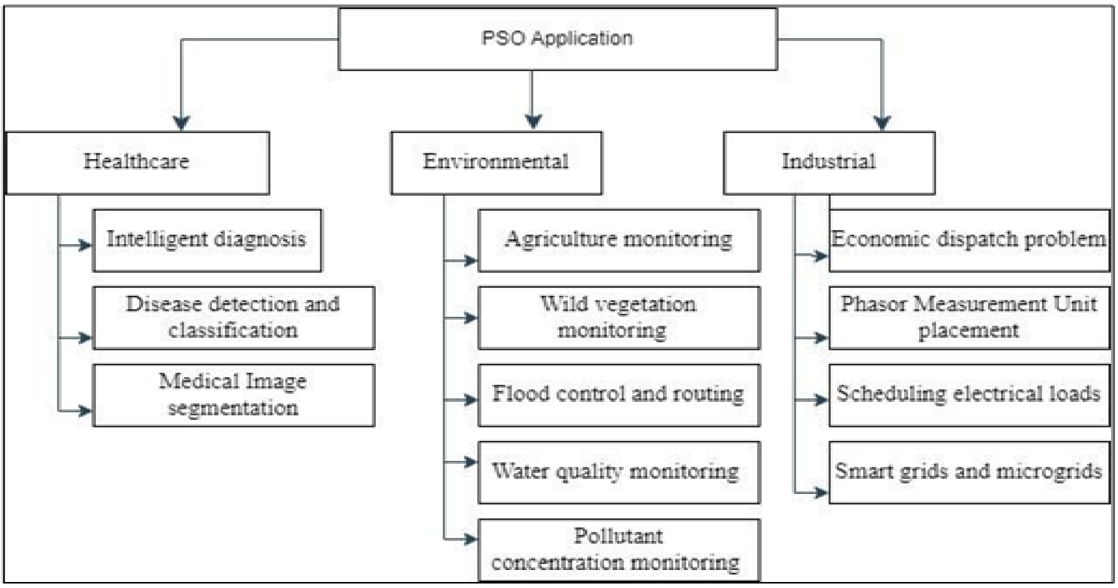

Fig. 3: Application of PSO

IV. OPTIMIZATION ALGORITHM

A. The Methodology of PSO

The PSO technique is a tool that solves optimization problems and is based on the movement of swarms [14], [15]. In general, it is investigated that a group of particles move in a limited, diverse space and in the iterative search for the optimal solution, the position of each of them is a potential solution. In each iteration, new positions are generated for the particles, which are obtained by means of a speed calculated according to the best current position of each particle and the best global position of the swarm. The quality of the position of each particle is obtained by evaluating the objective function each time it takes a new position. This process is repetitive and ultimately leads to an optimal solution where all the particles converge [16]. The terminology used are the following:

x_i = [xi1,xi2,........x in represents the position of the I th particle, which has m components or coordinates.

The best previous position of the ith particle is:

pbestt = pbestt1,pbestt2, ... , pbesttn the best global position of the swarm (gbest) corresponds to the swarm particle with the best search behavior.

Vi = Vi1, Vi2, ... Vin is the velocity of the ith particle.

The swarm of particles evolves in the search space by modifying their velocites and position of each particle in the next iteration are calculated by the expressions in eq 1:

$$vik+1 = wVik + C1rand \times (pbestt - xtk) + C2rand \times (gbestt - xtk) \quad (1)$$

Where

Vik - Current velocity of particle i at iteration k

w- Inertia weight

r and - Random number in the range [0, 1]

C1 and C2 - Acceleration coefficients

xtk- Current position of particle i at iteration k

pbestt is the best position of the current particle achieved so far, while it gbestt is the global best position achieved by all informants. The new position of each particle is given by Eq. 2.

$$xtk+1 = xt + vtk+1 \quad (2)$$

B. Algorithm and Mathematical Model

In this paper, the particles that constitute the swarm are defined by the voltage magnitude of the buses [14]. As the IEEE 6 bus system is used to present the case, the population consists of a total of 6 particles that are moving at their own velocities in the search space. The particle position is defined by the voltage, magnitide, and phase angle of the bus. A swarm of particles updates their relative positions from one iteration to another. To get the optimum solution, each particle moves towards its prior personal best position (Pbest) and the global best position (Gbest) in the swarm [18], [19]. The personal best position of the particle *'i'* is the best possible value of the particle among all the values of its position in different iterations. When the voltage of a particle*'i'*approaches near unity, the particle whose value is closest to unity isconsidered Pbest. The global best is the position that is considered the best among all the particles in the search space. The voltage that is closest to unity among all theparticles is considered Gbest, as defined by Eq. 2 [11]. The flowchart of PSO shown in fig.4.

The inertia weighting factor for the velocity of particle'i' is defined by the inertial weight approach as in

Eq 3. wt = wmax − wmax− wminitermax × iter (3)

Where w max and w min are the upper and lower limits of the inertia weighting factor, respectively. w is the inertia weight, a parameter that controls the impact of the particle's current velocity on its future velocity.

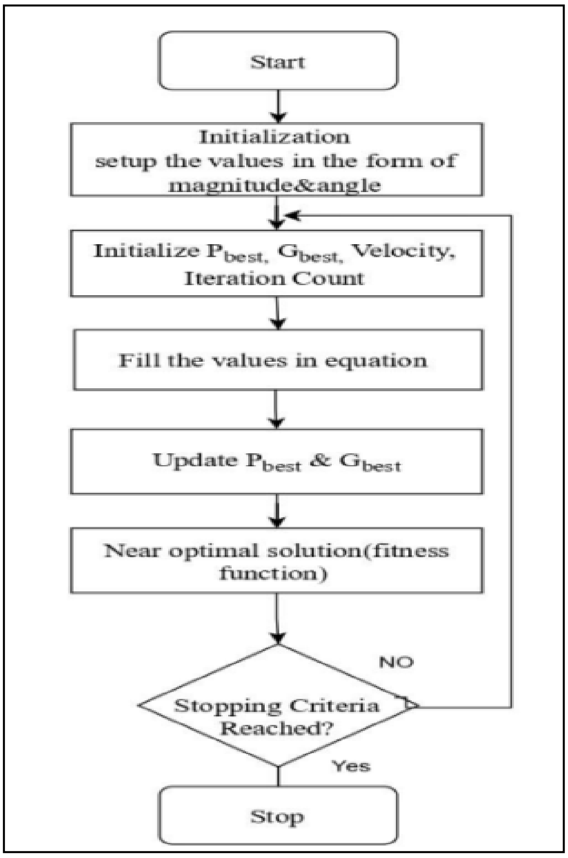

Fig. 4: Flowchart of PSO

The particle swarm optimization algorithm uses a fitness function (x) to evaluate the quality or fitness of a potential solution. It takes the solution parameters (x) as input and returns a single scalar value representing the fitness of the solution.

$$Fitnessfunction = f(x) \quad (4)$$

One of the commonly used equations for power loss optimization is the power loss equation for a component, as in Eq. 5 [22].

$$F_1 = P_{Loss} = \sum_{K=1}^{N_L} g_k(V_t^2 + V_j^2 - 2V_tV_j cos\emptyset_{ij} \quad (5)$$

Where NL is the number of transmission lines, gk is the conductance of branch k between buses i and j, Vi tis voltage magnitude at i bus, Øij is the voltage angle difference between bus i and j. It is observed that the losses in the system have changed from 3.984 p.u. to 0.1670 p.u. by using the above equation. The optimization of voltage involves minimizing the load bus voltage difference and, hence, improving the voltage profile of the system.

$$F_2 = w\sum_{i=1}^{6} |v_i - 1| \quad (6)$$

Where *w* is the weighting factor, with the help of this equation, we can reduce the voltage deviation. It is observed that the voltage deviation is reduced from 0.173 p.u. to 0.1095 p.u. as given in Table 3. The objective function is proposed in order to minimize losses and improve the voltage profile. The objective function can be expressed in the below Eq. 7.

$$F = F_1 + F_2 \quad (7)$$

F represents the fitness function, which evaluates the quality or fitness of a particle's position in the search space. The goal of PSO is to find the optimal solution by maximizing or minimizing this fitness function, depending on the problem. The fitness function F has successfully decreased from 4.157 to 0.2765.

Each particle in the swarm represents the voltage magnitude of the IEEE 6 bus system. The particles undergo a change in velocity as per Eq. 1, and their position changes as per Eq. 2 for each iteration. The voltage of each bus is therefore updated after each iteration. The graphical representation of the bus voltages is shown from Fig. 5 to Fig. 10. The optimization of power loss in a system typically involves minimizing various sources of dissipation, such as resistive losses, switching losses, and other losses associated with components and the operation of the system.

Table 2: Parameters of PSO

Parameters	Values
Population size	06
C1 and C2	0.3
Inertia weight	00.3
Iteration	15

Table 3: Summary of calculation results by the proposed method

	IEEE busdata	Particle Swarm Optimization	
F1 (losses in p.u.)		**1st iterations**	**15th iterations**
F2 (Voltage Deviation in p.u.)	3.984	0.041	0.1670
Total F	0.173	0.15	0.1095
	4.157	0.191	0.2765

V. SIMULATION AND RESULTS

In the PSO simulation, the optimization problem is formulated as finding the best solution in a multi-dimensional search space. The solution is represented as a particle, and a population of particles (referred to as a swarm) is created to explore the search space. Each particle has a position and a velocity, which are updated iteratively based on its own experience and the collective knowledge of the swarm. This paper proposes load flow analysis using the PSO algorithm. The voltage and loss optimization approach was applied to an IEEE 6 bus power system. The parameters used are as given in Table 2. The results obtained from PSO depend on various parameters, such as the specific problem being solved, the parameter setting of the algorithm (e.g., number of particles, maximum iterations, inertia weight, acceleration coefficients), and the characteristics of the search space. All these parameters are used in this paper to reduce losses as well as optimize the voltage profile of the system.

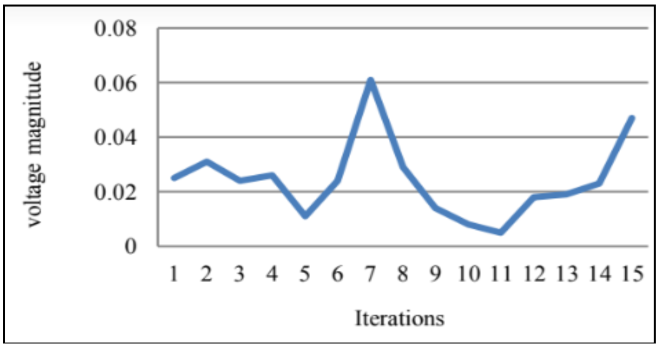

Fig. 5: Voltage magnitudes for the 1st bus

The basic configuration of the IEEE 6 bus system is shown in Figure 2, and according to the parameter sensitivity analysis for the IEEE 6 bus system (15 trials), based on the trials in Fig. 4, in horizontal direction shows voltage magnitude and the vertical direction shows iterations. On 11th iteration, the value decreased.

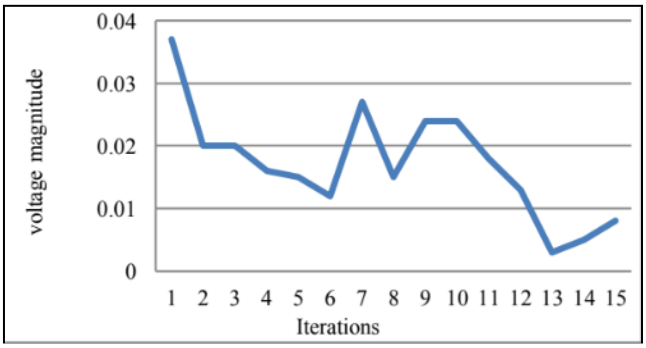

Fig. 6: Voltage magnitudes for the 2nd bus

The basic configuration of the IEEE 6 bus system is shown in Figure 2, and according to the parameter sensitivity analysis for the IEEE 6 bus system (15 trials), based on the trials in Fig. 6, in horizontal direction shows voltage magnitude and the vertical direction shows iterations. On 13th iteration, the value decreased.

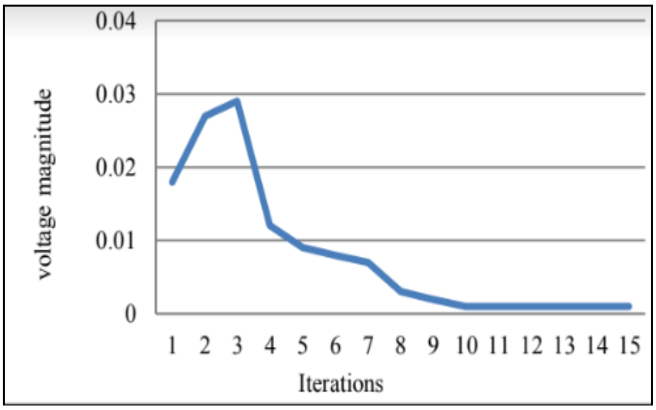

Fig. 7: Voltage magnitudes for the 3rd bus

The basic configuration of the IEEE 6 bus system is shown in Figure 2, and according to the parameter sensitivity analysis for the IEEE 6 bus system (15 trials), based on the trials in Figure 7, in horizontal direction shows voltage magnitude and the vertical direction shows iterations. On 10th iteration, the value decreased.

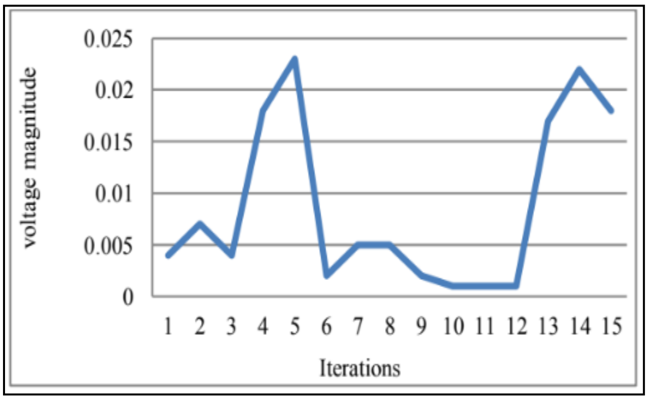

Fig. 8: Voltage magnitudes for the 4th bus

The basic configuration of the IEEE 6 bus system is shown in Figure 2, and according to the parameter sensitivity analysis for the IEEE 6 bus system (15 trials), based on the trials in Fig. 8, in horizontal direction shows voltage magnitude and the vertical direction shows iterations. On 12th iteration, the value decreased.

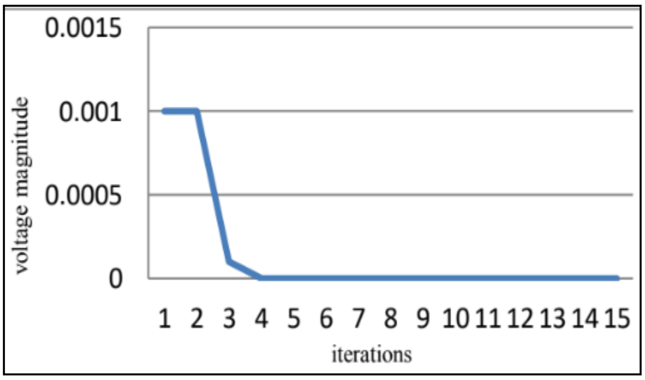

Fig. 9: Voltage Magnitudes for the 5th Bus

The basic configuration of the IEEE 6 bus system is shown in Figure 2, and according to the parameter sensitivity analysis for the IEEE 6 bus system (15 trials), based on the trials in Fig. 9, in horizontal direction shows voltage magnitude and the vertical direction shows iterations. On 4th iteration, the value decreased.

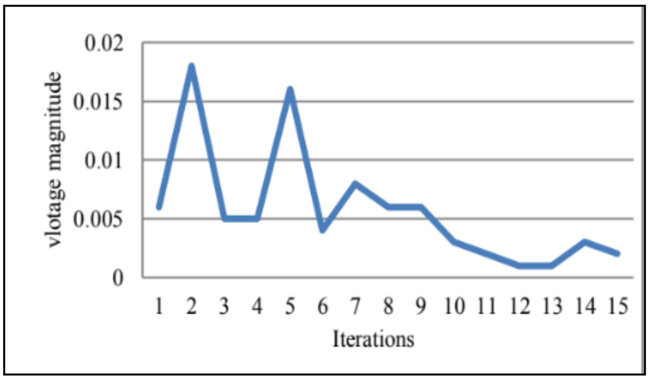

Fig. 10: Voltage Magnitudes for the 6th Bus

The basic configuration of the IEEE 6 bus system is shown in Figure 2, and according to the parameter sensitivity analysis for the IEEE 6 bus system (15 trials), based on the trials in Fig. 10, in horizontal direction shows voltage magnitude and the vertical direction shows iterations. On 13th iteration, the value decreased.

Table 4: Parameter Sensitivity Analysis for the IEEE 6 Bus System (15 Trials)

S.N	Iteration No	Bus No	Velocity	Position	S.N	IterationNo	Bus No	Velocity	Position
1	1	1	0.025∠-136.7	0.981∠-1.037	46	8	4	0.005∠88.36	0.910∠6.891
2	1	2	0.037∠119.4	0.979∠-2.387	47	8	5	0.∠0	0.91∠-5.60
3	1	3	0.018∠-174.1	0.982∠-4.753	48	8	6	0.006∠89.72	0.911∠-7.212
4	1	4	0.004∠-148.9	0.926∠-4.867	49	9	1	0.014∠-45.46	0.886∠6.234
5	1	5	0.∠0	0.91∠-5.60	50	9	2	0.024∠-94.22	0.909∠-0.752
6	1	6	0.006∠144.8	0.934∠-6.431	51	9	3	0.002∠122.8	0.913∠-6.460
7	2	1	0.031∠-131.9	0.961∠-2.434	52	9	4	0.002∠84.63	0.909∠-6.702
8	2	2	0.020∠-176.5	0.959∠-2.509	53	9	5	0.∠0	0.91∠-5.60
9	2	3	0.027∠-138.5	0.963∠-5.939	54	9	6	0.006∠87.26	0.910∠-6.642
10	2	4	0.007∠-130.3	0.920∠-5.22	55	10	1	0.008∠-15.8	0.893∠-63.20
11	2	5	0∠0	0.91∠-5.60	56	10	2	0.024∠-92.75	0.908∠-2.264
12	2	6	0.018∠-113.8	0.928∠-7.496	57	10	3	0.001∠11.34	0.912∠-63.56
13	3	1	0.024∠-133.6	0.944∠-3.566	58	10	4	0.001∠78.23	0.909∠-67.02
14	3	2	0.020∠145.5	0.924∠-1.861	59	10	5	0.0∠0	0.91∠-5.60
15	3	3	0.029∠-127.2	0.948∠-7.442	60	10	6	0.003∠93.36	0.909∠-6.624
16	3	4	0.004∠-136.6	0.916∠-5.034	61	11	1	0.005∠2.511	0.896∠0.013
17	3	5	0.0∠0	0.91∠-5.60	62	11	2	0.018∠-92.16	0.908∠-3.399
18	3	6	0.005∠-179.1	0.922∠-7.534	63	11	3	0.001∠103.8	0.911∠-6.297
19	4	1	0.026∠-118.9	0.933∠-5.030	64	11	4	0.001∠76.81	0.909-6.639
20	4	2	0.016∠-137.7	0.930∠-2.565	65	11	5	0∠0	0.91∠∠-5.60
21	4	3	0.012∠-172.6	0.936∠-7.636	66	11	6	0.002∠82.69	0.909∠-6.515
22	4	4	0.018∠-99.11	0.915∠-6.208	67	12	1	0.018∠-79.05	0.899∠-1.125
23	4	5	0.0∠0	0.91∠-5.60	68	12	2	0.013∠-91.77	0.908∠-4.281
24	4	6	0.005∠125.8	0.918∠-7.284	69	12	3	0.001∠95.14	0.910∠-6.235
25	5	1	0.011∠-135.6	0.860∠-11.06	70	12	4	0.001∠75.35	0.903∠0.104
26	5	2	0.015∠-122.7	0.922∠-3.386	71	12	5	0∠0	0.91∠-5.60
27	5	3	0.009∠-150.8	0.927∠-74.22	72	12	6	0.001∠77.61	0.909∠-6.454
28	5	4	0.023∠-96.75	0.915∠-76.48	73	13	1	0.019∠-83.01	0.901∠-0.076
29	5	5	0∠0	0.91∠--5.60	74	13	2	0.003∠-90.93	0.908∠--4.406
30	5	6	0.016∠-102.1	0.916∠-83.24	75	13	3	0.001∠86.28	0.909∠-6.172
31	6	1	0.024∠-127.4	0.849∠12.55	76	13	4	0.017∠-88.04	0.903∠-0.973
32	6	2	0.012∠-116.3	0.917∠-4.087	77	13	5	0∠0	0.91∠-5.60
33	6	3	0.008∠130.7	0.921∠-7.098	78	13	6	0.001∠75.69	0.909∠-6.39
34	6	4	0.002∠119.6	0.913∠-75.13	79	14	1	0.023∠86.03	0.902∠13.80

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35	6	5	0.∠0	0.91∠-5.60	80	14	2	0.00∠-90.39	0.908∠-4.720
36	6	6	0.004∠105.7	0.914∠-80.83	81	14	3	0.001∠77.33	0.909∠-6.109
37	7	1	0.061∠-79.66	0.862∠-3.991	82	14	4	0.022∠-88.23	0.904∠-2.365
38	7	2	0.027∠-97.12	0.914∠1.679	83	14	5	0∠0	0.91∠-5.60
39	7	3	0.007∠116.6	0.917∠-6.725	84	14	6	0.003∠75.33	0.909∠-6.203
40	7	4	0.005∠94.60	0.911∠-7.205	85	15	1	0.047∠83.21	0.909∠4.310
41	7	5	0.∠0	0.91∠-5.60	86	15	2	0.008∠-59.02	0.912∠-51.27
42	7	6	0.008∠91.38	0.912∠-7.587	87	15	3	0.001∠75.64	0.909∠-6.046
43	8	1	0.029∠-65.34	0.876∠-56.55	88	15	4	0.018∠87.95	0.904∠-12.24
44	8	2	0.015∠-99.76	0.911∠0.725	89	15	5	0∠0	0.91∠-5.60
45	8	3	0.003∠123.8	0.915∠6.582	90	15	6	0.002∠75.28	0.909∠-6.090

VI. CONCLUSION

Particle swarm optimization is an iterative optimization algorithm that simulates the social behavior of bird flocking or fish schooling. By iteratively updating particle position and velocity, the algorithm aims to converge towards the optimal solution. This paper has successfully presented a power flow algorithm that implements PSO, where particles represent the buses and position represents the voltage and phase angle at each bus. The iterative procedure shows a substantial improvement in the voltage profile of the system as the voltage deviation is reduced from 0.173 p.u. to 0.1095 p.u. It is also observed that system line losses change from 3.984 p.u. to 0.1670 p.u. Overall, the fitness function has improved from 4.157 p.u. to 0.2765 p.u. It is concluded that in the context of power flow analysis, PSO can help to find the optimal or near optimal operating point of an electrical network by adjusting the voltage and angle at each bus to minimize a given objectivefunction (e.g., system losses or voltage deviations). Overall, PSO offers a flexible and powerful approach for power flow analysis, capable of efficiently exploring solution spaces and providing optimal or near-optimal solutions for complex electrical networks.

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