Choosing PSO under Different Overloads to Provide Best Power Flow for IEEE - 57 Bus

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Abstract

This study investigates the impact of Particle Swarm Optimization (PSO) on power loss and production cost reduction in overloaded transmission lines. PSO is used to manage power flow in congested transmission lines and reduce power losses. The proposed technique was tested using the IEEE large-scale 57-bus test system. Optimal power flow (OPF) is crucial for modern power systems, aiming to minimize active and reactive power distribution while considering technological and economic constraints. PSO is presented as a solution to the OPF problem, focusing on actual power losses, hypothetical power losses, and overload consequence. PSO is presents.as a solution, and various methods, such as genetic algorithms and linear programming, will be used to compare PSO results. The suggested PSO yields reduced power losses with higher loads in case studies. The approach is evaluated for IEEE -57 buses and produces superior results when used with the MATLAB environment. PSO reduces the target function's real power loss from its starting condition (24.98) MW to its ideal state (16.75) MW with a reduction of 8.23 MW. Additionally, PSO reduces the target function's active power loss by 20% overload from its initial state (56.042 MW) to the optimal state of 46.23 MW with a reduction of 9.812 MW.

Keywords- Optimal Power Flow; Real Power Loss; PSO, Power Loss Minimization; Overload; IEEE-57 bus.

I. INTRODUCTION

The electric power sector has seen a significant transition over the last ten years, and this trend is anticipated to continue. Previously, the electric power sector was under government control or regulation and enjoyed a monopoly in its service region. Electricity was available to all local companies, organizations, and economic sectors thanks to the area's dominant power supplier. From a technological as well as a legal perspective, it was essential. Over the past ten years, however, nations have started to break up these monopolies in favor of the free market.[1][2][3]. This highly functional necessity of power system functioning has spurred the development of OPF solution approaches over time [4][5]. Since it was initially put out, the optimal power flow problem has been investigated.[6] . It has taken decades to find effective solutions to the OPF. To solve it, several mathematical methods have been used. An innovative heuristic approach is particle swarm optimization. To comprehend the motives driving the behavior of animals like fish schooling, bird flocking, etc., a technique that integrates social psychology principles with evolutionary computing is applied. The behavior of a colony or swarm of insects, such as ants, termites, bees, and wasps, serves as the basis for particle swarm optimization, or PSO. The particle swarm optimization method imitates these social species' behaviors. A particle is a group of insects, such as a colony of bees or a flock of birds. Each person or particle in a swarm uses their intellect and the collective intelligence of the group to behave dispersedly. Because of this, even if the other particles in the swarm are dispersed from the starting particle, they may all quickly follow it if the good path leads to food. Swarm intelligence-based optimization tactics, as opposed to evolution-based ones like genetic algorithms, are known as behaviorally inspired algorithms. The PSO approach was initially proposed by Eberhard and Kennedy [7]. The IEEE-57 bus system is a widely used benchmark for testing and evaluating different OPF techniques and algorithms. Recent studies have proposed various methods to solve the OPF problem for the IEEE-57 bus system under overloads, including PSO, multi-objective optimization, load uncertainties, and contingency analysis.

Position and velocity are regarded as the two characteristics of each particle. Every particle in the system explores the design space and keeps track of the optimal location where it locates the desired function value. The particles exchange information or advantageous positions through communication, altering their positions and velocities in response to the information [8]. Biologically based metaheuristics have grown over the last two decades; they can arrive at a satisfying answer more quickly than conventional approaches while resolving some of the latter's shortcomings. Adopting metaheuristics-based systems has the benefit of solving difficult combinatorial problems, such as OPF issues, more quickly [9]. Many different mathematical techniques have been employed to solve it. The OPF is a non-linear, non-convex optimization problem since it involves many power plants integrated into the power grid and their cost functions and constraints. Numerous traditional optimization techniques have already been used in this field, including mixed integer programming, nonlinear programming, the interior point approach, and quadratic programming. Several approaches have even been applied in the industrial setting because of their quick convergence and durability.

However, such methods linearize the OPF problem without taking into account the non-convex, non-differentiable, and non-smooth characteristics of the system. Because these methods focus on the root cause of the issue, many modern heuristic optimization algorithms have been developed for power system optimization [10],[11]. Heuristic algorithms often fall under the single-solution or population-based technique groups. The majority of the methodologies addressed in the literature employ one of the following five techniques: Newton's approach, linear programming, gradient technique, and equal incremental cost criteria approach (also known as the lambda iteration method). In contrast to linear programming and genetic algorithms based on optimum power flow, many of the strategies used in this study depend on particle swarm optimization. The generator's active power is used as a control parameter. OPF is used to determine the recommended PSO, LP, and GA as well as the values of the lowest production costs. IEEE 57 bus has been used to research and test the suggested solution. After optimization, the transmission losses and convergence rates of each test system are compared. The best PSO outcomes in this study are also contrasted with the LP and GA outcomes published in the literature. PSO performs better than other techniques in the literature as a result, finding lower-cost values more rapidly. The outcomes of the simulation can compare the overall cost of generation for the best option with that for the worst-case scenario. If the cost of generation for the optimal solution is lower than the cost of generation for the base case solution, the proposed algorithm is considered effective in reducing the cost of generation. The road map for the current investigation can be summarized as follows: The issue of the problem statement is presented in section 2, the target functions are shown in section 3 whilst the optimal power flow application on IEEE 57-buses is discussed in section 4, simulation results, and economic feasibility for optimal power flow is discussed in section 5. Lastly, a conclusion is reached in section 6.

II. PROBLEM STATMENT

The following is a mathematical definition of an optimum power flow problem:

1- The Target feature *is min f* (x, u).
2- Equality constraints are important. *g (x, u) = 0*.
3- Inequality constraints are *h (x, u) ≤ 0*.

The vector variables *x*, in this case, are the slack power *Pg1* vector, the load bus voltage vector, the imaginary output *Qg* vector, and the transmission line loading vector Sl vector. The vector of independent variables comprises the slack real power output Pg1, slack bus voltage vector Vg, transformer tap settings vector T, and shunt compensation settings vector *Qc.* Common load flow analysis is represented by the equality constraints *h (x, u)* [12],[13]. The system operating restrictions are represented by the inequality constraint g *(x, u),* which may be constructed as follows. *(x):* The state vector, or vector of dependent variables. The vector of independent variables (control variables) is denoted by *(u).*[14]

• The generator's maximum and minimum real and imaginary powers:

• The greatest and lowest tap ratios for transformers that change taps while under load.

• Shunt compensators' maximum and minimum limitations

• Maximum and lowest bus voltage and line flow levels to maintain electrical service quality and system security [15]:

2-1 Target Functions

Case 1: **Computation of Real Power Loss**

In this case, the total real power losses are [16]

$$P_{Loss} = \sum_{k=1}^{NTL} Gij(Vi^2 + Vj^2 - 2ViVj\cos\theta ij \qquad (1)$$

where, $\theta_{ij} = \theta_i - \theta_j$ is the conductance between *bus i* and *bus j*; *G ij* is the voltage angle difference between *bus i and bus j*; *V (i,), V (j,)* indicates the voltage value at *bus i* and *bus j*; and NTL is the number of transmission lines.

Case 2: Computation of Imaginary Power Loss

$$Q_{loss} = \sum_{k=1}^{NTL} Bij(Vi^2 + Vj^2 - 2ViVj \sin\theta ij) \quad (2)$$

Where $\theta_{ij} = \theta_i - \theta_j$ is the difference in voltage angle between bus i and j; *V (i), V (j)*, which stands for the value of the voltage at *bus i* and *bus j*, respectively; *B ij*, which stands for the susceptance between *bus i and bus j*; and NTL, which stands for the number of transmission lines

case 3: Overloaded Transmission Lines

The active and reactive power in each line may be computed from: to limit power flow in overload lines

$$PGi - PLi = Vi \sum_{i=1}^{Nb} Vj\left(Gij\cos(\delta i - \delta j) + Bijsin(\delta i - \delta j)\right) \quad (3)$$

$$QGi - QLi = Vi \sum_{i=1}^{Nb} Vj\left(Gij\sin(\delta i - \delta j) + Bijcos(\delta i - \delta j)\right) \quad (4)$$

Case 4: Fuel Cost

The most fundamental objective function of OPF has always been explored in the literature. Following is a description of the objective function that needs to be minimized: The quadratic relationship provides the bulk of the explanation for the relationship between fuel expense ($/h) and generating power.

$$F = Cost = \sum_{i=1}^{NG} ai + biPGi + CiPGi^2 \quad (5)$$

where a_i , b_i , c_i are fuel cost coefficients of the i-th generator.

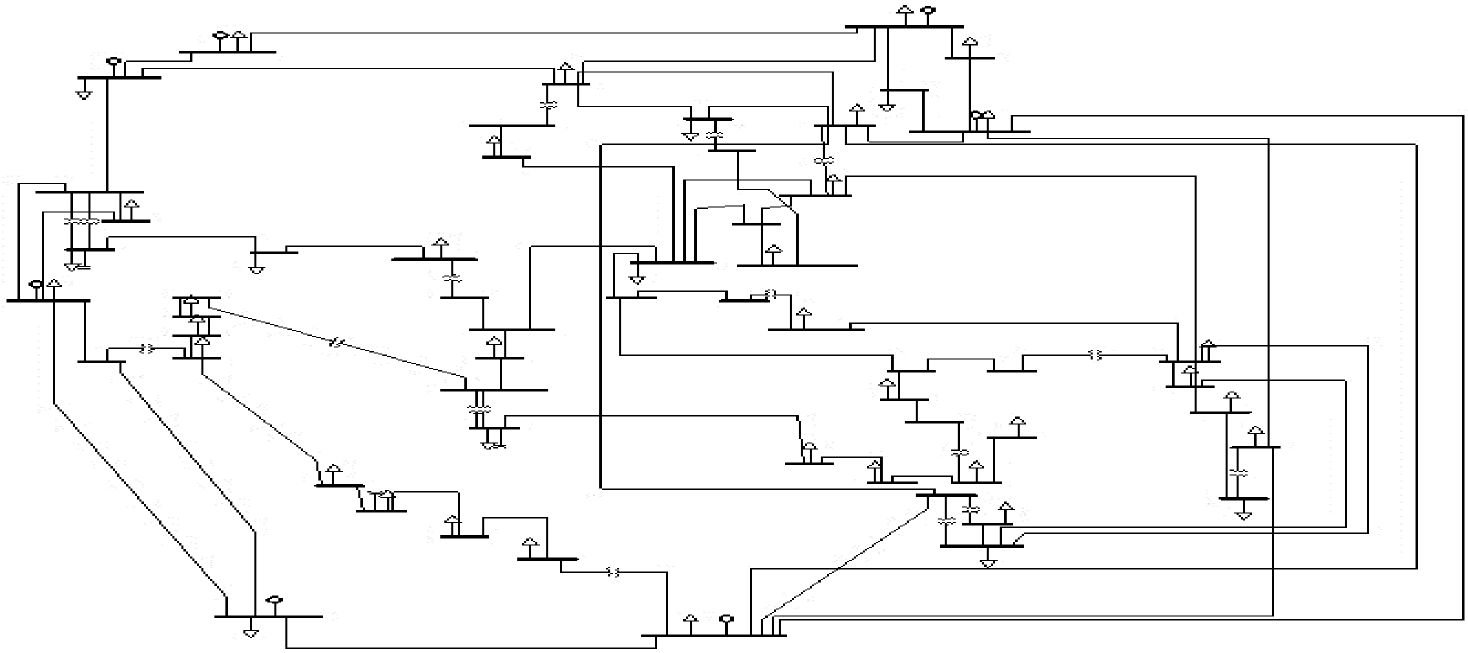

Fig.2. Single Line Diagram for IEEE 57-bus represented

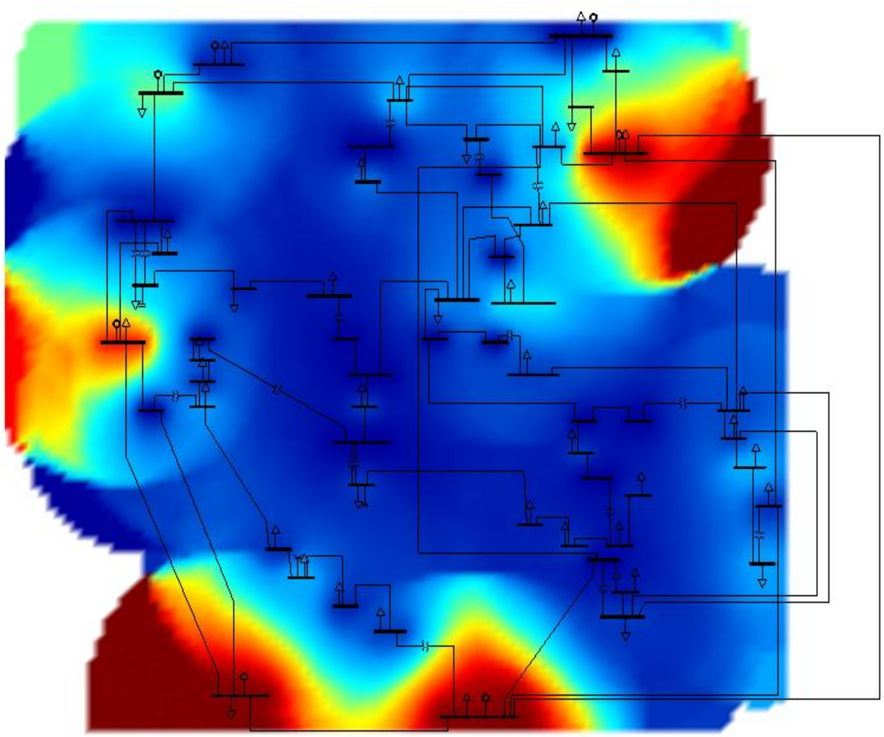

Fig.3. The loading effect in IEEE 57 bus transmission line at 20% of rated load.

III. RESEARCH METHOD

3-1Particle Swarm Optimization in Power System:

PSO, one of the current heuristic optimization approaches, was created by Kennedy and Eberhard. The PSO method searches through a population of particles, each of which is a candidate solution, to identify the best response. A solution to the issue. PSO is a metaheuristic optimization technique that depends on user input. The idea behind this optimization technique, PSO, is that it can help us communicate with an international group of stupid people [17]. In search of the optimal answer (the quickest route to the food), the dust traverses the search space randomly, with each particle shifting positions following its intelligence. It improves particle sensing of the environment (swarm intelligence). Each element includes a past that acts as a memory. Keep it headed in the greatest path possible based on where it was before at its finest. The best value among all local best positions (pbest) of the particles in the swarm is their global best position (pbest) (g best). Each particle's best position is its local best position (pbest). The particles adjust their position and velocity at every step [11] to reach their pbest and Gbest positions. The optimal solution is then discovered through an iterative process.

$$v_i^{k+1} = wv_i^k + c1r1(p_{besti\_}\ x_i^k) + c2r2(G_{best} - x_i^k) \quad (5)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (6)$$

where v_i^k and $vi\ (k+1)$ denote the velocity of the *i-th* particle at iteration k and the updated velocity of the *i-th* particle at iteration $k + 1$, respectively; w denotes the weight factor of the particles; $c1$ and $c2$ denote the respective coefficients of a particle, and $r1$ and $r2$ denote random variables. The updated of *i'th* particle at iteration *k+1* is $vi(k+1)$, and $pbesti$ displays the best fitness of *i'th* particle based on experience during each iteration. G_{best} represents the overall best fitness of a particle in a swarm. The following are the processes employed by PSO to remedy the OPF**.** Fig. 3 illustrates the flowchart of the particle swarm optimization in OPF.

1) Initialization: The particles' population is generated randomly after choosing the first population size and generation number. It is determined what the weight factor and acceleration coefficients are.
2) Identify the fitness of each particle: To determine each particle's fitness value.
3) Select the ideal particle location: This method will discover the optimal locations for each particle and the population.

4) Determine the position and update velocity: After determining *p*best *i* and *G*best *i*, use (1) and (2) to calculate the next step velocity for updating each particle's position.
5) The velocity and position of each particle are modified following the computation, and then, similar to step 2, the new location of each particle is evaluated to see if the updated particles are fit. Continue to step 3 after reaching the maximum number of iterations [14].

3- 2 Optimal Power Flow Application on IEEE 57-Buses

Power flow issues in power systems are often resolved using the metaheuristic optimization approach known as Particle Swarm Optimization (PSO). The following actions may be done to implement PSO to offer the optimal power flow for the IEEE-57 bus system under various overloads:[18],[19].

1- Create the power flow equation for the IEEE-57 bus system with various overloads. Setting up the network and load equations as well as any other limitations that must be taken into account results in the power flow equations.
2- Specify the PSO algorithm's parameters, such as the particle count, the number of iterations that may be made at most, the inertia weight, the acceleration factors, and the search area.
3- Create the initial population of particles in step three. Each member of the population stands for a potential answer to the power flow issue.
4- Determine each particle's fitness within the population. The objective function that has to be maximized in this scenario is the fitness function. The aim function can be maximizing the voltage stability margin, reducing the voltage departure from the nominal value, or minimizing the overall power loss.
5- Adjust each particle's position and speed in accordance with the optimal solution that it and the swarm as a whole have discovered.
6- Continue performing steps 4 and 5 until a termination requirement is satisfied. A minimal error threshold, a maximum calculation duration, or a maximum number of iterations might all constitute the termination condition.

7- Choose the PSO algorithm's best result as the IEEE-57 bus system's optimal power flow solution under the specified overload situation.

8- If there is a change in the overload state, repeat steps 1 through 7 to find the best power flow solution. As shown in Fig.4

It is very important for one to understand that picking the right algorithm parameters and the goal function are essential to the PSO algorithm's performance. Additionally, adjustments to the PSO algorithm may be necessary to manage restrictions like power flow limitations, voltage limits, and reactive power limits. Bus 1 is the slack bus in the system's IEEE 57 bus, which is shown in Fig. 2. As seen in Table 1, this system likewise has 17 control variables [20][21].

Table 1: Description of the IEEE 57 bus system

System	IEEE 57
Number of buses	57
No. of lines	80
No. of generators	**7**
No. of tap positions	17
No. of shunt positions	3

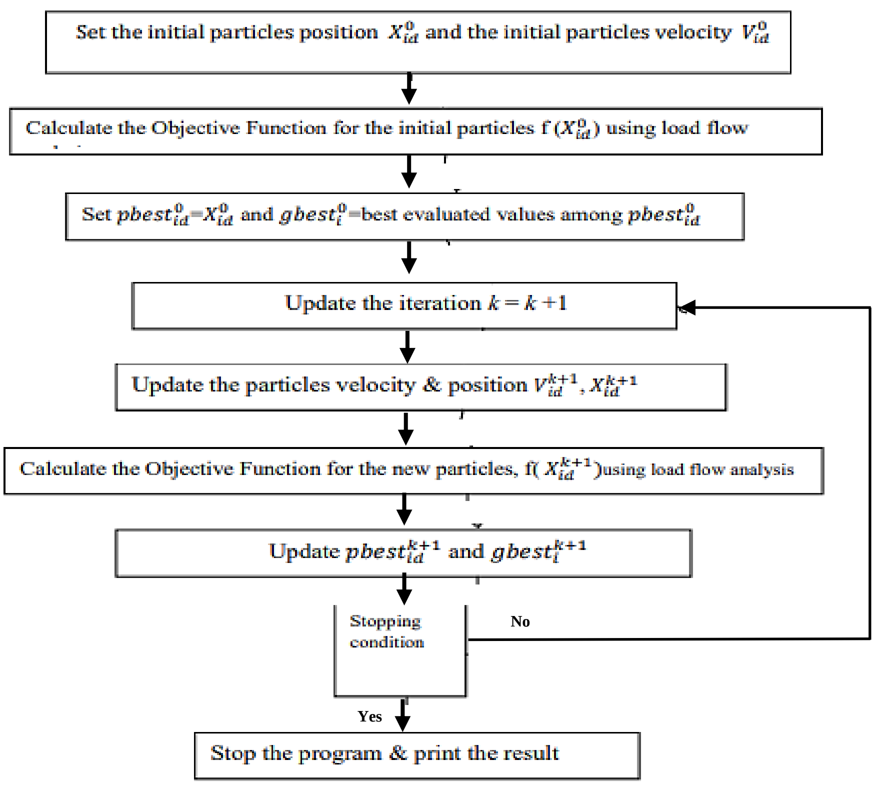

Fig4. Flowchart of PSO used in Optimal Power Flow.

IV. RESULT AND DISCUSSION

4-1 Reduction power losses.

As seen in Fig.2 [22], the suggested technique is used with the IEEE 57 bus system. The proposed method performs better when used to IEEE -57 buses and when utilized with the MATLAB environment R2018a. To assess the performance of Optimal Power Flow (OPF) solutions for the IEEE-57 bus system under overloads, simulation results and discussions are crucial. The simulation results demonstrate how well the suggested algorithms or methodologies minimize generating costs, preserve system stability, and adhere to power system limitations. Figure 2 shows how the standard IEEE 57-bus system, which has 63 lines, 57 buses, seven generators, 42 loads, and 17 transformers, is represented in the PSSE software. References [23],[24],[25] offer values and data from the IEEE bus-57 standards. On a 100 MVA basis, the system's active and reactive power requirements are 1195.8 MW and 316.4 Mvar, respectively. The OPF for IEEE fifty -seven buses using PSO dealt individually with each of the four steps, increasing 5% load (real power losses, and imaginary power losses and cost), as listed in Table 2.

Table 2: A Comparison of the Results MATLAB for Power Losses of the IEEE -57 Bus Test System with and without PSO

Increasing Load	Total Generation MW	P. LOSS MW	Q. LOSS MVar
Normal Case without PSO	1275.780	24.980	138.553
With pso		16.75	104.053
5%	1344.060	30.720	160.529
With pso		26.28	139.636
10%	1414.834	38.954	191.638
With pso		30.534	153.4
15%	1484.824	46.404	219.641
With pso		31.774	157.473
20%	1557.002	56.042	256.724
With PSO		46.23	213.204

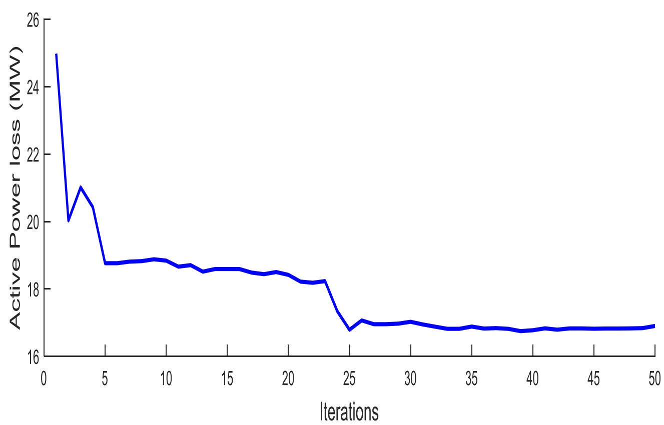

Fig.5 Best Reduction for Power Loss in Normal Condition

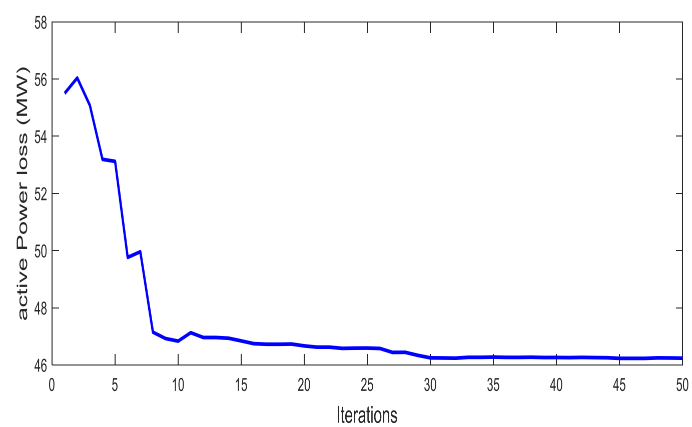

Fig6. Best Reduction for Power Loss in 20% Overload

According to PSO, Fig.5 shows the best reduction in active power losses for IEEE 57 bus in normal conditions. Fig.6 clarifies the best reduction in power losses in case of 20% overload. At the same time, Fig.7 specifies the best reduction in reactive power loss for healthy cases. Fig.8 illustrates the best reduction in imaginary power losses in 20% overload for 50 iterations.

Additionally, PSO reduces the target function's real power loss from its starting condition of (24.98) MW to its ideal state of (16.75) MW with a reduction in the power of (8.23) MW. Also, PSO reduces the target function active power loss by 20% overload from the initial state of 56.042 MW to the optimal state of 46.23 MW with a reduction in the power is 9.812 MW.

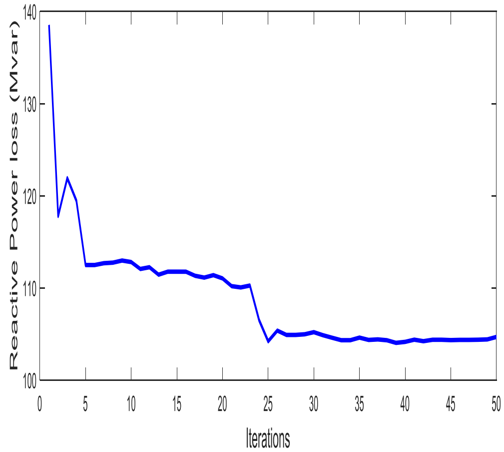

Fig.7. Best Reduction for Q-Loss in 0% O.L

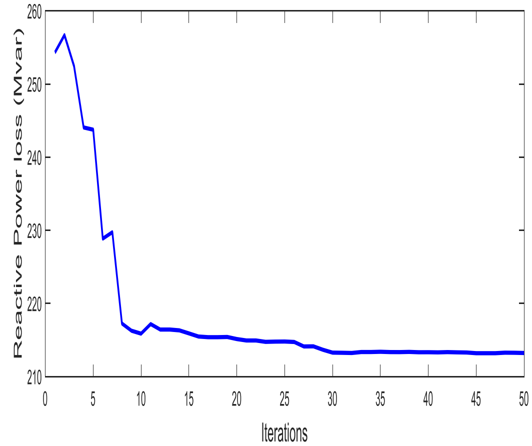

Fig.8. Best Reduction for Q-Loss in 20% O.L

PSO reduces the imaginary power losses of the target function from the initial state of 160.529 MVAR to the ideal state of 139.636 MVAR (the reduction in the imaginary power losses is 20.893 MVAR), and PSO reduces the imaginary power losses of the target function in 20%O. L from the initial state of 256.724 MVAR to the ideal state of 213.204 MVAR (the reduction in the imaginary power losses is 43.52 MVAR).

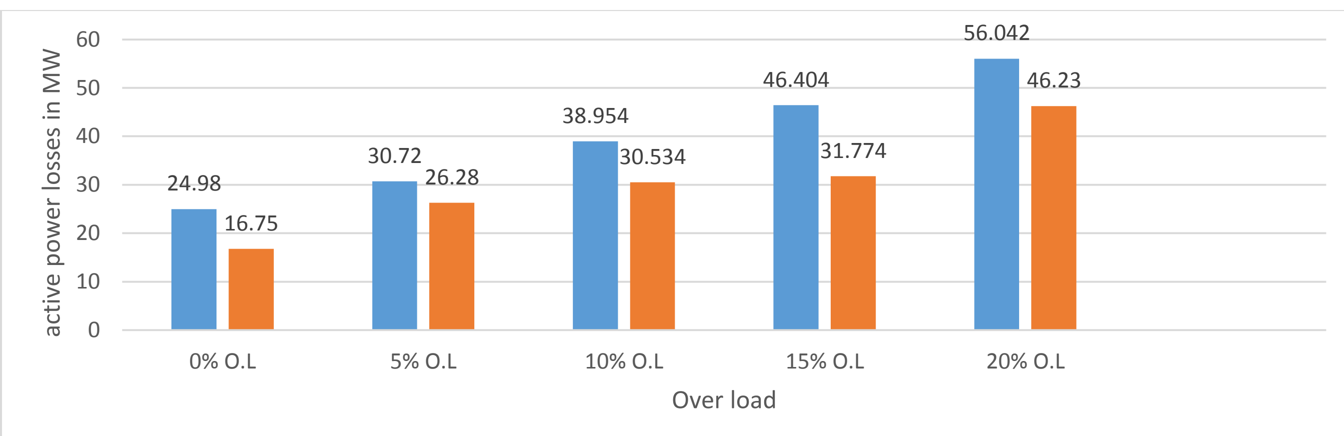

Fig. 9. Comparative of active power losses of IEEE 57 bus system without and with PSO for different load.

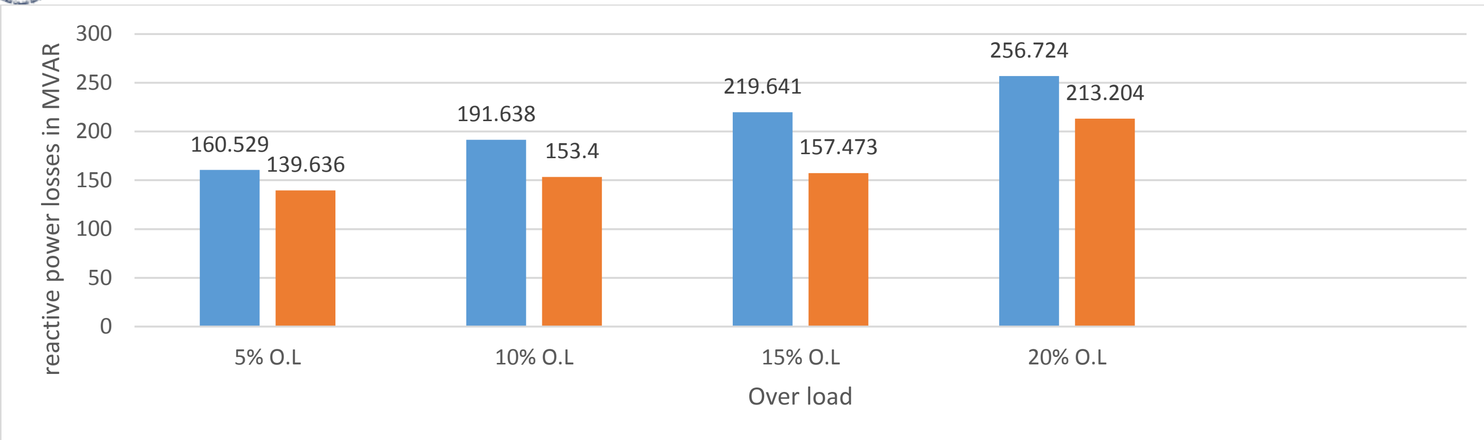

Fig. 10. Comparative of reactive power losses of IEEE 57 bus system without and with PSO for different load.

OPF was constructed in MATLAB R2018a. The test system for the IEEE-57 Bus is clarified in Fig. (2).and applying Load flow analysis using Newton Raphson and with PSO method is listed in Table (2). To ensure those system constraints are not violated. Optimal power flow manages variable control settings and optimizes system operating constraints that are not violated. The OPF system manages variable control settings, optimizes operating conditions, and addresses the power system flow issue. An optimized system will perform better overall and be more dependable and secure. Additionally, it provides a wide range of options for optimization goals, thus meeting all the needs of an entire power system in terms of optimization. Most control options in a transmission system are considered during the **4-2 Economic Feasibility for Optimal Power Flow**

Optimal Power Flow is a widely used technique for optimizing power system operation and ensuring the economic feasibility of power flow solutions. To determine the economic feasibility of optimal power flow for the IEEE-57 bus system under overloads, the following steps can be taken:

1- Formulate the IEEE-57 bus system's power flow issue under overloads. In order to do this, the power flow equations must be built up, taking into account any necessary limitations as well as network and load equations.
2- Describe the OPF problem's objective function. The goal may be to reduce overall production costs while still meeting power system requirements. Fuel costs, start-up costs, and shut-down costs for each producing unit are included in the overall cost of generation.
3- Include any additional constraints that need to be considered. These constraints may include transmission line limits, bus voltage limits, and generator output limits.
4- Use an optimization technique to solve the OPF problem and identify the power system's ideal operating point.
5- Compare the overall cost of generation for the best option with the cost of generation for the worst-case scenario to assess the optimal power flow system's economic viability. The power system functioning under typical operational conditions, without any overloads, is represented by the base case solution.
6- The best solution is economically feasible if the cost of generation for it is lower than the cost of generation for the worst-case scenario.

7-The optimal solution could not be economically feasible if the cost of generation for it is higher than the cost of generation for the base case solution. In this situation, extra steps may be required to assure the economic viability of the functioning of the power system during overloads, such as improving transmission lines or adding more producing units. The results are displayed in the table (3) below.

Table .3: Results of saving cost for IEEE 57 bus system with PSO for different load.

Cost $	**0% O. L**	**5%O. L**	**10%O. L**	**15%O. L**	**20%O. L**
Reduction value in $/hr	90	100	200	250	45
$/Day	2160	2400	4800	6000	1080
$/Month	64800	72000	1440000	180000	32400
$/Year	23652000	26280000	525600000	65700000	11826000

V. CONCLUSION

his study utilizes particle swarm optimization (PSO) to optimize both reactive and real power under various overload conditions. The proposed approach is quick and effective, and simulation findings show that a strategy that produces more optimal results than PSO may lead to superior options with increased dependability and effectiveness. The IEEE 57 bus system is used with four command variables, including generator voltage level, transformer tap switching, shunt injection capacitance, and active generator power at the PV bus. The state vectors are fictitious generator power, load bus voltage, and reference or slack bus active power. The OPF issue is addressed using three-goal functions that effectively handle real power losses, fictitious power losses, and overloading.

The PSO approach is provided after 50 iterations, resulting in a significant reduction in total power loss. HVAC lines with PSO perform better under heavy load, and the system remains stable even after increasing load ability. The suggested work can be applied in real systems. To determine the economic feasibility of optimal power flow for the IEEE-57 bus system under overloads, it is crucial to consider power flow models accuracy, optimization algorithm parameters, and uncertainties like load forecasting errors and fuel price fluctuations.

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