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Energy Efficiency in Modern Power Systems Utilizing Advanced Incremental Particle Swarm Optimization–Based OPF

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Abstract: Since the power grid grows and the necessity for higher system efficiency is due to the increasing number of renewable energy penetrations, power system operators need a fast and efficient method of operating the power system. One of the main problems in a modern power system operation that needs to be resolved is optimal power flow (OPF). OPF is an efficient generator scheduling method to meet energy demands with the aim of minimizing the total production cost of power plants while maintaining system stability, security, and reliability. This paper proposes a new method to solve OPF by using incremental particle swarm optimization (IPSO). IPSO is a new algorithm of particle swarm optimization (PSO) that modifies the PSO structure by increasing the particle size, where each particle changes its position to determine its optimal position. The advantage of IPSO is that the population increases with each iteration so that the optimization process becomes faster. The results of the research on optimal power flow for energy generation costs, system voltage stability, and losses obtained by the IPSO method are superior to the conventional PSO method.

Keywords: economic dispatch; generation cost; incremental particle swarm optimization; incremental social learning; optimal power flow; particle swarm optimization; voltage stability

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1. Introduction

Optimal power flow (OPF) is a method for efficiently scheduling power plants with the aim of minimizing the total production costs of the power plants while keeping the system safe and reliable and meeting the load demands by considering network losses and network constraints. OPF is one of the most essential studies in modern power systems operation to maintain and enhance system security, stability, and reliability. OPF will decide the optimal operational settings of the electricity grid that are experiencing operational and physical obstacles. Then by using the optimization algorithm technique, elements that regulate the optimal point are expressed and formulated. The main intention of the OPF method is to determine the control variable settings and the equation system that optimizes the value of the objective functions. The selection of this function must be based on a cautious examination of the technical and economic aspects of the electric power system. Moreover, the rapid growth of the network and the need for efficiency in the electrical system make the system operators look for fast and efficient methods in the electric power system operation and planning.

There are many methods for solving OPF problems, ranging from conventional methods, such as AC-OPF [1], DC-OPF [2], and SF-OPF [3,4], to using artificial intelligence or nature-inspired optimization techniques, such as bat algorithms [5], particle swarm optimization [6], bacterial foraging method [7], whale optimization algorithm [8], artificial bee colony [9], differential search algorithm [10], grey wolf optimizer and differential evolution [11], hunger games search (HGS) [12], moth swarm algorithm [13], gravitational search algorithm [14], teaching-learning-based optimization [15], circle search algorithm (CSA) [16], improved harmony search method [17], modified imperialist competitive algorithm [18], improved colliding bodies optimization algorithm [19], improved electromagnetism-like mechanism method [20], Gbest guided artificial bee colony [21], Lévy mutation teaching–learning–based optimization [22], and horse herd optimization [23]. A complete review of the most recent optimization techniques for OPF is presented in [24].

Metaheuristic optimization approaches do not constantly assure obtaining an absolute optimum answer to the problem, but a rational solution that is close to a global ideal solution. Therefore, new algorithms are always being developed, which are also motivated by the "No Free Lunch" theorem [25] that declares no optimization technique to be believed as the only pre-eminent method in solving all optimization problems. Some algorithms have succeeded in obtaining the optimum solution, but some algorithms are commonly slow in convergence. Some of these methods are easily trapped in the optimum locale, or other words converge prematurely. Some stochastic algorithms have been demonstrated to be very successful in nonlinear problems, although they do not guarantee optimum global solutions within time limits. Optimization has been tried with many constraints by developing mathematical programming and modern heuristic search. The evolution of the search method is no stranger to solving mathematical functions. Natural selection and metaheuristics are very useful for finding optimum global solutions. Specifically in the problem of OPF, since OPF is a vital and challenging issue in the operation of power systems and stability enhancement, power system researchers are continuously attracted to develop new algorithms for optimization or to enhance the existing approaches to acquire a more effective solution of OPF.

One of the optimization methods often used to solve OPF problems is the particle swarm optimization (PSO) method [6,26,27]. The PSO method is an optimization technique based on the swarm population that utilizes the experience of the cognitive and social principles of each swarm particle. The advantages of the PSO algorithm are its simple concept and memory, and the initial population is preserved, based on a "productive teamwork" among particles, so it is easy to implement and computationally efficient. Nevertheless, the shortcoming of this algorithm is due to its fast convergence, in which sometimes, throughout the optimization procedure, PSO cannot find a wider solution space and results in a quick loss of diversity, which inevitably becomes caught in local optima or unwanted premature converges, meaning quickly finding solutions to local solutions [28].

The concept of the metaheuristic method is to make a trade-off between exploration and exploitation [13]. This technique starts with high exploration or high population diversity and then, through the search process, reduces its diversity. However, decreasing diversity will not always lead to worthy exploitation or rapid convergence. Therefore, the diversity of the population is still a trapped dilemma and requires careful and clever handling.

In a system consisting of many learning particles or agents, each particle/agent not only must familiarize itself with the characteristics of the environment but also must adjust itself to variations of other particles' behavior. This issue becomes crucial in the research of swarm intelligence especially if a large particle quantity is engaged in the study because the learning process becomes more difficult. Therefore, to overcome this challenge, in this paper, we propose an approach based on rising population numbers because in some circumstances, it can facilitate the scalability of the schemes composed of numerous learning particles. This technique is motivated by the societal learning prodigies of animal populations and is called incremental social learning (ISL) [29]. The ISL algorithm implemented on PSO produces an IPSO (incremental particle swarm optimization) algorithm, where the size of the population rises over time. In IPSO, once a new particle is inserted into the population, the position of the new particle is instigated using a "societal learning" instruction that will lead to a preference near the best particle.

IPSO is an optimization technique where each particle changes its position to determine its optimal position. The advantage of IPSO is that the population size increases with each iteration so that the optimization process becomes faster. In the literature, there is not much research implementing this IPSO method. A work by [30] compared the performance of PSO and IPSO, and their experimental results showed that IPSO was able to obtain better and faster solutions than PSO. A paper by [31] designed an IIR system identification task with a robust distributed algorithm based on incremental PSO, and the results showed excellent identification performance. A hybrid IPSO, ant colony optimization, and K-means (IPSOAntK-means) algorithm was proposed for automatic flower boundary extraction, and the results informed that this hybrid IPSO method was one of the best methods [32]. Economic dispatch was proposed using IPSO and deep learning (DL). The result was that IPSO required more time than DL, but the results of IPSO were better than DL [33]. Therefore, this paper proposes a novel method for OPF by using incremental particle swarm optimization, called IPSO-OPF. The proposed method is implemented in the IEEE 30-bus system.

The next section of this paper is structured as follows: Section 2 describes the objective functions and constraints in the optimal power flow. Section 3 outlines the proposed methodology of incremental particle swarm optimization. Section 4 provides the results and analysis; then Section 5 concludes the key outcomes of this study.

2. Optimal Power Flow

Optimal power flow (OPF) is a study that analyses the optimum settings in an electric power system. OPF was initially proposed by Carpentier in 1962 and has gone through a long time to develop various methods of solving power flow problems that can be applied today. The main role of OPF is to determine the optimum settings for the power system [34]. OPF optimizes objective functions that are problematic in the electric power system, such as the total cost function of generation or economic dispatch, the network losses function, and the voltage deviation function on each bus by taking into account the limitations that exist in the operation of the equipment [2,35,36]. While optimizing the system's objective function, OPF also maintains the system stability by keeping the system balance between electricity generation and consumption [37].

2.1. Objective Functions

In the multi-objective optimal power flow, there are several objective functions used, namely the generation cost function and the network losses function.

2.1.1. The Generation Cost Function

The objective function of OPF, also known as economic dispatch, is to obtain a minimization of generating fuel costs by not violating the security constraint of each generator. The generation cost function is a mathematical function modeling to be optimized. The objective function equation for the generation cost is a nonlinear function. The minimum generation cost formulation is derived as follows:

$$Min\ F = \sum_{i=1}^{N_G} F_i(P_{Gi}) \tag{1}$$

$$F(P_{Gi}) = \sum_{i=1}^{N_G} \alpha_i + \beta_i P_{Gi} + \gamma_i (P_{Gi})^2 \tag{2}$$

where,

F: total generation cost ($/h)

$F(P_{Gi})$: generation costs from the ith generator, which is a function of the generating power output ($/h)

P_{Gi}: the ith generator power output (MW)

N_G: number of generating units

α_i β_i, γ_i: coefficient of generation cost.

2.1.2. The Network Losses Function

With the network losses objective, all control settings are regulated to minimize the total active power losses. The network losses function is a mathematical modeling to find the value of network losses in the electric power system. The network losses function is also a nonlinear equation. The network losses function in the OPF problem is given in Equation (3):

$$P_{losses} = \sum_{k=1}^{N_{TL}} g_k \left[|V_i|^2 + \left|V_j\right|^2 + 2|V_i|\left|V_j\right| \cos\left(\delta_i - \delta_j\right) \right] \tag{3}$$

where

P_{losses}: total network active power losses (MW)

N_{TL}: number of transmission lines in the system

g_k: the conductance of the k-line connecting the i and j buses

$|V_i|$: voltage magnitude on the ith bus

$\left|V_j\right|$: voltage magnitude on the jth bus

δ_i: voltage angle of bus i

δ_j: voltage angle of bus j

2.2. System Constraints

2.2.1. Equality Constraints

The equality constraint functions are formulated by a balance equation between losses, generating power, and power absorbed by the load as well as the active and reactive power balance equations. Equations (4)–(8) provide the nonlinear power flow equations that control the system:

$$\sum_{i=1}^{N_G} (P_{Gi}) = P_{load} + P_{losses} \tag{4}$$

$$\Delta P_i = P_{Gi} - P_{Di} \tag{5}$$

$$\Delta P_i = \sum_{j=1}^{N} |V_i|\left|V_j\right|\left|Y_{ij}\right|\left(\theta_{ij} - \delta_i + \delta_j\right) \tag{6}$$

$$\Delta Q_i = Q_{Gi} - Q_{Di} \tag{7}$$

$$\Delta Q_i = \sum_{j=1}^{N} |V_i|\left|V_j\right|\left|Y_{ij}\right|\left(\theta_{ij} - \delta_i + \delta_j\right) \tag{8}$$

where

P_{load}: total system load (MW)

$\sum_{i=1}^{N_G}(P_{Gi})$: total active power generation (MW)

P_{Gi}: active power generation at bus i

P_{Di}: active power demand at bus i

Q_{Gi}: reactive power generation at bus i

Q_{Di} : reactive load power at bus i

$|Y_{ij}|$: the element of bus admittance matrix Y_{bus}
θ_{ij} : the angle of ij element on Y_{bus}

2.2.2. Inequality Constraints

The inequality constraints of the system are the formulation of continuous and discrete constraints that denote the security and operational constraints of the system, which are as follows:

1. The power plant constraints, which consist of active and reactive power outputs of the power plants, and voltages limited by minimum and maximum limits:

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max}, \quad i = 1, \ldots, N_G \tag{9}$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}, \quad i = 1, \ldots, N_G \tag{10}$$

$$|V_{Gi}^{min}| \leq |V_{Gi}| \leq |V_{Gi}^{max}|, \quad i = 1, \ldots, N_G \tag{11}$$

where
P_{Gi}^{min}: the minimum active power of the ith bus generator
P_{Gi}^{max}: the maximum active power of the ith bus generator
Q_{Gi}^{min}: the minimum reactive power of the ith bus generator
Q_{Gi}^{max}: the maximum reactive power of the ith bus generator
$|V_{Gi}^{min}|$: the minimum voltage magnitudes of the ith bus generator
$|V_{Gi}^{max}|$: the maximum voltage magnitudes of the ith bus generator
N_G: number of generator buses

2. Security constraints including the voltage magnitude limit of the load bus:

$$|V_{Lj}^{min}| \leq |V_{Lj}| \leq |V_{Lj}^{max}|, j = 1, \ldots, N_{load} \tag{12}$$

where
$|V_{Lj}^{min}|$: the minimum voltage magnitudes of the jth load bus
$|V_{Lj}^{max}|$: the maximum voltage magnitudes of the jth load bus
N_{load}: number of load buses

3. The settings of the discrete transformer tap

$$T_{Ti}^{min} \leq T_{Ti} \leq T_{Ti}^{max}, \quad i = 1, \ldots, N_T \tag{13}$$

N_T: number of transformers

4. The reactive power injection from compensators

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max}, \quad i = 1, \ldots, N_C \tag{14}$$

N_T: number of compensators

5. The loading of the transmission lines:

$$S_{TLi} \leq S_{TLi}^{max}, \quad i = 1, \ldots, N_{TL} \tag{15}$$

3. Proposed Methodology: The Incremental Particle Swarm Optimization–Based Optimal Power Flow

3.1. Incremental Social Learning (ISL)

Incremental social learning (ISL) is usually applied in multiagent algorithms. The basic concept of ISL is to add one agent or particle to a population according to its timetable [29]. The initial population comprises a small number of agents that allow the learning process to be carried out faster than the learning carried out by the larger population. New agents that are added on schedule to a population can quickly learn socially from more experienced agents who have been in the population for some time. Then, gradually, new agents are added to the population, aiming to allocate the optimal number of agents needed to complete a particular task. New agents can learn and acquire understanding from more knowledgeable agents through this social learning, without the new agents needing to spend "money" to obtain that knowledge. In this ISL, new agents can save time to learn new knowledge or to perform their duties. With the presence of a new agent in the inhabitants, the population will then adapt to new circumstances, but existing agents who have become part of the population do not need to be trained on the whole thing from the beginning.

3.2. Particle Swarm Optimization

Particle swarm optimization (PSO) is a metaheuristic method developed by Eberhart and Kennedy [38]. The meaning of swarm in PSO is individuals who flock together as in groups of birds or fish. PSO is a part of an evolutionary model algorithm inspired by the activities of flocks of birds and schools of fish in search of prey, where a flock does not have a front-runner to look for their food, so they will disperse to search for food in an unsystematic way.

In the PSO algorithm, the process of finding a solution is performed by a population containing some particles [39]. PSO is an optimization technique with a concept of population-based activities in a food-searching procedure where each individual is called a particle. Every particle will adjust its position with respect to time. PSO consists of an intelligent population within a given search space. The population is produced unsystematically with the lowest and the largest value. PSO is composed of particles traveling in the search space. Each individual particle signifies the position and location of the obstacle. Each particle travels around a multidimensional search space and adjusts its position according to its own individual experience and the near particle's experience. Each particle has a position denoted by $\chi_{i,j}^{t}$ and a velocity symbolized by $V_{i,j}^{t}$ in an N-dimensional search space, where i represents the ith particle and N represents the dimension of the space search or the number of unknown variables in a system of nonlinear equations. The following are equations that describe the position $\chi_{i,j}^{t}$ and the velocity $V_{i,j}^{t}$:

$$\chi_{i,j}^{t} = \chi_{i,1}^{t}, \chi_{i,2}^{t}, \chi_{i,3}^{t}, \ldots, \chi_{i,N}^{t} \tag{16}$$

$$V_{i,j}^{t} = V_{i,1}^{t}, V_{i,2}^{t}, V_{i,3}^{t}, \ldots, V_{i,N}^{t} \tag{17}$$

Each particle will look for the optimum answer with the intelligence obtained from its own experience by traversing the dimensions of the search space. Then each particle will adjust its own best position or best solution (local best or personal best—P_{best}) and then acclimatize the position of the best particle from the best value or solution from the entire population (global best—G_{best}) while crisscrossing the search space. PSO does not have crosses between individuals and does not have mutations, and the existing particles are not replaced by other particles during the search process. In every iteration, the particle position that signifies the solution is assessed for its accomplishment by incorporating its solution into the fitness function. Each particle is regarded as a spot in a particular dimension of space. The following equations are mathematical models that describe the mechanism for improving the state of the particle:

$$V_{i,j}^{t+1} = \psi\, V_{i,j}^{t} + \mu_1 \varepsilon_1 \left(\Psi_{i,j}^{t} - \chi_{i,j}^{t}\right) + \mu_2 \varepsilon_2 \left(\Upsilon_{i,j}^{t} - \chi_{i,j}^{t}\right) \tag{18}$$

$$\chi_{i,j}^{t+1} = \chi_{i,j}^{t} + V_{i,j}^{t+1} \tag{19}$$

where $\Psi_{i,j}^{t} = \Psi_{i,1}^{t}, \Psi_{i,2}^{t}, \ldots, \Psi_{i,N}^{t}$ represent the local best or personal best of the ith particle; $\Upsilon_{i,j}^{t} = \Upsilon_{i,1}^{t}, \Upsilon_{i,2}^{t}, \ldots, \Upsilon_{i,N}^{t}$ represent the global best from the whole flock; μ_1 and μ_2 are constants with the positive value, which are normally called acceleration coefficients or learning factors; ε_1 and ε_2 are positive random numbers between 0 and 1 produced at each iteration for each dimension; and ψ is an inertial parameter named the constriction factor, which indicates the effect of changing velocity from the old vector to the new vector. Equation (18) is employed to obtain the velocity of the new particle according to the preceding velocity, the distance between the present position and the local best position, and the current distance from the global best position. Then the particle flies to a new position based on Equation (19).

3.3. Implementation of Incremental Social Learning into Particle Swarm Optimization

The implementation of ISL into the PSO algorithm is called incremental particle swarm optimization (IPSO). In ISL, each time a new agent joins the population, the new member must study socially from a more experienced division of agents. In the IPSO algorithm, when a new agent or particle is entered into a population, the position of this new member is adjusted using information from agents who are already part of that population by "social learning" rules.

This process is applied as an initialization instruction that transfers a new particle from a randomly generated original position in the search space to a position closer to the particle position, which serves as a "model" for the new particle to emulate [29]. The rules for initializing the *j*th dimension of the new particle can be seen in the following equation:

$$\chi'_{new,j} = \chi_{new,j} + \tau(\wp_{model,j} - \chi_{new,j}) \quad (20)$$

where $\chi'_{new,j}$ is the regenerated position of the new particle, $\chi_{new,j}$ is the initial random position of the new particle, $\wp_{model,j}$ is the position of the model particle, and τ is a homogenously dispersed random number between 0 and 1. After this rule is implemented for every dimension, the best position of the previous new particle is modified to the $\chi'_{new,j}$ value, and its velocity is arranged to zero. For all dimensions, the τ value is the same to confirm that the renewed position of the new particle will be in any place alongside the vector of $\wp_{model,j} - \chi'_{new,j}$. Finally, the new particle neighbors, namely, the collection of particles that will receive information in the next iteration, are generated randomly, taking into account the topological connectivity level of the swarm population.

3.4. Algorithm and Flowchart of the Proposed Incremental PSO-Based OPF

The computational steps to calculate the optimal power flow based on IPSO are described in detail as follows, and the flowchart can be seen in Figure 1:

Step 1: Input data of the system (generator cost function, network losses function, active power generation constraints, transmission line data, and bus data)
Step 2: Input IPSO variables (IPSO inertial weighting factor)
Step 3: Set the iteration equal to 1
Step 4: Generate population size "N" where each particle in the IPSO algorithm is determined by various control variables
Step 5: Initialize the resulting population as P_{best} and eliminate the particles that do not satisfy the system inequality constraints
Step 6: Run the optimal power flow program for each particle
Step 7: Calculate and evaluate the fitness value for each particle and determine the G_{best} value among all particles
Step 8: Calculate and update each particle's velocity
Step 9: Adjust each particle's position and eliminate the particles that do not meet the constraints.
Step 10: Assess the fitness value of the new population with P_{best}; then select the better particle that also satisfies the constraints
Step 11: Particles with higher fitness function values are designated as P_{best}
Step 12: If iter < maximum iteration ($iter_{max}$), then add a new particle into the population whose position is adjusted according to the "rules of social learning" and go to Step 6; otherwise, go to Step 13.
Step 13: Print the G_{best} value that gives the optimal solution (minimum P_{losses}).

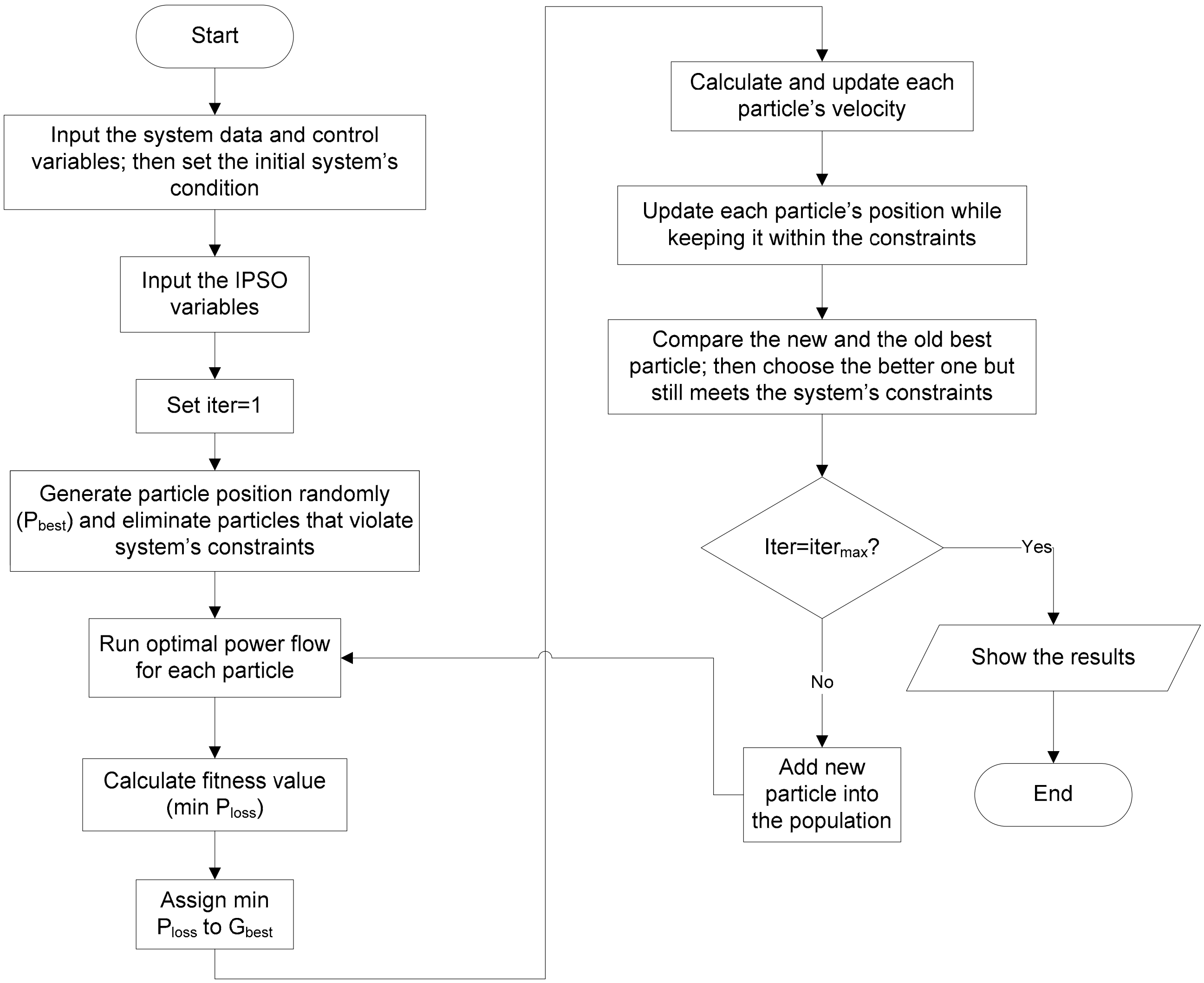


Figure 1. Flowchart of the optimal power flow based on incremental particle swarm optimization.

4. Results and Analysis

This paper uses the IEEE 30-bus system [40] as the case study. The IEEE 30-bus power system consists of two power stations on buses 1 and 2. This system consists of 22 load points spread over each bus with a total load of 283.4 MW of active power and 126.2 MVAr of reactive power. Figure 2 shows the single-line diagram of the IEEE 30-bus system.

Table 1 shows the generation data contained in the IEEE 30-bus system consisting of active power and reactive power generated by the generator, minimum and maximum active and reactive power that can be generated by the generator, and the generation coefficient of each generator. As for the voltage profile constraint on each bus, it is determined to be 0.95 p.u. as the lower limit and 1.05 p.u. as the upper limit.

In this study, the results of OPF based on IPSO are compared with conventional PSO. For OPF using the proposed method IPSO, it is named IPSO-OPF, and OPF using conventional PSO is called PSO-OPF. The fundamental modification of IPSO from PSO lies in the renewal of new particles. The update of new particles on PSO uses the constant chi = 0.729, while the renewal of new particles on IPSO uses random numbers between 0 and 1. This difference affects the speed of obtaining the best fitness.

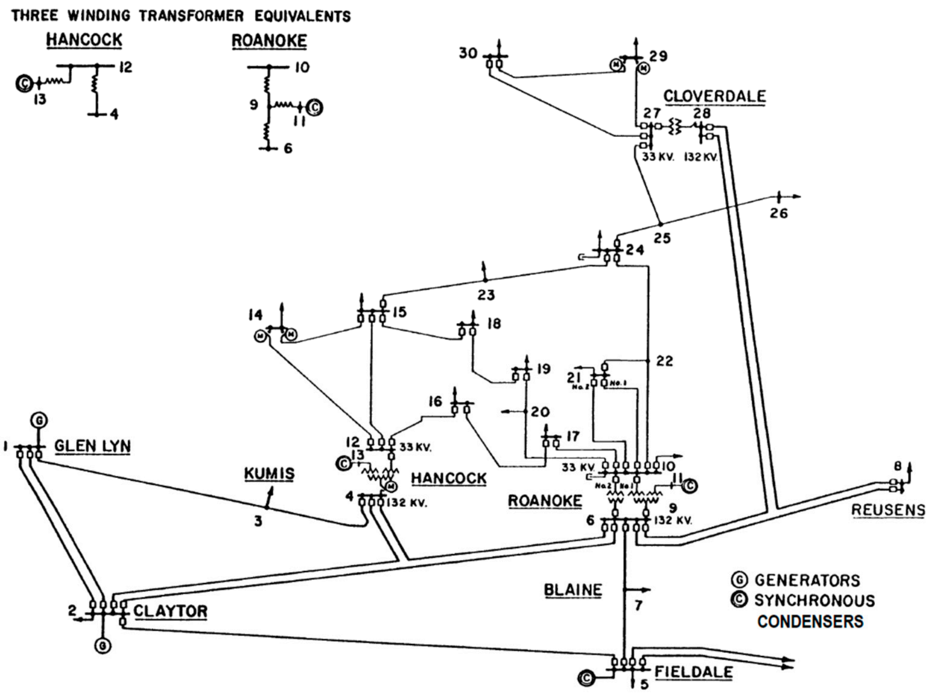
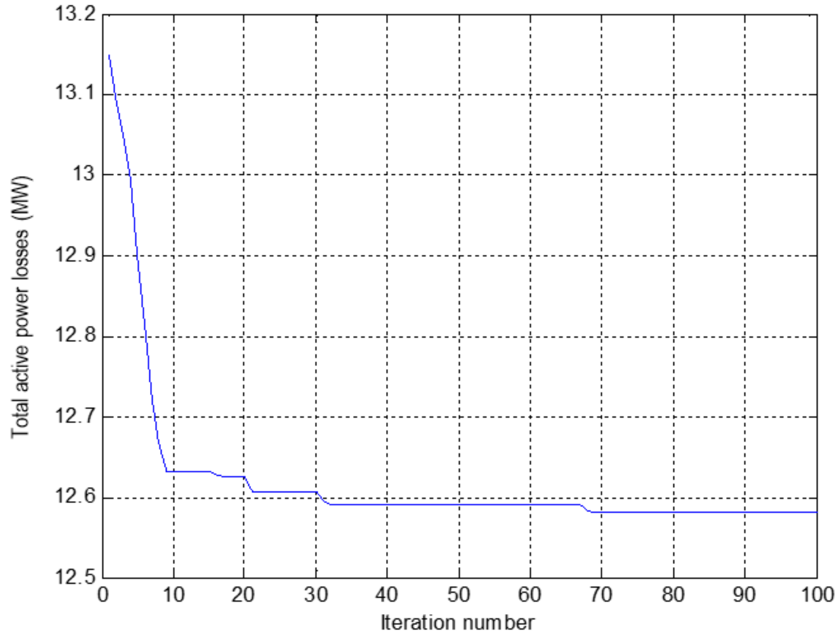


Figure 2. A single-line diagram of the IEEE 30-bus system [40].

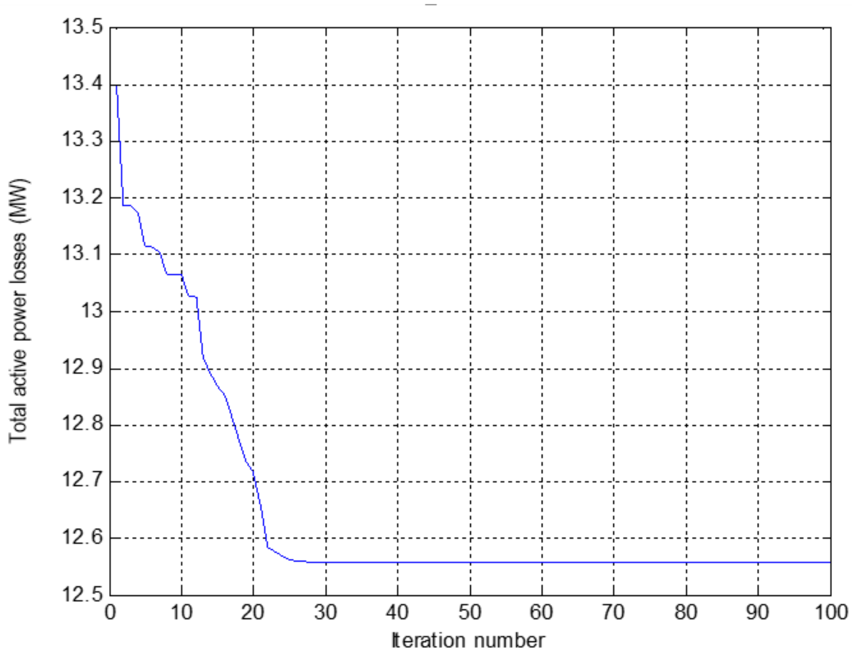
Table 1. Generator data and cost coefficient [40].

Bus	P_{Gi} (MW)	Q_{Gi} (MVAr)	Generator Constraints				Generation Cost Coefficients		
			P_{Gi}^{max} (MW)	P_{Gi}^{min} (MW)	Q_{Gi}^{max} (MVAr)	Q_{Gi}^{min} (MVAr)	α_i ($/h)	β_i ($/MWh)	γ_i ($/MW^{2}h)
1 (Gen 1)	191.7	29	191.7	20	30	−10	1243.53	38.301	0.035
2 (Gen 2)	40	10	140	5	50	−40	451.325	46.159	0.105

Figure 3 shows a comparison of the number of iterations between the PSO and IPSO methods in the optimal power flow in the IEEE 30-bus system. Utilizing the IPSO-OPF method in power flow optimization has a faster time to converge than the PSO-OPF method. Furthermore, the IPSO-OPF method obtained a convergent value of 12.56 MW of system active power losses in the 25th iteration, while the PSO-OPF method converged in the 69th iteration with a result of 12.58 MW of active power losses. Hence, it can be seen that in determining active power losses, the minimum value is obtained using the IPSO-OPF method with fewer iterations.



(**a**)



(**b**)

Figure 3. Number of iterations by using (**a**) the PSO-OPF method and (**b**) the IPSO-OPF method.

Table 2 shows a comparison of the generation costs between the IPSO-OPF method and the PSO-OPF method, including a summary of the comparison of optimal power flow results between the IPSO-OPF and PSO-OPF methods with iteration, active power losses, and generation costs as parameters. By using the PSO-OPF method, the total power generated by generator 1 is 191.7 MW, while the total power generated by generator 2 is 74.28 MW with a total cost of generating using the PSO-OPF method of USD 14,331/h. Meanwhile, using the IPSO-OPF method, the power generated by generators 1 and 2 is 191.7 and 74.26 MW, respectively. The total cost of generating the IPSO-OPF method is USD

14,330/h. Thus, it can be seen that by using the IPSO-OPF method, the generation cost obtained is slightly cheaper than the generation cost using the PSO-OPF method.

Table 2. Comparison of the generation costs of the PSO-OPF and IPSO-OPF methods.

Methods	Active Power (MW)		Cost ($/h)		Active Power Losses (MW)	Total Cost ($/h)	Number of Iterations
	Gen 1	Gen 2	Gen 1	Gen 2			
PSO	191.7	74.28	9872	4459	12.58	14,331	69
IPSO	191.7	74.26	9872	4458	12.56	14,330	25

It can be seen from Table 2 that the IPSO-OPF method converges faster at the 25th iteration than the PSO-OPF method, which converges at the 69th iteration. The active power losses obtained using the IPSO-OPF method are also lesser than the PSO-OPF method. As for the cost of generation, the IPSO-OPF method also produces a generation cost that is cheaper than the cost of generating the PSO-OPF method. Therefore, overall, the performance of IPSO-OPF is superior to the conventional PSO-OPF in solving optimal power flow, especially since IPSO-OPF converges faster than the conventional PSO-OPF.

Figure 4 shows a comparison of the voltage profiles on each bus using the IPSO-OPF and PSO-OPF methods. It is obvious that the voltage magnitude obtained from the IPSO-OPF method on average is higher than the voltage magnitude using the PSO-OPF method; consequently, in general, the system voltage stability performance obtained using the IPSO-OPF method is better than the PSO-OPF method.

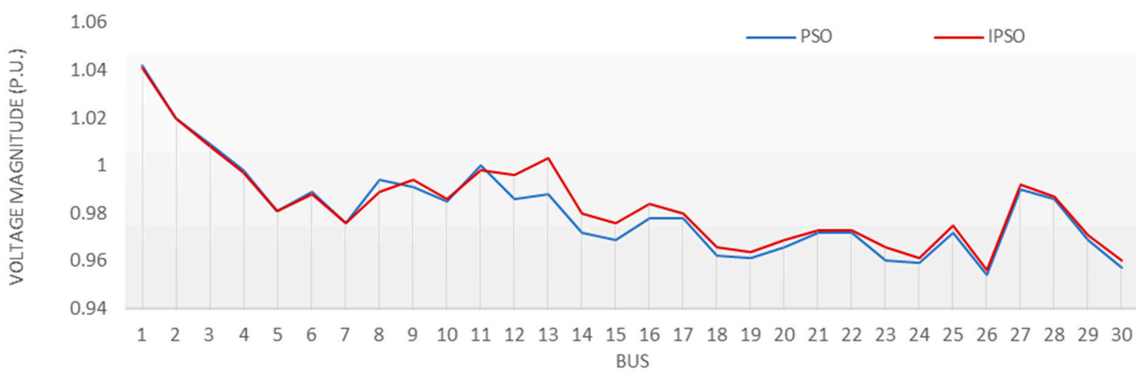


Figure 4. Voltage profile comparison between PSO-OPF and IPSO-OPF.

Voltage magnitudes, active power losses, and generation costs between the IPSO-OPF and PSO-OPF methods have values that are not much different. This is because the fundamental difference between the two methods is in the iteration speed to obtain a convergent value.

5. Conclusions

This paper proposes a new method for optimal power flow using incremental particle swarm optimization (IPSO). IPSO is the development of the metaheuristic PSO method in which incremental social learning (ISL) is implemented into the PSO algorithm. ISL is stirred by the phenomenon of societal learning in the society of animals. In IPSO, the population size grows from iteration to iteration. When a new particle joins the population, its position is adjusted using a "societal learning" rule that persuades a preference toward the best particle. The advantage of IPSO is that the population increases with each iteration so that the optimization process becomes faster. The simulation results using the IEEE 30-bus system show that the performance of IPSO-OPF is superior to conventional PSO-OPF in resolving the optimal power flow mainly because IPSO-OPF converges faster than conventional PSO-OPF. IPSO-OPF results in fewer iterations, lower active power loss, a better system voltage profile, and lower generation costs than the PSO-OPF method.

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