An Improved Particle Swarm Optimization Method to Optimal Reactive Power Flow Problems

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Abstract

This study proposes an improved particle swarm optimization method to find optimal power flow by using the power transmission loss as an objective function. In the literature, PSO is a well – known intelligent search method to handle the solution of optimal power flow problem. A novel scheme which is called Improved PSO (IPSO) is defined by modifying the initialization step of PSO algorithm and choosing the load bus voltages, generator active and reactive powers, line flow capacities as penalty functions in the objective function. PSO and IPSO-based optimal power flow solutions are compared with each other on IEEE 118 and 300 bus systems. According to the test results, the power loss obtained by IPSO-based solution has less power loss than PSO-based solution. This proposed method can be used to obtain faster desirable solutions and better power loss results for the optimal power flow problem in case of power loss minimization.

1. Introduction

Optimal reactive power flow (ORPF) is one of the major subjects of economic process of power system [1]. The goal of ORPF is to minimize objective function which is the active power loss in transmission lines via trying to find best adjustment of the power system variables while ensuring the security of the system and satisfying various equality and inequality constraints [2]. Power flow equations are used as equality constraints while limits on control variables, which are generator bus voltages, load bus voltages, reactive power output of generator, transformer tap settings, reactive power output of shunt compensators and line power flows of each branch, are handled as inequality constraints. Problems considering with ORPF has been argued for decades and various intelligence heuristic algorithms can be found in the literature such as Genetic Algorithm (GA), Evolutionary Programming (EP), and Particle Swarm Optimization (PSO) [3 - 6]. PSO algorithm is widely used one in the field of engineering. The most conspicuous advantage of PSO is its fast convergence speed [7]. Also difficulties related with limitations of mathematical programming increase the importance of PSO [8].

In this study, a new approach to compute ORPF by applying IPSO method is proposed. The main difference between PSO and IPSO algorithms is the determination of one of the particles of the initial swarm. The control variables used in the initial swarm are determined by load flow analysis in IPSO algorithm. Thus, the initial value of transmission loss can be decreased with these reasonable control variables.

IEEE 118 and 300 bus systems have been utilized for the analysis and the results indicate that IPSO is a more effective way to solve ORPF problems, by indicating fast feasible solution time and smaller value of transmission loss when compared with PSO.

2. Optimal Reactive Power Flow

2.1. Problem Formulation

The general optimal reactive power flow problem can be expressed as a constrained optimization problem as follows in (1):

$$\begin{array}{ll} \text{Minimize} & f(x), \text{ objective function} \\ \text{Subject to} & g(x) = 0, \text{ equality constraints} \\ & h(x) \le 0, \text{ inequality constraints} \end{array} \quad (1)$$

In the ORPF problem, both equality and inequality constraints are converted into penalty terms and then they are added to form the penalty function as shown in (2) below.

$$F(x) = f(x) + \Omega \quad (2)$$

$$\Omega = \rho\{g^2(x) + [\max(0, h(x))]^2\} \quad (3)$$

$$x = [P; Q; |V|; \delta; S; T, Q_{comp}] \quad (4)$$

where; $F(x)$ is objective function with penalty, $f(x)$ is objective function without penalty, Ω is the penalty function, ρ is the penalty factor, x is the vector of optimization variables, that consists of state and control variables, $g(x)$ are equality constraints, $h(x)$ are inequality constraints. The optimization variables consist of P, Q, |V|, θ, S, T, Q_{comp}. P is active power, Q is reactive power, |V| is bus voltage magnitude, S is line power flow capacity, T is transformer tap ratio, θ is bus voltage angle and Q_{comp} is reactive power source.

2.2. Objective Function

In this paper, the objective function is defined as power transmission loss function and it can be expressed as indicated in (5).

$$F_{loss} = \sum_{i=1}^{N_L} g_{i,j}\{|V_i^2|+|V_j^2| - 2|V_i||V_j|\cos(\delta_i - \delta_j)\} \quad (5)$$

where; the subscripts i, j show bus numbers, $|V_i|$, $|V_j|$ are the voltage magnitude at bus i and j respectively, $g_{i,j}$ is the conductance of line i-j, δ_i, δ_j are the voltage angle at bus i and j respectively, and N_L is the total number of transmission lines.

2.3. System Constraints

The objective is to minimize the transmission loss by chancing control variables within their limits. Hence, the system constraints, which are to be formed as equality (6) and (7), and inequality constraints from (8) to (12) as shown below, are needed.

2.3.1. Equality Constraint

This consists of power flow equations:

$$P_{G,i} - P_{D,i} - \sum_{j=1}^{N_B}|V_i||V_j||Y_{i,j}|\cos(\theta_{i,j} - \delta_i + \delta_j) = 0 \quad (6)$$

$$Q_{G,i} - Q_{D,i} + \sum_{j=1}^{N_B}|V_i||V_j||Y_{i,j}|\sin(\theta_{i,j} - \delta_i + \delta_j) = 0 \quad (7)$$

where;

$P_{G,i}$	is the real power generation at bus i
$P_{D,i}$	is the real power demand at bus i
$Q_{G,i}$	is the reactive power generation at bus i
$Q_{D,i}$	is the reactive power demand at bus i
N_B	is the total number of buses in the system
$\lvert V_i\rvert$, $\lvert V_j\rvert$	are the voltage magnitude at bus i and j respectively
$\theta_{i,j}$	is the angle of bus admittance element i, j
$\lvert Y_{i,j}\rvert$	is the magnitude of bus admittance element i, j.
δ_i, δ_j	are the voltage angle at bus i and j respectively

2.3.2. Inequality Constraints

These are composed of the limitations on variables.

$$V_i^{min} \le V_i \le V_i^{max} \quad (8)$$
$$T_i^{min} \le T_i \le T_i^{max} \quad (9)$$
$$Q_{comp,i}^{min} \le Q_{comp,i} \le Q_{comp,i}^{max} \quad (10)$$
$$P_{G,i}^{min} \le P_{G,i} \le P_{G,i}^{max} \quad (11)$$
$$S_{L,i} \le S_{L,i}^{max} \quad (12)$$

where;

$\lvert V_i^{min}\rvert, \lvert V_i^{max}\rvert$	are upper and lower limits of voltage magnitude at bus i
T_i^{min}, T_i^{max}	are upper and lower limits of tap position of transformer i
$Q_{comp,i}^{min}, Q_{comp,i}^{max}$	are upper and lower limits of reactive power source i
$P_{G,i}^{min}, P_{G,i}^{max}$	are upper and lower limits of active power generated by generator i
$S_{L,i}^{max}$	is apparent power flow limit of ith line

2.3.3. The Penalty Functions

These are added to the objective function. In this paper, only some of the inequality constraints are used as penalty functions. The main goal of penalty function is to maintain the system security. When power flow problem has too many constraints, sometimes a feasible solution cannot be obtained. To avoid this situation, some constraints are not enforced completely.

In this study, bus voltages, active power generations and line power flow capacities were chosen as penalty functions. Although constraints at penalty function can be violated, this violation should be very small and when violation at constraint increases, penalty function should increase quickly. Thus, quadratic penalty functions more suitable for ORPF problems are used in this study. The most significant advantage of quadratic penalty function is to control importance of constraint in ORPF by simply chancing value of penalty factor. Their equations are given in below as follows (13), (14), (15) and (16).

$$\Omega_V = \rho\sum_{i=1}^{N_B}\{\max(0, |V_i| - |V_i^{max}|)\}^2 + \rho\sum_{i=1}^{N_B}\{\max(0, |V_i^{min}| - |V_i|)\}^2 \quad (13)$$

$$\Omega_G = \rho\sum_{i=1}^{N_G}\{\max(0, P_{G,i} - P_{G,i}^{max})\}^2 + \rho\sum_{i=1}^{N_G}\{\max(0, P_{G,i}^{min} - P_{G,i})\}^2 \quad (14)$$

$$\Omega_S = \rho\sum_{i=1}^{N_L}\{\max(0, S_i - S_i^{max})\}^2 \quad (15)$$

$$\Omega_T = \Omega_V + \Omega_G + \Omega_S \quad (16)$$

where;

Ω_V	is the penalty function for bus voltages
Ω_G	is the penalty function for active power generations
Ω_S	is the penalty function for line power flow capacities
Ω_T	is the summation of three penalty functions
N_G	is the total number of generators.

3. Improved Particle Swarm Optimization for Optimal Reactive Power Flow

PSO is a population-based optimization search algorithm. It was first introduced by Kennedy and Eberhart in 1995 [9]. PSO is based on the behavior of individuals of swarm. In PSO, potential solutions are called particles and the population of particles is called swarm. In research space, each particle in PSO changes its position with time and moves to optimum position by updated velocity. To find the position and velocity of each particle, the equations are given in (17) and (18):

$$v_i^{(m+1)} = wv_i^{(m)} + c_1r_1(p_{best} - x_i^{(m)}) + c_2r_2(g_{best} - x_i^{(m)}) \quad (17)$$

$$x_i^{(m+1)} = x_i^{(m)} + v_i^{(m+1)} \quad (18)$$

where;

$v_i^{(m)}$	is the velocity of ith particle at mth iteration,
w	is inertia weight of the particle,
c_1, c_2	are positive constants having values between [0, 2.5],
r_1, r_2	are randomly generated numbers between [0, 1],
p_{best}	is the best position of the ith particle obtained based upon its own experience,
g_{best}	is global best position of the particle in the population
$x_i^{(m)}$	is the position of ith particle at mth iteration,

m	is the iteration index.

Suitable selection of inertia weight provides good balance between global and local explorations. It can be formulated as follows in (19):

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} iter \quad (19)$$

where;

w_{max}	is the value of inertia weight at the beginning of iteration
w_{min}	is the value of inertia weight at the end of iteration
$iter$	is the current iteration number
$iter_{max}$	is the maximum number of iterations.

The process of particle swarm optimization algorithm can be summarized as shown in Fig. 1. As it can be seen from equation (18) and flowchart, velocity and position have major role on this optimization technique.

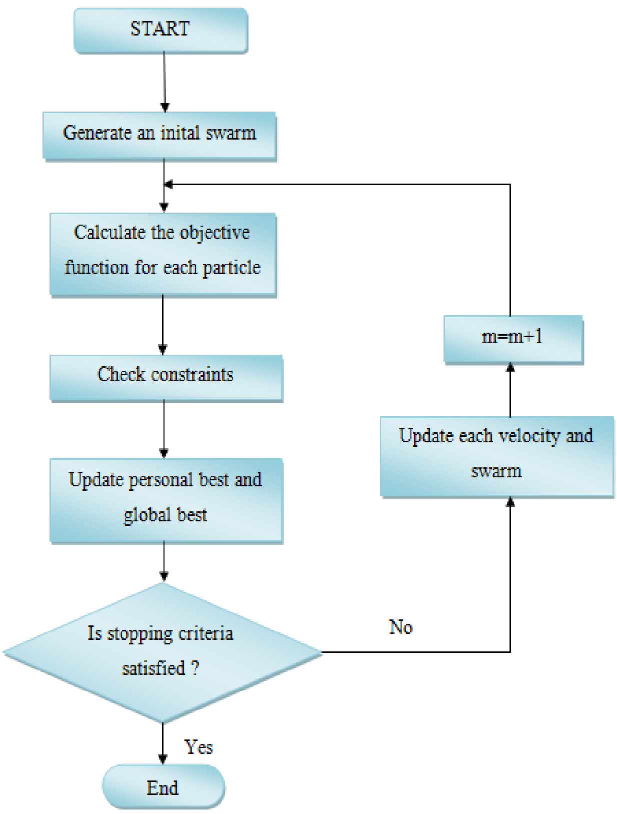

Fig. 1. Flowchart of PSO Process

In PSO algorithm, better results are obtained by following each iteration depending on particles' optimum position. If logical position for a particle is added to the initial swarm, the value of objective function starts with better values and moves to much better values with each iteration. Thus, improvement is done on initial position of swarm by adding chosen control variables as a particle to the swarm while PSO algorithm remained same in this study. These chosen values are obtained by computing the power flow via Matpower package function runpf [10]. By doing so, not only reduced initial transmission power loss was obtained, but also optimization process was resulted with better values.

4. Test and Results

In this study, simulations were performed by using Matpower package via Matlab software. For comparison purposes, both conventional particle swarm optimization and the proposed scheme, which is improved particle swarm optimization, were applied to solve test cases.

Each method was challenged by solving a given optimal reactive power flow problem of 40 trials randomly. To confirm the efficiency of IPSO, firstly IEEE 118 bus system as shown in Fig. 2 was tested. Related information about the test system is given in Table 1.

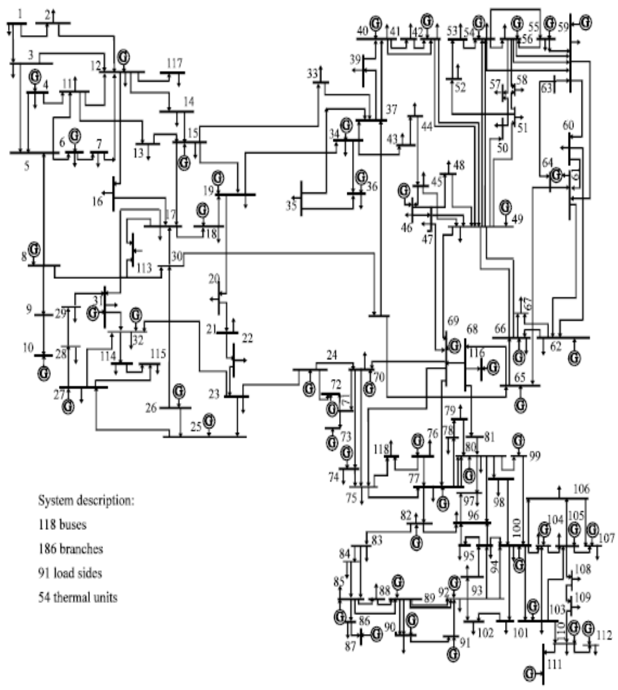

Fig. 2. IEEE 118 bus system

Table 1. IEEE 118 system data

Type of device	Number of devices
Bus	118
Generator	54
Branch	186
Transformer	9

Control variable limits used as system constraints during the simulations are given in Table 2.

Table 2. Variable limits for the IEEE 118 bus system

Variables	Limits	
	Min.	Max.
Generator Bus Voltage (p.u.)	0.94	1.06
Tap Ratio	0.95	1.05
Reactive Power Source (MVAr)	-40	20

For IEEE 118 bus system, best values of test results depending on two different particle numbers are shown in Table 3.

Table 3. IEEE 118 bus system power transmission losses

Method	Power Transmission Losses (MW)	
	Number of the Particle	
	15	50
PSO($iter_{max}$=25)	118.8	118
IPSO($iter_{max}$=25)	116.3	116.2
PSO($iter_{max}$=100)	118.3	117.7
IPSO($iter_{max}$=100)	115.6	115.3

To better understand positive effects of IPSO, IEEE 300 bus system was also tested and not only the best value of test results, but also worst and average values were calculated. IEEE 300 bus system information and control variable limits for the system are given in Table 4 and Table 5 respectively.

Table 4. IEEE 300 system data

Type of device	Number of devices
Bus	300
Generator	69
Branch	411
Transformer	107

Table 5. Variable limits for the IEEE 300 bus system

Variables	Limits	
	Min.	Max.
Generator Bus Voltage (p.u.)	0.94	1.06
Tap Ratio	0.95	1.05
Reactive Power Source (MVAr)	-300	325

Depending on two different particle numbers, best, worst and average values of test results are shown in Table 6 and Table 7.

Table 6. IEEE 300 bus system power transmission losses for 15 particles

Method	Power Transmission Losses (MW)		
	Worst	Average	Best
PSO($iter_{max}$=25)	441.8	429.6	420.3
IPSO($iter_{max}$=25)	406.4	403.1	397.6
PSO($iter_{max}$=100)	424.6	419.4	405.9
IPSO($iter_{max}$=100)	401.7	399	391.7

Table 7. IEEE 300 bus system power transmission losses for 50 particles

Method	Power Transmission Losses (MW)		
	Worst	Average	Best
PSO($iter_{max}$=25)	427.8	424.2	416.7
IPSO($iter_{max}$=25)	405.7	400.4	391.3
PSO($iter_{max}$=100)	423.6	415.3	404.4
IPSO($iter_{max}$=100)	400.1	398.5	390.2

Fig. 3 and Fig.4 show the comparison between PSO and IPSO in terms of power transmission losses for IEEE 300 bus system.

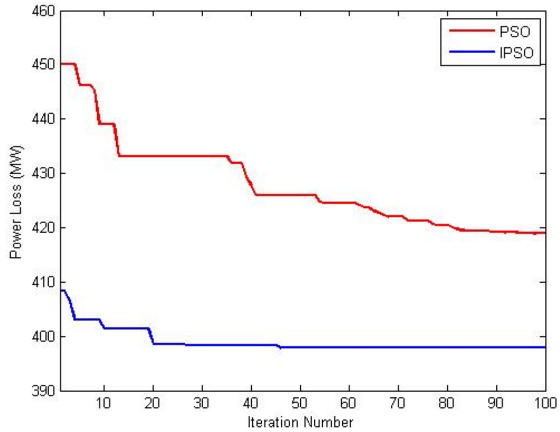

Fig. 3. The comparison between PSO and IPSO in terms of power transmission losses for 15 particles on IEEE 300 bus system

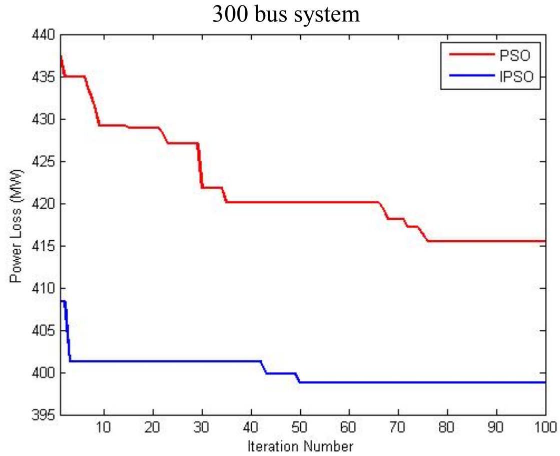

Fig. 4. The comparison between PSO and IPSO in terms of power transmission losses for 50 particles on IEEE 300 bus system

When IPSO method is used on the solution of the problem instead of PSO method, it takes less iteration to reach the minimum power loss. It means that IPSO method not only has the shorter solution time but also ensures the minimum power loss for OPRF problem. IPSO solution was utilized on the systems with increased size and as expected, better values in terms of power loss were obtained.

6. Conclusions

In this paper, IPSO and PSO methods have been used for solving ORPF problem. Both of these methods have been formulated with minimization of transmission power loss and they have been tested on IEEE 118 and IEEE 300 bus systems. The results show that IPSO method is constantly outperforming when compared to conventional PSO in terms of value of power loss. Thus IPSO for computing ORPF problems has better solution efficiency. In addition to this advantage, the better solution is obtained in the less iteration number. When system size is increased, the benefits of the IPSO method on ORPF problem are seen more obviously.

7. References

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