

Reactive Power Cost Optimization Using Improved Particle Swarm Optimization

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Abstract—Reactive power optimization (RPO) has an important role to play in the operation of power system. In this paper, the objective is to minimize the real power losses of the network along with the minimization of the investment cost associated with the reactive power sources. Lately, particle swarm optimization (PSO) is gaining more attention due to its convergence properties and ability to attain global optimal solution. In this paper, to solve the RPO problem an improved particle swarm optimization (IPSO) is used. The proposed approach is tested for RPO problem on standard IEEE 14-bus system and IEEE 30-bus system, proves that the improved PSO algorithm used in this paper for reactive power optimization gives better results. The proposed algorithm is simple, have higher convergence and thus suitable for solving reactive power optimization problems in the power system network.

Key words— Particle swarm optimization, improved particle swarm optimization and Reactive power optimization

1 INTRODUCTION

Main objective of a power system is to meet the load demand to the maximum extent with the available generation in an economic, secure and reliable manner. The load consists of both active and reactive elements, even the transmission of power over AC circuits also involves reactive elements and the generation of power also have the reactive participation. Therefore it is very important to monitor and control the reactive power sources and reactive power consuming elements to maintain proper voltages in the grid within their permissible limits. Voltage is an important factor for measuring the security and economy of the power system, while the reactive power is an important measure in affecting the voltage level. The reactive power should be reasonably distributed in the network to ensure the voltage quality. The rational flow of reactive power in the system helps in maintaining the reactive power balance to ensure the voltage quality improves the system stability and security, reduces the power loss, access to economic benefits. Thus reactive power optimization has a prime concern in power systems.

Reactive power optimization of power system is the structure of system parameters and load conditions under given Conditions; in order to meet the system operation mode constraint as a precondition through the optimization system variables to maximize system voltage stability to improve the voltage quality and reduce network losses [1]. As a part of power system's planning, reactive power optimization utilizes the voltage to control power system network, improves grid stability, reduces the network loss and through reactive power compensation it ensures a wider operating margin.

For solving different optimization problems, there is no particular optimization method available. In recent years plenty of optimization techniques have been established for solving different kinds of optimization problems. Linear programming (LP) [2-3], Non-linear programming (NLP) [4] and gradient based techniques are the traditional optimization techniques for solving Reactive Power optimization problems. But these traditional solution strategies suffer from algorithmic complexity, slow convergence rate, less accuracy and they converge to a local optimal solution instead of the global one. Hence evolutionary techniques are recommended for solving optimization problem. These methods include Evolutionary Programming (EP) [5], Genetic Algorithm (GA) [6], Neural Networks, Ant Colony Optimization (ACO) [7], Particle Swarm Optimization (PSO) [8-9] are used for setting the optimal reactive power limits.

Particle Swarm Optimization (PSO) was introduced by Kennedy and Eberhart [10]. PSO is an evolutionary computation method, which is inspired by social behavior of bird flocking and fish schooling. PSO provides a population based search procedure in which particles change their position with time. Each particle stores its best position and global best position obtained from its neighbors in its memory. Processing optimization problem with continuous variables and discrete variables with this method has more advantages comparatively. PSO is a very effective method for solving RPO problem. But PSO algorithm converges too fast, which gives access to a local

optimal solution. Hence the accuracy of getting a global optimal solution is not high.

In this paper, an improved PSO [11-12] has been presented, where inertia weight, shrinkage factor [13], neighbourhood model [14] are added into the traditional PSO algorithm and the improved PSO have a tendency to jump out of local optimal solution than the basic PSO, thus converge to a better solution, and improves the accuracy of convergence. Therefore, it is tested on standard IEEE 14 and IEEE 30 bus systems and its results shows that this method is effective.

2 MATHEMATICAL MODEL OF POWER SYSTEM REACTIVE POWER OPTIMIZATION

2.1 Objective function

2.1.1 Minimization of reactive power cost and active power loss cost

The objective of RPO is to minimize the real power loss in the transmission lines and the cost related to reactive power generation and the system active power loss. The cost of reactive power in the entire system includes the amount paid to generator units for their VAR support, the amount paid to reactive power compensators and the total cost of system real power loss. Mathematically, the RPO problem can be expressed as [15]:

$$\text{Min } f = \sum_{i \in N_G} C_{gqi}(Q_{gi}) + \sum_{j \in N_C} C_{cj}(Q_{cj}) + h \cdot P_{\text{loss}} \quad (1)$$

Where,

$$P_{\text{loss}} = \sum_{\substack{K \in N_L \\ K=(i,j)}} G_K (V_i^2 + V_j^2 - 2V_i V_j \cos \theta_{ij})$$

P_{loss} represents the mathematical model of active power loss. In eq. 1 the first part represents the cost paid to generator units for their VAR support, the second part represents the cost paid to the VAR support of the reactive power compensators and the last part represents the cost of system real power losses. h is a constant.

Reactive power cost of generators:

Generators provide reactive power support by consuming or supplying it with leading or lagging power factors. The reactive power production cost of generators is the opportunity cost of generator. For example, if a generator has to decrease its active power production in order to produce more reactive power, which reduces the opportunity of obtaining profits from the active power market. The opportunity cost is represented by the following equation [16].

$$C_{gqi}(Q_{gi}) = [C_{gpi}(S_{gi}^{\text{max}}) - C_{gpi}(\sqrt{S_{gi}^{\text{max}2} - Q_{gi}^2})]K_{gi} \quad (2)$$

Where,

Q_{gi} - the reactive power output of generator i ;

S_{gi}^{max} - maximum apparent power of generator i ;

K_{gi} - the assumed profit rates for active power generation at bus i ;

C_{gpi} - the active power production cost, which is modelled as a quadratic function

$$C_{gpi}(P_{gi}) = aP_{gi}^2 + bP_{gi} + c \quad (3)$$

Here P_{gi} is the active power output of generator i ; in eq.3 it is assumed that the generator is running at its full capacity.

Cost of reactive power compensators:

The reactive power compensators used here are assumed as static capacitors, owned by private investors, installed at some selected buses. The amount charged for using reactive compensators is assumed to be proportional to the amount of the reactive power output purchased and can be expressed as [16]:

$$C_{cj}(Q_{cj}) = r_j Q_{cj} \quad (4)$$

Where,

r_j - The reactive cost

Q_{cj} - The reactive power purchased

The depreciation rate of the capacitors can be set as the reactive price. The production cost of a capacitor is assumed as its capital investment return, which can be expressed as its depreciation rate. For example, if the investment cost of a capacitor is \$11600/MVA and their average working rate and life span are 2/3 and 15 years, respectively, the cost or depreciation rate of the capacitor can be calculated by [17]:

$$r_j = \frac{\text{investment cost}}{\text{operating hours}} = \frac{\$11600}{15 * 365 * 24 * 2/3} = \$0.1324/\text{MVAh}$$

2.2 Constraints

The objective function in eq.1 is subjected to the following equality and inequality constraints [18]:

Real power balance equation

$$P_i - V_i \sum_{j=1}^{N_B} V_j [G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}] = 0 \quad (5)$$

$$i = 1, 2, \dots, N_{B-1}$$

Reactive power balance equation

$$Q_i - V_i \sum_{j=1}^{N_B} V_j [G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}] = 0 \quad (6)$$

$$i = 1, 2, \dots, N_{PQ}$$

Slack bus real power generation limit

$$P_s^{\text{min}} \leq P_s \leq P_s^{\text{max}} \quad (7)$$

Generator reactive power generation limit

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max} \quad (8)$$

$$i \in N_{pv}$$

Bus voltage limits

$$V_i^{min} \leq V_i \leq V_i^{max} \quad (9)$$

$$i \in N_B$$

Transformer tap limit

$$t_k^{min} \leq t_k \leq t_k^{max} \quad (10)$$

$$i \in N_T$$

Line flow limits

$$S_l = S_l^{max} \quad (11)$$

$$l \in N_l$$

Shunt compensator limits

$$Q_{shi}^{min} \leq Q_{shi} \leq Q_{shi}^{max} \quad (12)$$

$$i \in N_{sh}$$

Where,

P_s^{max} And P_s^{min} are maximum and minimum real power limits of slack generator.

Q_g^{max} And Q_g^{min} are maximum and minimum reactive power limits of generators except slack generator.

V^{max} And V^{min} are maximum and minimum voltage limits of bus.

t^{max} And t^{min} are maximum and minimum tap setting limits of transformer.

Q_{sh}^{max} And Q_{sh}^{min} are maximum and minimum shunt compensator limits.

S^{max} is Maximum transmission line thermal limit.

From the mathematical formulation of the RPO problem, it is found that it is a non-linear optimization problem. Conventional optimization techniques are not efficient in solving this complex optimization problem. The details of the PSO and IPSO-based approach for solving this complex optimization problem are presented in next sections.

3 BASIC PARTIAL SWARM OPTIMIZATION

Kennedy and Eberhart developed the basic Particle Swarm Optimization algorithm in 1995 [12] based on the behaviour of bird flocking and fish schooling. Particle swarm optimization (PSO) method a population-based search algorithm. In PSO, the population is called Swarm and the individuals are called particles. Particles fly through an N dimensional search space with some velocity. The particles need to update two extremes in each round of iteration, one is the individual extreme which is the accumulation of their own experience of the individual, and the other one is the global extreme which is the accumulation of the group experience. The velocity with which the particles fly and the updated position is given by

$$V_{ij}(t+1) = V_{ij}(t)$$

$$+ C_1 r_{1j}(t) (P_{ij}(t) - x_{ij}(t)) \quad (13)$$

$$+ C_2 r_{2j}(t) (P_{gj}(t) - x_{ij}(t))$$

$$x_{ij}(t+1) = x_{ij}(t) + V_{ij}(t+1) \quad (14)$$

where i is the number of particles, j is the dimensional number of particles, t is the iteration number, C_1 and C_2 are the accelerating factors, they are usually between 0 to 2, r_1 and r_2 are the independent random variables in the range [0,1], $x_i=(x_{i1}, x_{i2}, \dots, x_{in})$ is the current position of the i particle, $v_i=(v_{i1}, v_{i2}, \dots, v_{in})$ is the current velocity of the i particle, $p_i=(p_{i1}, p_{i2}, \dots, p_{in})$ is the best position that the i particle has passed in the movement, and $p_g=(p_{g1}, p_{g2}, \dots, p_{gn})$ is the best position that all the particles have passed in the movement. By analyzing the basic PSO algorithm in eqn.4 and 15, we can see the factors C_1 and C_2 make the particles move to the direction toward the individual and global optimal position.

4 IMPROVEMENT OF BASIC PARTICLE SWARM ALGORITHM

PSO algorithm convergence fast, but it has some shortcomings such as easy accessing to local convergence and low convergence precision. This is because in the optimal process, all particles consider the optimal particle as the goal, then search toward the same direction, which lead to lose the ability to explore unknown area. Therefore, basic particle swarm algorithm need to make some expansion and modification.. The main improvement measures are as follows:

4.1 Inertia weight

To improve the convergence performance of PSO algorithm, Shi and Eberhart introduced inertia weight in speed evolution equation:

$$V_{ij}(t+1) = wV_{ij}(t)$$

$$+ C_1 r_{1j}(t) (P_{ij}(t) - x_{ij}(t)) \quad (15)$$

$$+ C_2 r_{2j}(t) (P_{gj}(t) - x_{ij}(t))$$

Where W is called inertia weight, W is a scale factor which is related with the previous speed, it controls the impact of previous iteration speed on to the next iteration velocity. Higher the value of W, results in global search whereas lower the value of W results in local search. So if using a same value of W in the whole process of PSO iterations, the algorithm cannot be easily suitable for global search and local search. In this paper, W will decrease linearly from 0.9 to 0.4 in the whole iteration process: Specific improvement measures are as follows:

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} k \quad (16)$$

w_{max} and w_{min} are the max and min values of w and $iter_{max}$ is the maximum no. of iterations where k is the current iteration.

4.2 Shrinkage factor and neighbourhood model

Shrinkage factor:

Clerc has introduced a constriction factor K , stating in order to improve the convergence of PSO shrinkage factor should be included. He developed a mathematical model to explain the behaviour of simple PSO model in its search for an optimal solution to insure the convergence of the PSO algorithm, the velocity of the constriction factor based approach can be expressed as follows:

$$V_{ij}(t+1) = K(wV_{ij}(t) + C_1r_{1j}(t)(P_{ij}(t) - x_{ij}(t)) + C_2r_{2j}(t)(P_{gj}(t) - x_{ij}(t))) \quad (17)$$

Among them, the shrinkage factor is:

$$K = \frac{2}{|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}|} \quad (18)$$

$$\varphi = C_1 + C_2, \varphi > 4 \quad (19)$$

φ is used to control the convergence of the system and φ should be greater than 4 to ensure stability. Research has shown that introducing the shrinkage factor to control particle velocity evolution equation usually has better convergence.

Neighbourhood model:

In an individual social cognitive system, apart from their own experience and excellent information absorbed from the whole society, an individual generally learns from their best neighbourhood. Based on this idea, the neighbourhood mode of PSO algorithm is introduced which improves the social cognitive system of PSO algorithm. This approach results in changes in the velocity update equations, although the position update equations remain unchanged in this model. Its velocity equation is :

$$V_{ij}(t+1) = wV_{ij}(t) + C_1r_{1j}(t)(P_{ij}(t) - x_{ij}(t)) + C_2r_{2j}(t)(P_{gj}(t) - x_{ij}(t)) + C_3r_{3j}(t)(P_{nj}(t) - x_{ij}(t)) \quad (20)$$

Where C_3 is an accelerating constant, r_3 is a random number in the range $[0, 1]$; p_{nj} is the position vector of the best individual in domain. The two principals used in choosing a neighbourhood particle, firstly it must be adjacent to it and its fitness should be higher than other particles.

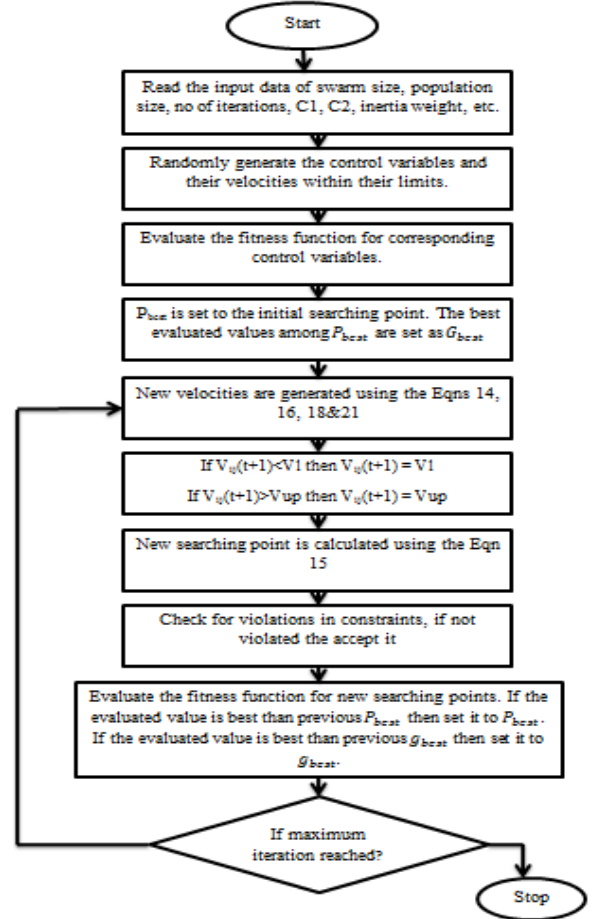
Shrinkage factor+ Neighbourhood model:

By observing the behaviour of both shrinkage factor and neighbourhood mode a new approach is presented in this paper by adding the neighbourhood features and shrinkage factor to the velocity of the particles to improve the convergence criteria and reach to a global optimal solution. The velocity equation of this approach is shown below:

$$V_{ij}(t+1) = K(wV_{ij}(t) + C_1r_{1j}(t)(P_{ij}(t) - x_{ij}(t)) + C_2r_{2j}(t)(P_{gj}(t) - x_{ij}(t)) + C_3r_{3j}(t)(P_{nj}(t) - x_{ij}(t))) \quad (21)$$

Where K is the shrinkage factor shown in eq.19 and C_3 is an accelerating constant, r_3 is a random number in the range $[0, 1]$; p_{nj} is the position vector of the best individual in domain.

5 REACTIVE POWER OPTIMIZATION USING IMPROVED PARTICLE SWARM ALGORITHM



6 RESULTS AND DISCUSSIONS

Programs are written in MATLAB® programming language for the proposed method. The program is tested on both IEEE 14 bus test system and IEEE 30 bus test systems

[19] and the results obtained are presented in the tables below.

6.1 IEEE 14 Bus system

Table.1: Solution for Reactive power Optimization for IEEE 14 bus test system.

	Base Case Load flow Solution	RPO using PSO	RPO using PSO with Inertia weight	RPO using PSO with Shrinkage Factor & Neighborhood Model
Real loss (MW)	13.386	12.507	12.489	12.472
Loss cost (\$/hr)	401.58	375.224	374.657	374.167
Generator cost (\$/hr)	8.11	7.36	5.049	4.118
Capacitor cost (\$/hr)	2.81	2.347	3.650	2.573
Total cost (\$/hr)	412.49	384.93	383.357	381.01

Table.2: Control variables for IEEE 14 Bus system

Control variables	Base Case Load flow Solution	RPO using PSO	RPO using PSO with Inertia weight	RPO using PSO with Shrinkage Factor & Neighborhood Model
V1	1.06	1.1	1.1	1.1
V2	1.045	1.0825	1.077	1.075
V3	1.01	1.0409	1.0464	1.039
V6	1.07	1.0564	1.0572	1.059
V8	1.09	1.0546	1.0459	1.068
Q _{sh9}	-21.20	-17.73	-27.57	-19.43
T ₄₋₇	0.978	1.0170	0.9909	1.0158
T ₄₋₉	0.969	0.9386	0.9938	0.9603
T ₅₋₆	0.932	0.9682	0.9928	0.9732

6.2 IEEE-30 bus test system

Table.3: Solution for Reactive power Optimization for IEEE 30 bus test system.

	Base Case Load flow Solution	RPO using PSO	RPO using PSO with Inertia weight	RPO using PSO with Shrinkage Factor & Neighborhood Model
Real power loss (MW)	17.559	16.146	16.132	16.131
Loss cost (\$/hr)	526.76	484.376	483.95	483.92
Genreactive cost (\$/hr)	16.353	13.452	9.247	9.259
Capacitor cost (\$/hr)	3.340	5.032	5.251	5.270
Total cost (\$/hr)	546.45	502.861	498.45	498.45

Table.4: Control variables for IEEE 30 bus

Control variables	Base Case Load flow Solution	RPO using PSO	RPO using PSO with Inertia weight	RPO using PSO with Shrinkage Factor & neighborhood model
V1	1.06	1.10	1.1	1.1
V2	1.04	1.081	1.0804	1.0805
V5	1.01	1.041	1.036	1.036
V8	1.01	1.046	1.04	1.042
V11	1.08	1.036	1.083	1.080
V13	1.07	1.08	1.078	1.078
Q _{sh10}	-20.74	-27.77	-27.95	-27.95
Q _{sh24}	-4.49	-10.24	-11.71	-11.86
T ₆₋₉	0.978	1.0058	1.0123	1.020
T ₆₋₁₀	0.969	0.9710	1.0134	1.001
T ₄₋₁₂	0.932	0.9919	0.9857	0.9854
T ₂₈₋₂₇	0.968	0.9752	0.9667	0.9670

From Table 1 & 3 it can be observed that using Inertia weight in PSO method, better convergence of the PSO method in solving RPO problem for the two test systems considered can be felt in terms of cost and losses. The control variables of the two test systems are presented in Tables 2 & 4. The convergence characteristics prove the reliability and efficiency of the proposed method.

7 CONCLUSION

Now a day's power system optimization problems are being solved using PSO techniques, due to its better convergence properties and robustness. It was also observed that variants of PSO method like the Improved Particle Swarm optimization are also yielding competitive results when compared to PSO [20]. The present work solved the Reactive power optimization problem using IPSO. From the results obtained by the developed programs, it is clear that the real power loss and the cost of reactive sources obtained by PSO and its variant are better than the base case results. The results also show that IPSO gave better result in solving Reactive power Optimization problem for IEEE 14 bus and 30 bus systems. This proves that the IPSO approach gives accurate results, has higher convergence and gives a global optimal solution than the basic PSO algorithm when used for solving RPO problem. This might be by virtue of its shrinkage factor and neighbourhood model approach, which helps to attain global optimal solution.

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