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# Comprehensive learning particle swarm optimization for reactive power dispatch

K. Mahadevan [a,*], P.S. Kannan [b]

[a] Electrical & Electronics Engineering, Kalasalingam University, Krishnankoil – 626 190, Tamilnadu, India
[b] Electrical & Electronics Engineering, Thiagarajar College of Engineering, Madurai – 625 015, Tamilnadu, India

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ABSTRACT

Reactive power dispatch (RPD) is an optimization problem that reduces grid congestion by minimizing the active power losses for a fixed economic power dispatch. RPD reduces power system losses by adjusting the reactive power control variables such as generator voltages, transformer tap-settings and other sources of reactive power such as capacitor banks and provides better system voltage control, resulting in an improved voltage profile, system security, power transfer capability and over all system operation. In this paper, RPD problem is solved using particle swarm optimization (PSO). To overcome the drawback of premature convergence in PSO, a learning strategy is introduced in PSO, and this approach called, comprehensive learning particle swarm optimization (CLPSO) is also applied to this problem and a comparison of results is made between these two. Three different test cases have been studied such as minimization of real power losses, improvement of voltage profile and enhancement of voltage stability through a standard *IEEE* 30-bus and 118-bus test systems and their results have been reported. The study results show that the approaches developed are feasible and efficient.



## 1. Introduction

The reactive power dispatch (RPD) problem is an optimization problem of noncontinuous and nonlinear functions with uncertainties arising out of large-scale power systems [18]. RPD is a very important aspect of power systems. The loads require reactive power for magnetizing purposes at no load conditions. On loads, reactive power is required depending on the nature of the load, which is primarily decided by the magnetic circuit configuration. Reactive power requirement changes continuously with load and voltage level. Voltage control in a power system is mainly related to the control of reactive power. RPD in addition to control of reactive power in the power system may have such advantages as reduction of real-power losses and improvement of power factor in the distribution system [2]. Reactive power/voltage control in the power system can be achieved by employing reactive power compensation devices such as shunt inductors, shunt capacitors, series capacitors, static VAR compensators (SVCs), tap changing of transformers, and automatic voltage regulators (AVRs). The purpose of the RPD problem is to minimize the real-power losses and improve the voltage profile by regulating the generator bus voltage, switching on or off SVCs, changing tap-settings of the transformer, and so on. This is a complex combinatorial optimization problem involving nonlinear functions having multiple local minima and nonlinear and discontinuous constraints.

The problem of reactive power/voltage control using conventional optimization methods (e.g., linear programming [3,7,10,27,28], nonlinear programming [30], mixed-integer programming [6,11,12,20], decomposition technique [9], dynamic programming [24]) has been studied. Hsiao et al. [13] provided an approach for the simulated annealing method using the modified fast decoupled power flow to solve VAR planning problem. However, only the new configuration (VAR installation) is checked with the load flow, and existing resources such as generators and regulating transformers are not fully exploited. Some new methods based on artificial intelligence have been used in RPD to solve local minimum problems and uncertainties [1,25,31]. The advantages of evolutionary algorithms in terms of the modeling capability and search power have encouraged their application to the RPD problem in power systems [14,19,21,26,32]. Iba [14] presents probably the first application of genetic algorithms (GA) for the RPD problem. The method decomposes the system into a number of sub-systems and employs interbreeding between the subsystems to generate new solutions. All the controller states, including those with a continuous nature, are discretized and represented as integer values. Lee and Park [21] present a modified simple GA for reactive power planning. The population selection and reproduction use Bender's cut in the decomposed system and successive linear programming is used to solve the operational

* Corresponding author. Tel.: +91 4563 289042; fax: +91 4563 289322.
*E-mail addresses:* mahadevand@rediffmail.com (K. Mahadevan), psk_kannan@yahoo.co.in (P.S. Kannan).

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optimization sub-problems. However, a binary representation of control variables introduces an element approximation at the representation stage itself. Ma and co-workers [19,26,32] present an evolutionary programming (EP) approach for solving RPD. The technique uses a floating point representation for control variables. Mutation, used with an adaptive probability is the only reproduction operator in the technique. An inner loop is used for function minimization without any consideration for constraints. Constraint satisfaction is carried out in an outer loop. Non-feasible solutions in the outer loop are rejected by attaching a penalty to their fitness values. Yoshida et al. [34] have presented a PSO for reactive power and voltage control and compared their results with the reactive tabu system (RTS) and enumeration method on a practical power system.

This paper proposes the application of PSO and CLPSO to solve the RPD problem. Standard test systems of *IEEE* 30-bus system and *IEEE* 118-bus system have been employed to carry out the simulation study. Both the PSO and CLPSO methods perform well in such systems for RPD and give satisfactory results. The study involves different objectives like minimization of voltage deviations in all load buses and improvement of voltage stability apart from the prime objective of minimization of real-power losses.

## 2. Problem formulation

The objective of the reactive power dispatch is to minimize the active power losses of the system which can be described as follows:

$$\min P_{\text{loss}} = \sum_{\substack{k \in N_E \\ k=(i,j)}} g_k(U_i^2 + U_j^2 - 2U_iU_j\cos\theta_{ij}) \tag{1}$$

subjected to equality constraints

$$0 = P_i - U_i \sum_{j \in N_i} U_j(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) \quad i \in N_{B-1} \tag{2}$$

$$0 = Q_i - U_i \sum_{j \in N_i} U_j(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}) \quad i \in N_{PQ} \tag{3}$$

and a set of inequality constraints

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max}, \quad i \in N_g \tag{4}$$

$$T_k^{\min} \le T_k \le T_k^{\max}, \quad k \in N_T \tag{5}$$

$$U_i^{\min} \le U_i \le U_i^{\max}, \quad i \in N_B \tag{6}$$

where $N_E$ is the number of branches; $N_i$ is the number of buses adjacent to bus $i$, including bus $i$; $N_{PQ}$ is the number of $PQ$ buses, which are load buses with constant $P$ and $Q$ injections; $N_g$ is the number of generator buses; $N_T$ is the number of tap-setting transformer branches; $N_B$ is the total number of buses; $N_{B-1}$ is the total number of buses, excluding slack bus; $g_k$ is the conductance of branch $k$; $U_i$ is the voltage magnitude at bus $i$; $\theta_{ij}$ is the voltage angle difference between bus $i$ and bus $j$ (rad); $P_i$, $Q_i$ are the real and reactive powers injected into network at bus $i$; $G_{ij}$, $B_{ij}$ mutual conductance and susceptance between bus $i$ and bus $j$; $G_{ii}$, $B_{ii}$ are the self-conductance and susceptance of bus $i$; $Q_{gi}$ is the reactive power generation at bus $i$; $T_k$ is the tap-setting of transformer branch $k$.

## 3. Overview of PSO and CLPSO

PSO developed by Eberhart and Kennedy [16] is one of the evolutionary computation techniques. PSO, like GA, is a population-based optimization algorithm. The swarm initially has a population of random solutions. Each potential solution, called particle, is given a random velocity and is flown through the solution space. The particles have memory and each particle keeps track of its previous best position, called *pbest* and corresponding fitness. The swarm remembers another value called *gbest*, which is the best position discovered by the swarm. Velocity and position of the particles are changed according to Eqs. (7) and (8) respectively.

$$\begin{aligned} V_{jd}^{(k+1)} = & wV_{jd}^{(k)} + c_1 \times rand \times (Pbest_{jd} - X_{id}^{(k)}) \\ & + c_2 \times rand \times (gbest_d - X_{jd}^{(k)}) \end{aligned} \tag{7}$$

$$X_{jd}^{(k+1)} = X_{jd}^{(k)} + V_{jd}^{(k+1)}, \quad j = 1, 2, \ldots, m \tag{8}$$

where $V_{jd}$ and $X_{jd}$ represent the velocity and position of $d$th dimension of $j$th particle respectively and '*rand*' is a uniform random number in the range $[0, 1]$. Inertia weight $w$ is set according to the following equation:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \tag{9}$$

where '$iter_{\max}$' is the maximum number of iterations, and '*iter*' is the current number of iterations.

Clerc [8] proposed the use of a constriction factor approach in PSO and modified the velocity such that $V_i^{k+1} = \chi V_i^k$, where $\chi$ is called constriction factor. However, this method, unlike other EC methods ensures the convergence of search procedures based on the mathematical theory. It considers only dynamic behavior of one agent and the effect of the interaction among agents. Moreover, the equations were developed with fixed best positions (*pbests* and *gbest*) although *pbests* and *gbest* can be changed during search procedure in the basic PSO equations.

Angeline [5] introduced a natural selection mechanism in PSO and this method is called hybrid PSO (HPSO). HPSO uses the basic concept of PSO such as velocity updating, position modification and the selection mechanism of EC techniques. In competitive selection process, the agents with worst fitness function values are replaced by those one with better fitness function values, whereas in simple PSO the searching point is changed successively from the knowledge obtained from *pbest* and *gbest*. The main feature of other PSO methods that preserves all the particles (irrespective of their fitness values) to next iteration is not maintained in this algorithm.

Recently, cooperative PSO becomes increasingly popular among the researchers and this technique splits the solution vector into small vectors, where each sub-vector is optimized using a separate PSO. Again the performance of this algorithm depends on one more parameter called 'split factor'.

Though there are numerous PSO variants, premature convergence is still the main deficiency of the most PSO based algorithms [20]. In the original PSO, each particle learns from its *pbest* and *gbest* simultaneously and its social learning factor is restricted to only *gbest*. Furthermore, all particles in the swarm learn from the *gbest* even if the current *gbest* is far from the global optimum. In such situations, particles may easily be attracted and trapped into an inferior local optimum if the search environment is complex with numerous local solutions.

As the fitness value of a particle is decided by all dimensions, a particle which has discovered the value corresponding to the global optimum in one dimension may have a low fitness value because of the poor solutions in other dimensions. This good genotype may be lost in this situation. In order to prevent this, a