

Reactive Power Dispatch Based on Self-Adaptive Differential Evolution Hybrid Particle Swarm Optimization

C. Wang, Y.C. Liu, H.H. Guo, Y. Chen

Marine Engineering College
Dalian Maritime University
People's Republic of China

Abstract—Reactive power dispatch, which may have many local optima, is an important and challenging task in the operation and control of electric power system. This paper presents a Self-adaptive Differential Evolution hybrid Particle Swarm (SaDEPS) optimization algorithm for optimal reactive power dispatch problem. In this method, each particle is updated by a randomly selected strategy from a candidate pool, which contains strategies with different searching behaviors. SaDEPS applied to optimal reactive power dispatch is evaluated on IEEE 14-bus system. The numerical results, show that SaDEPS could find high-quality solutions with higher convergence speed and probability.

Keywords-reactive power dispatch; particle swarm optimization (PSO); self-adapting hybrid strategy; global optimization; differential Evolution (DE)

I. INTRODUCTION

Reactive power dispatch problem has a significant influence on secure and economic operation of electric power systems. Reactive power dispatch optimization determines control variables, such as generator voltages, transformer taps and shunt capacitors. Meanwhile, a given set of physical and operating constraints should be satisfied, such as nonlinear power flow equations, equality and inequality constraints. Since transformer tap ratios and outputs of shunt capacitors have a discrete nature, while bus-voltage magnitudes and angles of generators are continuous variables, the reactive power dispatch problem can be formulated as a large-scale mixed integer nonlinear programming problem with a mixture of discrete and continuous variables. This complex combinatorial optimization problem involving nonlinear functions may have many local optima, which is very difficult to obtain satisfying solutions.

Many techniques ranging from conventional mathematical methods to computational intelligence-based techniques have been applied to solve this problem. The classical methods, such as linear programming [1], nonlinear programming [2], quadratic programming [3], the mixed integer programming [4], the Newton method [5] and interior point techniques [6, 7] have been used. The above methods would offer fast convergence in comparison with other methods. Nevertheless, these methods have severe troubles in handling the nonlinear and discontinuous objective functions with many local optima.

In order to maintain population diversity adaptively for optimal reactive power dispatch problem, this paper proposes

a Self-adaptive Differential Evolution hybrid Particle Swarm (SaDEPS) optimization algorithm. In the presented method, each particle is renewed by a randomly selected strategy according to its dynamic probability in candidate pool by trial-and-error scheme. Furthermore, a self-adaptive learning framework is used to probabilistically steer updating strategies with different features in parallel to optimize problems with different fitness landscapes. The presented method is tested on IEEE 14-bus, 30-bus and 57-bus systems, comparing with several other state-of-the-art variants of PSO algorithms. The rest of this paper is organized as follows: Section 2 describes mathematical formulation of optimal reactive power dispatch. SaDEPS is introduced in detail in Section 3. Section 4 proposes comparative experiments and analyzes the experimental results. Finally, the conclusion and future work are summarized in Section 5.

II. PROBLEM FORMULATION

A. Active Power Loss Minimization

The objective of the reactive power dispatch optimization is to minimize the active power loss in the transmission network, which is defined as follows:

$$f_1 = P_{loss} = \sum_{k=1}^N G_k \left[V_i^2 + V_j^2 - 2V_i V_j \cos(\theta_i - \theta_j) \right] \quad (1)$$

where N is the number of transmission lines; G_k is the conductance of the kth line; V_i and V_j are the voltage magnitude at the end buses i and j of the kth line, respectively; and θ_i and θ_j are the voltage phase angle at the end buses i and j.

B. Voltage Profile Improvement

Bus voltage is one of the most important security and service quality indices. Improving voltage profile can be obtained by minimizing the load bus voltage deviations from 1.0 per unit. The objective function can be expressed as:

$$f_2 = \sum_{i=1}^{NPQ} |V_i - 1.0| \quad (2)$$

where NPQ is the set of numbers of PQ buses; V_i is the voltage magnitude at bus i.

C. Objective Function of Reactive Power Dispatch

Control variables are self-constrained and dependent variables are constrained by adding them as penalty terms to the objective functions. Thus, the above-mentioned problem can be generalized as follows:

Minimize

$$f = \omega_1 \cdot f_1 + \omega_2 \cdot f_2 + \lambda_V \sum_{\alpha} \Delta V_L^2 + \lambda_Q \sum_{\beta} \Delta Q_G^2 \quad (3)$$

where λ_V and λ_Q are penalty factors having large positive value, which are set as 500 in this study; ω_1 and ω_2 are weight coefficients, which are selected as 0.9 and 0.1, respectively; α is the set of numbers of load-buses on which voltage is violation, β is the set of numbers of generator buses on which generator reactive power is violation; ΔV_L is the violation of load-bus voltages, ΔQ_G is the violation of generator reactive power.

III. SELF-ADAPTIVE DIFFERENCE EVOLUTION HYBRID PARTICLE SWARM OPTIMIZATION ALGORITHM

A. R3ps0

In canonical PSO algorithm, each particle in the population (swarm) flies to its previous best position and the global best position. The mechanism of this motion can result a fast convergence rate, but easily trapped in local optima for multimodal problems. Niching is an important technique for multimodal optimization. In that variant of PSO, the velocity updating equation is displayed as follows:

$$V_i^d = \chi \left(V_i^d + \varphi_1 \text{rand}_{i1}^d (pbest_i^d - X_i^d) + \varphi_2 \text{rand}_{i2}^d (pnbest^d - X_i^d) \right) \quad (4)$$

$$t_X^d = X_i^d + V_i^d \quad (5)$$

where the constriction factor $\chi = \frac{2}{|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}|}$, is set to 0.7298 with $\varphi = \varphi_1 + \varphi_2 = 4.1$, φ_1 and φ_2 are both set to 2.05. $pbest_i$ represents the best location in the search space ever visited by particle i and $gbest$ has been replaced by $pnbest_i$; $pnbest_i$ denotes best-fit personal best in the i th neighborhood, representing the neighborhood best for the i th particle. Here, $pnbest_i$ is now used as the local leader for the i th particle; rand_{i1} and rand_{i2} are two uniformly distributed random numbers independently generated within $[0, 1]$ for the d th dimension; t_X is a trial vector. Note that, there are 4 variants of lbest PSO known as r2ps0, r3ps0, r2ps0-lhc and r3ps0-lhc. In SaDEPS, r3ps0 is employed due to its relatively moderate parallel search and convergence capability, compared with other variants of lbest PSO.

B. DbV

In most velocity updating strategies, such as the one described in Eq. (10), the generated velocity vector can be treated as the moderate modification of the old velocity vector according to the influences of neighborhood particles, which

results in the fact that it is hard to be quickly adapted to the different optimization stages of reactive power dispatch problem. Motivated by the strategy DE/current-to-rand/1, DbV avoids progressively changing the velocity but completely recombines the velocity based on the difference information. Different to DE/current-to-rand/1, DbV not only utilizes the difference information to recombine the velocity vector. Instead, the $pbest$ is used as an attractor to guide the flying direction of particle. In the DbV strategy, the following velocity updating equation is used:

$$Viad_i^d = X_{r1}^d - X_{r2}^d \quad (6)$$

$$V_i^d = c \cdot Viad_i^d + c \left(pbest_i^d - X_i^d \right) \quad (7)$$

where X_{r1} and X_{r2} are the d th variables of two randomly selected other particles; $Viad_i$ is the difference vector; c represents one number randomly generated according to the Gauss distribution with mean 0.5 and standard deviation 0.2; V_{max} and V_{min} represent the pre-defined maximum and minimum velocity. The difference information is obtained by Eq. (6-7) is used to generate the new velocity vector. It can be observed that this velocity updating does not rely on the past experience.

C. MDE

1) Mutation

First, MDE operator employs the mutation operation to produce a mutant vector $V_{i,G}$ from the mutation operator family below with respect to each individual $X_{i,G}$, so-called target vector, in the current population. For each target vector $X_{i,G}$ at the generation G , its associated mutant vector can be generated via certain mutation strategy. In this paper, the following mutation strategies are randomly selected by roulette wheel selection with equal probability, yielding a greatly diversified mutant vector. As a result, this multi-mutation operator may be helpful for reactive power dispatch problem to escape from local optima. The most frequently used mutation strategies are modified for reactive power dispatch as follows:

DE/rand/1

$$V_{i,G} = X_{r1,G} + F \cdot (X_{r2,G} - X_{r3,G}) \quad (8)$$

DE/rand/2

$$V_{i,G} = X_{r1,G} + F \cdot (X_{r2,G} - X_{r3,G}) + F \cdot (X_{r4,G} - X_{r5,G}) \quad (9)$$

DE/best/1

$$V_{i,G} = X_{best,G} + F \cdot (X_{r1,G} - X_{r2,G}) \quad (10)$$

where the indices $r1$, $r2$, $r3$, $r4$, $r5$ are mutually exclusive integers randomly generated within the range from 1 to

population size, which are also different from the index i . These indices are randomly generated once for each mutant vector. The scale factor F is a positive control parameter for scaling the difference vector. K is randomly chosen within the range $[0, 1]$. In this paper, the parameter F is approximated by a normal distribution with mean value 0.5 and standard deviation 0.02, denoted by $N(0.5, 0.02)$.

2) Crossover

After the mutation phase, crossover operation is applied to each pair of the target vector $X_{i,G}$ and its corresponding mutant vector V_i to generate a trial vector: U_i . In the basic version, DE employs the binomial (uniform) crossover defined as follows :

$$U_{i,G}^j = \begin{cases} V_{i,G}^j & \text{if } rand_j \leq Cr \text{ or } j = j_{rand} \\ X_{i,G}^j & \text{otherwise} \end{cases} \quad j=1,2,\dots,D \quad (11)$$

3) Selection

The selection operation can be expressed as follows :

$$X_{i,G+1} = \begin{cases} U_{i,G}, & \text{if } f(U_{i,G}) < f(X_{i,G}) \\ X_{i,G}, & \text{otherwise} \end{cases} \quad (12)$$

D. Self-Adapting and Re-Initialization Mechanism

In principle, it is the ultimate purpose that we use a self-adaptive mechanism to increase the probabilities of using suitable updating strategies for different problems, based on the feedback of their previous performance. In this paper, updating strategy is selected from the candidate pool according to the probability learned from its success rate in generating improved solutions. More specifically, at each generation, the probabilities of choosing each strategy in the candidate pool are summed to 1. These probabilities are gradually adapted during evolution in the following manner. Assume that the probability of applying the k th strategy in the candidate pool in the current population is p_k , $k = 1, 2, \dots, K$, where K is the total number of strategies contained in the pool. The probabilities with respect to each strategy are initialized as $1/K$, i.e., all strategies have the equal probability to be chosen. We use the roulette wheel selection method to select one strategy for each particle in the current population. At each generation, each particle i is updated by k th strategy as p_k . The probability of choosing the k th strategy is updated by

$$p_k = \begin{cases} \frac{cs_k + 1}{count + 1}, & \text{if } \text{fit}(t_X_i) < \text{fit}(X_i) \\ p_k, & \text{otherwise} \end{cases} \quad (13)$$

IV. NUMERICAL RESULTS

In order to obtain comparative results, eight algorithms including the proposed SaDEPS are selected to optimize the test power systems. The max population size for each algorithm is 20. For each algorithm, the experiment consists of 31 independent runs. And the Max Fitness Evaluations (MAX_FEs) equals 5000 (14-bus) for each run. Weight

coefficients ω_1 and ω_2 are selected as 0.9 and 0.1. The penalty factors λ_V and λ_Q are constants with values 500. The IEEE 14-bus power system, which is shown in Fig. 1, consists of 17 branches, 5 generator buses and 11 load-buses.

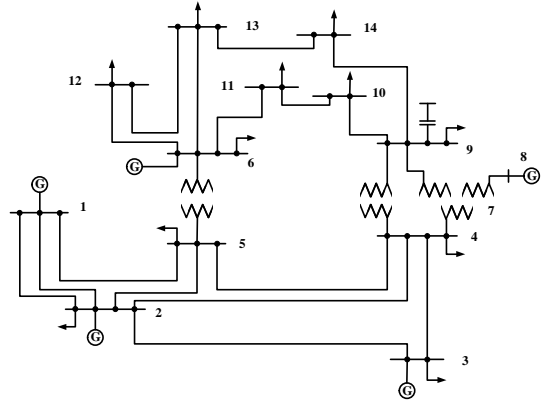


FIGURE I. IEEE 14-BUS POWER SYSTEM

Table 1 lists the results of the experiments that conducted on the IEEE 14-bus system with regard to the final solution quality. We sort the solutions in 31 runs from the smallest (best) to the largest (worst) and present the following: minimum (Min), median (Med), maximum (Max), average (Mean), standard deviation (Std) function values. The best results among the peer algorithms are shown in bold.

TABLE I. CALCULATED FITNESS VALUE OF IEEE 14-BUS POWER SYSTEM. (P. U.)

Methods	Min	Med	Max	Mean	Std
PSO	0.0762	0.0859	9.1640	0.7946	1.6810
R3PS	0.0762	0.0790	1.5082	0.3925	0.4591
R3PS-Is	0.0847	1.2356	7.6779	1.3750	1.3592
CLPS	0.0785	0.0949	1.1448	0.1935	0.2560
GOPS	0.0788	0.0877	1.0432	0.1789	0.2447
DNSPS	0.0773	0.0807	0.0851	0.0805	0.0022
SLPS	0.0767	0.0777	0.0807	0.0780	0.0008
SaDEPS	0.0762	0.0762	0.0833	0.0769	0.0016

V. CONCLUSION

SaDEPS optimization algorithm has been proposed to deal with the application of reactive power dispatch in power system. In this work, each particle is updated by a randomly selected strategy from a candidate pool, which contains strategies with different searching behaviors. The probabilities of different strategies in the candidate pool change dynamically according to their previous successful searching memories. The proposed mechanism may effectively increase the diversity of the swarm population, resulting much a stronger global search capability. Thus, it could be very suitable for reactive power dispatch problem, especially with large scale of power grid and many local optima. The performances of SaDEPS demonstrated on IEEE 14-bus, 30-bus and 57-bus power system show that the proposed method has powerful ability to search high-quality solutions with higher stability and advantageous convergence precision.

Accordingly, SaDEPS may be an effective tool to optimize reactive power dispatch.

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