Diminishing the Power Loss by Merged Algorithm

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Abstract
This paper presents Amplified Particle Swarm optimization (APSO) algorithm for solving reactive power problem in a power system. Particle swarm optimization (PSO) has received increasing interest from the optimization community due to its simplicity in implementation and its inexpensive computational overhead. However, PSO has premature convergence, especially in complex multimodal functions. Extremal Optimization is a recently developed local-search heuristic method and has been successfully applied to a wide variety of hard optimization problems. To overcome the limitation of PSO, this paper proposes a novel hybrid algorithm, called amplified algorithm, through introducing extremal optimization into PSO. The hybrid approach elegantly combines the exploration ability of PSO with the exploitation ability of Extreme optimization. In order to evaluate the proposed algorithm, it has been tested on IEEE 30 bus system and simulation results show the better performance of the proposed algorithm.

Key words
Optimal Reactive Power, Transmission Loss, Particle Swarm,Particle Swarm Optimization, Extremal Optimization,

I. INTRODUCTION

Optimal reactive power dispatch problem is one main problem in power systems. Reactive power dispatch problem involves best utilization of the existing generator bus voltage magnitudes, transformer tap setting and the output of reactive power sources so as to minimize the loss and to enhance the voltage stability of the system. Numerous mathematical techniques have been adopted to solve this optimal reactive power dispatch problem. These include the gradient method [1-2], Newton method [3] and linear programming [4-7].The gradient and Newton methods suffer from the difficulty in handling inequality constraints. To apply linear programming, the input- output function is to be expressed as a set of linear functions which may lead to loss of accuracy. RecentlyGlobal Optimization techniques such as genetic algorithms have been proposed to solve the reactive power flow problem [8-12]. Particle Swarm Optimization (PSO) algorithm is a recent addition to the list of global searchmethods. This derivative-free method is particularly suited to continuous variable problems andhas received increasing attention in the optimization community. PSO is originally developedby Kennedy and Eberhart [13] and inspired by the paradigm of birds flocking. PSO consists ofa swarm of particles and each particle flies through the multi-dimensional search space witha velocity, which is constantly updated by the particle's previous best performance and bythe previous best performance of the particle's neighbours. PSO can be easily implementedand is computationally inexpensive in terms of both memory requirements and CPU speed [14].Recently, a general-purpose local-search heuristic algorithm named Extremal Optimization(EO) has been proposed by Boettcher and Percus [15, 16]. To avoid premature convergence of PSO, an idea of combining PSO with EO is addressedin this paper called as Amplified Particle Swarm optimization (APSO) algorithm. The performance of APSOhas been evaluated in standard IEEE 30 bus test system and the results analysis shows that our proposed approach outperforms all approaches investigated in this paper.

II. PROBLEM FORMULATION

The objectives of the reactive power dispatch problem considered here is to minimize the system real power loss. This objective is achieved by proper adjustment of reactive power variables like generator voltage magnitude (Vgi), reactive power generation of capacitor bank (Qci), and transformer tap setting (tk).Power flow equations are the equality constraints of the problems, while the inequality constraints include the limits on real and reactive power generation, bus voltage magnitudes, transformer tap positions and line flows

A. Minimization of Real Power Loss

It is aimed in this objective that minimizing of the real power loss (Ploss) in transmission lines of a power system. This is mathematically stated as follows.

$$P_{loss}=\sum_{\substack{k=1\\k=(i,j)}}^{n} g_{k}(V_i^2+V_j^2-2V_iV_j\cos\theta_{ij}) \quad (1)$$

Where n is the number of transmission lines, g_k is the conductance of branch k, V_i and V_j are voltage magnitude at bus i and bus j, and θij is the voltage angle difference between bus i and bus j.

B. Minimization of Voltage Deviation

It is aimed in this objective that minimizing of the Deviations in voltage magnitudes (VD) at load buses. This is mathematically stated as follows.

$$\text{Minimize VD} = \sum_{k=1}^{nl}|V_k - 1.0| \quad (2)$$

Where nl is the number of load busses and V_k is the voltage magnitude at bus k.

C. System Constraints

In the minimization process of objective functions, some problem constraints which one is equality and others are inequality had to be met. Objective functions

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are subjected to these constraints shown below.

Load flow equality constraints:

$$P_{Gi} - P_{Di} - V_{i\sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, i = 1,2 \ldots., nb$$
(3)

$$Q_{Gi} - Q_{Di} V_{i\sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, i = 1,2 \ldots., nb$$
(4)

where, *nb*is the number of buses.
Generator bus voltage (V_{Gi}) inequality constraint:
$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max}, i \in ng$(5)

Load bus voltage (*VLi*) inequality constraint:

$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max}, i \in nl$ (6)

Switchable reactive power compensations (*QCi*) inequality constraint:
$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max}, i \in nc$ (7)
Reactive power generation (*QGi*) inequality constraint:

$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}, i \in ng$ (8)

Transformers tap setting (T_i) inequality constraint:

$T_i^{min} \leq T_i \leq T_i^{max}, i \in nt$(9)

Transmission line flow (S_{Li}) inequality constraint:

$S_{Li}^{min} \leq S_{Li}^{max}, i \in nl$ (10)

Where, nc, ng and nt are numbers of the switchable reactive power sources, generators and transformers.

III. Particle Swarm Optimization (PSO)

PSO is a population based optimization tool, where the system is initialized with a populationof random particles and the algorithm searches for optima by updating generations. Supposethat the search space is *D*-dimensional. The position of the*i*-th particle can be representedby a *D*-dimensional vector $X_i = (x_{i1}, x_{i2}, .., x_{iD})$ and the velocity of this particle is $V_i = (v_{i1}, v_{i2}, .., v_{iD})$ .The best previously visited position of the *i*-th particle is represented by $P_i = (p_{i1}, p_{i2}, .., p_{iD})$ and the global best position of the swarm found so far is denoted by $P_g = (p_{g1}, p_{g2}, .., p_{gD})$. The fitness of each particle can be evaluated through putting itsposition into a designated objective function. The particle's velocity and its new position areupdated as follows:

$v_{id}^{t+1} = \omega^t v_{id}^t + c_1 r_1^t (p_{id}^t - x_{id}^t) + c_2 r_2^t (p_{gd}^t - x_{id}^t)$ (11)

$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1}$(12)

Where $d \in \{1,2, .., D\}, i \in \{1,2, .., N\}N$ is the population size, the superscript *t* denotesthe iteration number, ω is the inertia weight, r_1 and r_2 are two random values in the range[0,1], c_1 and c_2 are the cognitive and social scaling parameters which are positive constants.

IV. Extremal Optimization (EO)

EO is inspired by recent progress in understanding far-from-equilibrium phenomena in termsof self-organized criticality, a concept introduced to describe emergent complexity in physicalsystems. EO successively updates extremely undesirable variables of a single sub-optimalsolution, assigning them new, and random values. Moreover, any change in the fitness value of avariable engenders a change in the fitness values of its neighbouring variable.
Procedure of EO algorithm.

1. Randomly generate algorithm $X = (x_1, x_2, ., x_D)$. Set the optimal solution $X_{best} = X$ and the minimum cost function $C(X_{best}) = C(X)$.
2. For the current solution X ,
   a. Evaluate the fitness λ_i for each variable x_i , $i \in \{1,2, .. D\}$,
   b. Rank all the fitness and find the variablex_j, with lowest fitness i.e.$\lambda_j \leq \lambda_i$for all i.
   c. Choose one solution X′ in the neighbourhood X, such that j-th variable must change its state.
   d. Accept X=X′ unconditionally
   e. If $C(X) < C(X_{best})$ then set $X_{best} = X$ and $C(X_{best}) = C(X)$.
3. Repeat set 2 as long as desired
4. Return X_{best} and$C(X_{best})$.

Note that in the EO algorithm, each variable in the current solution *X* is considered “species”. In this study, we adopt the term “component” to represent “species” which isusually used in biology. For example, if $X = (x_1, x_2, x_3)$, then x_1,x_2 and x_3 are called “components” of *X*. From the EO algorithm, it can be seen that unlike genetic algorithms whichwork with a population of candidate solutions, EO evolves a single sub-optimal solution *X* and makes local modification to the worst component of *X*. A fitness value ¸*i*is required foreach variable *xi* in the problem, in each iteration variables are ranked according to the value of their fitness. This differs from holistic approaches such as evolutionary algorithms that assign equal-fitness to all components of a solution based on their collective evaluation against anobjective function.

V. AMPLIFIED PSO Algorithm

Note that PSO has great global-search ability, while EO has strong local-search capability. Inthis work, we propose anAmplified PSO algorithm which combines the merits of PSO andEO. This hybrid approach makes full use of the exploration ability of PSO and the exploitationability of EO. Consequently, through introducing EO to PSO, the proposed approach mayovercome the limitation of PSO and have capability of escaping from local optima. In the main procedure of Amplified PSO algorithm, the fitness of each particle is evaluated through putting its position into the objective function.However, in the EO procedure, in order to find out the worst component, each component ofa solution should be assigned a fitness value. We defined the fitness of each component of asolution for an unconstrained minimization problem as follows. For the i-th particle, the fitness λ_{ik} of the k-th component is defined as the mutation cost, i.e. $OBJ(X_{ik})$ - $OBJ(P_g)$, where$X_{ik}$is the new position of the i-th particle obtained by performing mutation only on the k-thcomponent and leaving all other components fixed, $OBJ(X_{ik})$ is the objective value of X_{ik},and $OBJ(P_g)$ is the objective value of the best position in the swarm found so far.

EO algorithm for the RPO problem

1. Set the index of the current particle i=1.
2. for the position $X_i = (x_{i1}, x_{i2}, .., x_{iD})$ of the i-th particle
   a. perform mutation on each component ofX_i One by one, while keeping other components fixed. Then D new positions $x_{ik}(k = 1, .., D)$ can be obtained;
   b. evaluate the fitness λ_{ik} =OBJ(X_{ik}) - OBJ(P_g) of each component X_{ik} , $k \in \{1, .., D\}$.
   c.compare all the components according to their fitness values and find out the worst adapted component x_{iw} ,and then $x_{iw}$is the new position corresponding to x_{iw} ,$w \in \{1, .., D\}$.
   d. if OBJ(x_{iw})< OBJ(x_i) then set X_i=X_{iw} , and OBJ(x_i) = OBJ(x_{iw})continue the next step. Otherwise,X_i keeps unchanged and go to Step 3;
   e.update p_i and p_g
3. If iequals to the population size N , return the results; otherwise, set i= i+1 and go to Step 2.

APSO Algorithm for solving reactive power dispatch problem.

1. Initialize a swarm of particles with random positions and velocities N on D dimensions.

Set iteration = 0 .

2. Evaluate the fitness value of each particle, and update $P_i = (i = 1, .., N)$and P_g.
3. Update the velocity and position of each particle using Eq.11 and Eq.12, respectively.
4. Evaluate the fitness value of each particle, and update$P_i = (i = 1, .., N)$and P_g.
5. If (iteration mod INV)=0, the EO procedure is introduced. Otherwise, continue the next step.
6. If the terminal condition is satisfied, go to the next step; otherwise, set iteration = iteration +1, and go to Step 3.
7. Output the optimal solution and the optimal objective function value.

VI. Simulation Results

APSO algorithm has been tested on standard IEEE 30-bus, 41 branch system. It has a total of 13 control variables as follows: 6 generator-bus voltage magnitudes, 4 transformer-tap settings, and 2 bus shunt reactive compensators. Bus 1 is the slack bus, 2, 5, 8, 11 and 13 are taken as PV generator buses and the rest are PQ load buses. The calculated security constraints are the voltage magnitudes of all buses, the reactive power limits of the shunt VAR compensators and the transformers tap settings limits. The variables limits are listed in table 1.

Table 1: Initial Variables Limits (PU)

Control variables	Min. value	Max. value	Type
Generator : Vg	0.95	1.1	Continuous
Load Bus: VL	0.95	1.05	Continuous
T	0.90	1.1	Discrete
Qc	-0.11	0.30	Discrete

The transformer taps and the reactive power source installation are discrete with the changes step of 0.01. The power limits generators buses are represented in Table2. Generators buses are: PV buses 2,5,8,11,13 and slack bus is 1.the others are PQ-buses.

Table 2: Generators Power Limits in MW and MVAR

Bus n°	Pg	Pgmin	Pgmax	Qgmin
1	94.00	50	200	-20
2	80.00	20	80	-20
5	21.00	15	55	-13
8	20.00	10	31	-13
11	20.00	10	25	-10
13	20.00	11	40	-13

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Table 3: Values of Control Variables after Optimization and Active Power Loss

Control Variables (p.u)	APSO
V1	1.0298
V2	1.0243
V5	1.0110
V8	1.0198
V11	1.0597
V13	1.0398
T4,12	0.00
T6,9	0.01
T6,10	0.90
T28,27	0.90
Q10	0.10
Q24	0.10
PLOSS	4.8762
VD	0.9082

The proposed approach succeeds in keeping the dependent variables within their limits.
Table 4 summarizes the results of the optimal solution obtained by SGA, PSO and APSO methods. It reveals the decrease of real power loss after optimization.

Table 4: Comparison Results of Different Methods

AGA[17]	PSO[18]	APSO
4.98 Mw	4.9262Mw	4.8762Mw

VII. Conclusion

In this paper a novel approach APSO algorithm used to solve optimal reactive power dispatch problem. The effectiveness of the proposed method is demonstrated on IEEE 30-bus system. simulation results reveal about the better performance of the proposed algorithm and real power loss has been considerably reduced.

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