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Combined Algorithm for Reducing Real Power Loss

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Abstract

This paper presents combination of three algorithms for solving reactive power dispatch problem in power system. Evolutionary algorithms and Swarm Intelligence based algorithms (EA, SI), a part of Bio inspired optimization algorithm, have been widely used to solve numerous optimization problem in various science and engineering domains.Recently, the use of the particle swarm optimization(PSO) technique for the reactive power problemfrom the optimization community due toits simplicity in implementation and its inexpensive computationaloverhead. However, the basic PSO algorithm is easily trapping intolocal minimum and may lead to the premature convergence. When alocal optimal solution is reached with PSO, all particles gather aroundit, and escaping from this local optima becomes difficult. To overcomethe premature convergence of PSO, we propose a newcombined algorithmof particle swarm optimization (PSO), simulated annealing (SA) and Tabu search algorithm (TS) for solving the reactive power dispatch problem called as Combined Algorithm (CA).The incorporation of Tabu search (TS) and simulated annealing (SA)as local improvement approaches enable the hybrid algorithm tooverleap local optima and intensify its search ability in local regions.In order to evaluate the proposed algorithm, it has been tested instandard IEEE 57,118 bus test systems &compared to standard reported algorithms. SimulationResults show that proposed Combined Algorithm (CA) is more efficient in reducing real power loss.

Keywords

particle swarm optimization (PSO), simulated annealing (SA), Tabu search algorithm (TS), Swarm Intelligence, optimal reactive power, Transmission loss.

1. Introduction

Optimal reactive power dispatch problem is one of the difficult optimization problems in power systems. The sources of the reactive power are the generators, synchronous condensers, capacitors, static compensators and tap changing transformers. The problem that has to be solved in a reactive power optimization is to determine the required reactive generation at various locations so as to optimize the objective function. Here the 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. It involves a non linear optimization problem. Various 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. Recently Global Optimization techniques such as genetic algorithms have been proposed to solve the reactive power flow problem [8]. To bypass the difficulties, global stochastic methods such asthe genetic algorithm (GA), Tabu search (TS) and simulated annealing (SA) have becomeattractive alternatives for reactive power dispatch problem[9-14].Although PSO is a good and fast search algorithm for the reactive power compensation problem, there are still many complex situations where the PSO has premature convergence and tends to converge to local optima, especially in a complex high dimensional problem space. In the worst case, when the best solution found by the group and the particles are all located at the same local minimum, it is almost impossible, due tothe velocity update equation, for particles to fly out and do further searching. Thus, this paper develops a new hybrid technique which combinesPSO algorithm with the simulated annealing algorithm (SA) and Tabu search (TS) and apply it to solve the reactive power dispatch problem. SA and TS are powerful optimization procedures that havebeen successfully applied to a number of combinatorial optimizationproblems. They have the ability to avoid convergence to local minima.By integrating SA and TS to the PSO, the new algorithm, which wecall it combined algorithm cannot only escape from local minimum trap in thelater phase of convergence, but also simplify the implementation of thealgorithm. In other words, PSO contributes to the hybrid approachin a way to ensure that the search converges faster, while the SA andTS make the search to jump out of local optima due to their stronglocal-search ability.The performance of CAhas been evaluated in standard IEEE 57,118 bus test systems and the results analysis shows that our proposed approach outperforms all approaches investigated in this paper.

2. Problem Formulation

The objectives of the reactive power problem is to minimize the real power loss.

2.1 Active power loss

The objective of the reactive power dispatch problem is to minimize the active power loss and can be written in equations as follows:

$$F = P_L = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}\right) (1)$$

Where F- objective function, P_L – power loss, g_k- conductance of branch,V_i and $V_j$are voltages at buses i,j, Nbr- total number of transmission lines in power systems.

2.2 Voltage profile improvement

To minimize the voltage deviation in PQ buses, the objective function (F) can be written as:

$$F = P_L + \omega_v \times VD \qquad (2)$$

Where VD - voltage deviation,ω_v- is a weighting factor of voltage deviation.

And the Voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \ (3)$$

Where Npq- number of load buses

2.3 Equality Constraint

The equality constraint of the problem is indicated by the power balance equation as follows:

$$P_G = P_D + P_L (4)$$

Where P_G- total power generation, P_D - total power demand.

2.4 Inequality Constraints

The inequality constraint implies the limits on components in the power system in addition to the limits created to make sure system security. Upper and lower bounds on the active power of slack bus (P_g), and reactive power of generators (Q_g) are written as follows:

$$P_{gslack}^{min} \le P_{gslack} \le P_{gslack}^{max} \qquad (5)$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}, i \in N_g \qquad (6)$$

Upper and lower bounds on the bus voltage magnitudes (V_i) is given by:

$$V_i^{min} \le V_i \le V_i^{max}, i \in N \qquad (7)$$

Upper and lower bounds on the transformers tap ratios (T_i) is given by:

$$T_i^{min} \le T_i \le T_i^{max}, i \in N_T \qquad (8)$$

Upper and lower bounds on the compensators (Q_c) is given by:

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$$Q_c^{\min} \le Q_c \le Q_C^{\max}, i \in N_C \quad (9)$$

Where N is the total number of buses, N_g is the total number of generators, N_T is the total number of Transformers,N_c is the total number of shunt reactive compensators.

3. Combination of particle swarm optimization (PSO), simulated annealing (SA), Tabu search (TS)

The proposed algorithm combines PSO with SAand TS. Due to combination of different search mechanisms, not only the PSO operators can keep diversity, but also SA and TS can keep thebalance of global search and local search, so the entire search ability ofthe algorithm can be improved.

Particle swarm optimization (PSO) is inspired by social behavior patterns of organisms. Thetraditional PSO model consists of a number of particles movingaround in the search space. In a space of *D* dimensions, eachparticle in the swarm is represented by the following characteristics:X_i= [X_{i1},X_{i2},…X_{iD}]: The current position of the particle;V_i= [V_{i1}, V_{i2},..,V_{iD}]: The current velocity of the particle; P_i =[P_{i1}, P_{i2},..,P_{iD}]: The personal best position of the particle. Thepersonal best position of particle *i*is the best position visited byparticle *i*so far. The position of a particle *i*is influenced bythe local best position P_i visited by itself, i.e., its own experienceand the position $P_g$of the global best particle in the swarm. Theperformance of each particle is measured using a fitness function thatvaries depending on the optimization problemand it inspired by the social behaviours of animal, bird flocking and fishing. The particle is endowed with two factors: velocity and position which can be regarded as the potential solution in the *D* dimension problem space. In basic PSO, they can be updated by following formulas:

$$v_{id}(t+1) = \omega v_{id}(t) + c_1 r_{1d}\left(P_{id}(t) - x_{id}(t)\right) + c_2 r_{2d}\left(P_{gd}(t) - x_{id}(t)\right) \quad (10)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (11)$$

Wherei = 1,…..,N, d = 1,…,D, Nis the number of particles. ω isthe inertia weight factor to control the exploration and exploitation.$r_{1d}$and $r_{2d}$are two random numbers within the range [0, 1]. $v_{id}(t)$ and$x_{id}(t)$ are the velocity and position of the current particle *i* at timestep tin the dth-dimensional search space respectively. When $v_{id}(t)$and $x_{id}(t)$ are beyond the boundary, the solution may be illegal. So,the treatment of boundaries in the PSO method is important in orderto prevent the swarm from explosion . In many practical problems,the search range $x_{id}$is in [$X_{\min}$;$X_{\max}$]D. v_{id}should be clamped to amaximum magnitude $V_{\max}$. $p_i$is the previous best position of particle *I* which is also called "personal best", and its *d*th-dimensional part is p_{id}. The global best" $p_g$is the best position found in the whole particles,and its *d*th-dimensional part is p_{gd}. c_1, c_2 are the acceleration constantswhich change the velocity of a particle towards the $p_i$and p_g.Concerning the simulated annealing algorithm(SA) is a probabilistic variant of the local search method,but it can in contrast, escape local optima. A standard SA procedurebegins by generating an initial solution at random. At initial stages,a small random change is made in the current solution X_c. Then theobjective function (representing the cost functional *F*) value of thenew solution $X_n$is calculated and compared with that of the currentsolution. The probability *p* of accepting a new solution which called

Metropolis law is given as follows:

$$P = \begin{cases} 1, if(X_n) < F(X_c), \\ exp\left(\frac{-|F(X_n)-F(X_c)|}{T}\right), otherwise \end{cases} \quad (12)$$

The calculation of this probability relies on a parameter *T*, whichis referred to as temperature, since it plays a similar role as the temperature in the physical annealing process. To avoid getting trapped at a local minimum point, the rate of *T* reduction shouldbe slow. In our case, *T* decrease as follow:

$$T(n+1) = \beta T(n) \quad (13)$$

Where the annealing rate satisfies 0 <β<1. In this paper, the initial temperature is determined by the following empirical formula:

$T_0 = -\frac{F_{max}-F_{min}}{\ln 0.1}$ (14)

Where$F_{\max}$ and $F_{\min}$ denote the maximum and minimum objective values of the solutions in the initial swarm, respectively. Thus, at the start of SA most worsening moves may be accepted,but at the end only improving ones are likely to be allowed. This canhelp the procedure jump out of a local minimum.As a third algorithm, it is the Tabu search (TS) and has been used to solve a wide range ofhard optimization problems. TS start with a random solution and evaluate the fitness function for the given solution. Then all possibleneighbours of the given solution are generated and evaluated. TS havetwo main features: (a) the capability to avoid local optimization. TSuses a Tabu list (TL) to memory the better local neighbours whichhave been searched and will be neglected; (b) the capability to find better resolution. TS use an aspiration rule to exploit a prohibitedresolution. During a situation that all the resolution in the TLis prohibited, the aspiration can make the whole search processingcontinue. In this work, the following aspiration criterion was employed when all available moves are classified Tabu: a Tabu move that losesits Tabu status by the least increase in the value of current iteration isfreed from the Tabu list.

4. Combined Algorithm

In PSO algorithm, particles always chase the current overall optimalpoint and history optimal point found. Then theparticle speed closes to 0 quickly and cannot escape from localminimum. In order to avoid earliness convergence, the algorithmmust escape from local minimum and search in other solution space,until solve overall optimal solution. SA and TS algorithms accepta worse solution, it has the ability of escaping from local optimalsolution and can restrain earliness convergence, increase the diversity ofPSO. The new developed hybrid technique, called combined algorithm (CA), consistsin a strong cooperation of PSO, SA and TS, since it maintains theintegration of the three techniques for the entire run. The proposed hybrid algorithm makes full use of the exploration ability of PSO andthe exploitation ability of SA and TS and offsets the weaknesses of eachother. Consequently, through introducing SA and TS to PSO, CA is capable of escaping from a local optimum. The algorithmstarts with a population of particles generated randomly and everyparticle $X_i$searches its local best $X_{i,lbest}$using SA or TS algorithmsto update individual personal best $P_i$and the global P_g. The particlesare then subjected to PSO for further refinement. The PSO algorithmhandles the global search for the solution while SA and TS facilitatesthe local search. The driving parameter of the combined algorithm (CA) is the Hybridization Coefficient (HC) between SA and TS; it expressesthe percentage of population that in each iteration is evolved with SA: SoHC = 0 means the procedure is a pure TS (the whole populationis updated according to TS operators), HC = 1 means pure SA,while 0 < HC <1 means that the corresponding percentage of thepopulation is developed by SA, the rest with TS. So, for HC = 0the hybridization is carried out only between PSO and TS and thealgorithm will be named PSO-TS. If HC = 1, the hybridization iscarried out only between PSO and SA and the algorithm will be named combined algorithm (CA). The step of CA is given below:

Step 1: Randomly initialize the population of Np particles within thevariable constraint range.

Step 2: Evaluate each particle in the population from the fitnessfunction F.

Step 3:

- Select randomly the particles in population that are evolved withSA.
- Every selected particle $X_i$generates a new neighbourX_i'in itslocal area and then according to the accepting rule of SA decideswhether to accept the new solution or not. After L iterations, every particle finds its local best solution $X_{i,lbest}$.
- Calculate the new temperature T specified.

Step 4:

- The rest of the population is evolved with TS. Every particle finds its local best solution $X_{i,lbest}$by applying a TS procedure.
- Update the Tabu list (TL).

Step 5: Update personal best $P_i$and the global best P_g. For each particle, the adaptive fitness value $F(X_{i,lbest})$ is compared with one of the historical best position P_i, if the adaptive value is better than one of P_i. Then, $X_{i,lbest}$is consider as the best position P_i, otherwise, P_i remain unchanged.

$$P_i = \begin{cases} X_{i,lbest}\,, if\ F(X_{i,lbest}) < F(P_i), \\ P_i, otherwise \end{cases} \quad (15)$$

After updating every particles personal best value, we can get the newglobal best value P_g.

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Step 6: Update the position and velocity of each particle by PSOoperators according to (10) and (11).

Step 7: Repeat Steps 2, 6 until a stopping criterion, such as a sufficiently good solution being discovered or a maximum number ofgenerations being completed, is satisfied.

5. Simulation Results

ProposedCombined Algorithm (CA) is tested in standard IEEE-57 bus power system. The reactive power compensation buses are 18, 25 and 53. Bus 2, 3, 6, 8, 9 and 12 are PV buses and bus 1 is selected as slack-bus. The system variable limits are given in Table 1.

The preliminary conditions for the IEEE-57 bus power system are given as follows:

P_{load}= 12.116 p.u. Q_{load} = 3.013 p.u.

The total initial generations and power losses are obtained as follows:

$\sum P_G$ = 12.5511 p.u. $\sum Q_G$ = 3.3212 p.u.

P_{loss}= 0.25718 p.u. Q_{loss} = -1.2029 p.u.

Table 2 shows the various system control variables i.e. generator bus voltages, shunt capacitances and transformer tap settings obtained after CA based optimization which are within the acceptable limits. In Table 3, shows the comparison of optimum results obtained from proposed CA with other optimization techniques. These results indicate the robustness of proposed CA approach for providing better optimal solution in case of IEEE-57 bus system.

TABLE 1. VARIABLE LIMITS

Reactive Power Generation Limits							
Bus no	1	2	3	6	8	9	12
Qgmin	-1.4	-.015	-.02	-0.04	-1.3	-0.03	-0.4
Qgmax	1	0.3	0.4	0.21	1	0.04	1.50

Voltage And Tap Setting Limits					
vgmin	**Vgmax**	**vpqmin**	**Vpqmax**	**tkmin**	**tkmax**
0.9	1.0	0.91	1.05	0.9	1.0

Shunt Capacitor Limits			
Bus no	18	25	53
Qcmin	0	0	0
Qcmax	10	5.2	6.1

TABLE 2. CONTROL VARIABLES OBTAINED AFTER OPTIMIZATION

Control Variables	**CA**
V1	1.1
V2	1.027
V3	1.031
V6	1.029
V8	1.025
V9	1.010
V12	1.020
Qc18	0.0656
Qc25	0.200
Qc53	0.0465
T4-18	1.010
T21-20	1.059
T24-25	0.871
T24-26	0.876
T7-29	1.052
T34-32	0.874
T11-41	1.018
T15-45	1.033
T14-46	0.910

T10-51	1.020
T13-49	1.054
T11-43	0.910
T40-56	0.900
T39-57	0.950
T9-55	0.950

TABLE 3. COMPARISON RESULTS

S.No.	Optimization Algorithm	Finest Solution	Poorest Solution	Normal Solution
1	NLP [15]	0.25902	0.30854	0.27858
2	CGA [15]	0.25244	0.27507	0.26293
3	AGA [15]	0.24564	0.26671	0.25127
4	PSO-w [15]	0.24270	0.26152	0.24725
5	PSO-cf [15]	0.24280	0.26032	0.24698
6	CLPSO [15]	0.24515	0.24780	0.24673
7	SPSO-07 [15]	0.24430	0.25457	0.24752
8	L-DE [15]	0.27812	0.41909	0.33177
9	L-SACP-DE [15]	0.27915	0.36978	0.31032
10	L-SaDE [15]	0.24267	0.24391	0.24311
11	SOA [15]	0.24265	0.24280	0.24270
12	LM [16]	0.2484	0.2922	0.2641
13	MBEP1 [16]	0.2474	0.2848	0.2643
14	MBEP2 [16]	0.2482	0.283	0.2592
15	BES100 [16]	0.2438	0.263	0.2541
16	BES200 [16]	0.3417	0.2486	0.2443
17	Proposed CA	0.22121	0.23139	0.22172

Then Combined Algorithm (CA) has been tested in standard IEEE 118-bus test system [17] .The system has 54 generator buses, 64 load buses, 186 branches and 9 of them are with the tap setting transformers. The limits of voltage on generator buses are 0.95-1.1 per-unit., and on load buses are 0.95-1.05 per-unit. The limit of transformer rate is 0.9-1.1, with the changes step of 0.025. The limitations of reactive power source are listed in Table 4, with the change in step of 0.01.

TABLE 4. LIMITATION OF REACTIVE POWER SOURCES

BUS	5	34	37	44	45	46	48
QCMAX	0	14	0	10	10	10	15
QCMIN	-40	0	-25	0	0	0	0
BUS	74	79	82	83	105	107	110
QCMAX	12	20	20	10	20	6	6
QCMIN	0	0	0	0	0	0	0

The statistical comparison results of 50 trial runs have been list in Table 5 and the results clearly show the better performance of proposedCA algorithm.

TABLE 5. COMPARISON RESULTS

Active power loss (MW)	BBO [18]	ILSBBO/ strategy1 [18]	ILSBBO/ strategy1 [18]	Proposed CA
Min	128.77	126.98	124.78	116.92
Max	132.64	137.34	132.39	120.02
Average	130.21	130.37	129.22	117.22

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6. Conclusion

In this paper a novel approach combined algorithm (CA) successfully solved optimal reactive power problem.This paper develops a new hybrid technique which combines PSO algorithm with the simulated annealing algorithm (SA) and Tabu search (TS) and solved the reactive power dispatch problem. The effectiveness of the proposed method is demonstrated on IEEE 57,118 bus test systems.and the results analysis shows that our proposed approach outperforms all approaches investigated in this paper.

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