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A Novel Adaptive Particle Swarm Optimization for Reactive Power and Voltage Control

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Abstract—*Keeping the voltage within the allowable range for vast power systems network is as a challenging task. Reactive power optimization (RPO) problem can be considered as one of the important mixed-integer/non-linear optimization problem (MINLOP) which includes continuous as well as discrete state variables satisfying both equality and inequality constraints.*
This paper presents Adaptive Particle Swarm Optimization (APSO) as a novel approach to solve the RPO problem. In APSO different agents are assigned with different tasks and inertia weight is updated according to their performance. The effectiveness of the proposed method is verified on standard IEEE 30-bus system and compared with conventional Particle Swarm Optimization (PSO) with promising results.

Index Terms: *Evolutionary computation, reactive power optimization, mixed-integer nonlinear optimization problem, particle swarm optimization, reactive power and voltage control, adaptive particle swarm optimization.*

1. INTRODUCTION

POWERSystem operation research has always the problem of transmission loss minimization.There are a number of techniquesof achieving this goal. The reactive poweroptimization(RPO), is one of them has attractedgreat attention in the last decades because it can greatlyimprove power systemsecurityandeconomy. As Electric load varies from time to time, the reactive power requirements of the power system also varies and hence voltage. Since the reactive power cannot be transmitted over a long distance, voltage has to becontrol by directly injecting the reactive powerin target power systems according to the loads variation.

Voltage stability also known as load stability is now a major concern of power system security analysis,as it is well known that voltage instability and collapse mayresult in major system failures or blackouts.Hence for the power system operator or planner has the important operating task is to maintain the load voltages within the allowable limit for high quality consumer service.The main objective of reactive power optimum control is to minimize the real (active) power losses in transmission networks, voltage profile improvement at load buses and voltage stability improvement of the power system.This objective can be achieved by utilizingthe various equipmentssuch as automatic voltage regulator (AVR) of generators, tap changing transformers (OLTC), static condensers (SC), and shunt reactors (ShR).

Since tap ratios of transformers and output of shunt capacitors/reactors are discrete state variables, whereas reactive power output of generators and static condensers and bus-voltages (magnitude/angle) are continuous state variables.

Hence, RPO can be considered as one of the importantmixed-integer/non-linear optimization problem (MINLOP) which includes continuous as well as discrete state variables satisfying both equality and inequality constraints.

Today, we have a large number of conventional optimization techniques such as Linear programming [1], Non- linear programming [2], Quadratic programming [3], Gradient method[4], Newton method [5], and Interior point method [6] to solve this problem. Unfortunately, these classical techniques are failed in handling discrete- continuous/non-linear functions and constraints. Apart from these, time consuming, insecure convergence on local minima and complexity in mathematical formulation are the limitations of them. In the recent years, several evolutionary algorithms (EA) [7] such as genetic algorithm (GA), fuzzy control approach [8], reactive tabu search (RTS) [9], etc has been developed to solve RPO problem.

Particle Swarm Optimization (PSO) [10] is one of the evolutionary computation (EC) techniques based on Swarm intelligence. This technique is improved and relatively simple to implement in various problems [11]-[13].The simple PSO is able to handle continuous state variables only. However, the technique can be expanded to handle both continuous as well as discrete variables with ease. Therefore, the technique can be applicable to solve a multi-objective RPO model minimizing real power loss and voltage deviation of the system, simultaneously.

On employing the PSO, initially the solution converges to optimum quickly. However,later to obtain the further improvement is very difficult and for very small improvement it takes a large computation time. PSO is very effective in solving static optimization problem but is not as efficient when applied to a dynamic system in which the optimal value may change repeatedly.To overcome this problem Adaptive Particle Swarm Optimization (APSO) [14] is proposed in this paper. The result of the proposed method for RPO problem is demonstrated and compared with PSO on practical system in terms of real power loss and voltage profile and gives better optimized solution within short duration.

2. PROBLEM FORMULATION

2.1 Problem Formulation

There are several ways to formulate RPO. Minimization of the real power loss in transmission networkis one option, which can be described as follows:

$$min\ P_{Loss}(x,y) = \sum_{k=1}^{m} Loss_k$$

$$= min \sum_{k=1}^{m} G_k \left[V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)\right] \qquad (1)$$

Where,
mthe number of branches,

xcontinuous state variables,

ydiscrete state variables,

$G_k$theconductance of the kth line,

$V_i \angle\delta_i$ voltageat end bus i of the kth line,

$Loss_k$ real power loss (P_{Loss}) at branch k,

2.2 Operating Constraints

Minimization of the above objective function is subjected to a number of constraints [15], which are mainly classified in two categories.

B.1.Equality Constraints **(Load Flow Constraints)**

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{n} V_j \left[G_{ij}\ \cos(\delta_i - \delta_j) + B_{ij}\ \sin(\delta_i - \delta_j)\right] = 0 \qquad (2)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{n} V_j \left[G_{ij}\ \cos(\delta_i - \delta_j) + B_{ij}\ \sin(\delta_i - \delta_j)\right] = 0 \qquad (3)$$

Where,i = 1, 2, 3, . . . , n;n is the number of buses

$P_{Gi}$and$P_{Di}$are the active (real)power of generator and load respectively;Q_{Gi} andQ_{Di} are thereactive power of generator and load respectively; $Gij$and $Bij$are the Transconductance and Susceptance between$i$ and j respectively.

B.2. Inequality Constraints (System Operating Constraints)

This control variable may be of continuous or discrete type.

Continuous variables:

$$V_{G\,i}^{\ min} \le V_{G\,i} \le V_{G\,i}^{\ max},\ i= 1,2,3,\ldots\ldots,N_G \qquad (4)$$

Discrete variables:

$$T_{G\,i}^{\ min} \le T_{G\,i} \le T_{G\,i}^{\ max},\ i= 1,2,3,\ldots\ldots,N_T \qquad (5)$$

$$Q_{C\,i}^{\ min} \le Q_{C\,i} \le Q_{C\,i}^{\ max},\ i = 1,2,3,\ldots\ldots,N_C \qquad (6)$$

$$V_{PQ\,i}^{\ min} \le V_{PQi} \le V_{PQ\,i}^{\ max},\ i = 1,2,3,\ldots.,N_{PQ} \qquad (7)$$

$$Q_{G\,i}^{\ min} \le Q_{G\,i} \le Q_{G\,i}^{\ max},\ i = 1,2,3,\ldots\ldots,N_G \qquad (8)$$

Where,

$N_G$the number of generators,

$T_G$the number of transformers,

$N_C$the number of VAR compensators,

$N_{PQ}$the number of PQ buses,

The *max* and *min*term represent the upper and lower limits of the corresponding constraint variables respectively.

Total real power loss of the target power system is calculated using load flow analysis with both continuous and discrete state variables. In load flow calculation voltage and power constraints can be checked and penalty values are added in state variables, if exceed the constraints limit.

3. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) [10] is an evolutionary computation (EC) technique developed by Dr. Russell Eberhart and Dr. James Kennedy in 1995, which was inspired by the intelligent social behavior of bird flocking or fish schooling.Initially, it was designed to simulate birds seeking food which is defined as a “cornfield vector”. PSO uses a number of agents (particles) that constitute a swarm (a set of particles) moving around in the search space seeking for the best solution by combining self-experiences with social-experiences.The position of each agent is represented by *XY*-

axes position and also the velocity is expressed by V_X (the velocity along X-axis) and V_Y (the velocity along Y-axis).Modification of the particle position is realized by using the position and velocity information.

Each agent knows its best value so far (*pbest*) and its *XY*position. This information is analogy of personal (self) experiences of each agent. Moreover, each agent also knows the best value so far in the group (*gbest*) among *pbests*. This information is analogy of social experiences of neighbors around them. In PSO each particle's neighborhood never changes (is always fixed). Each agent modifies its position according to the current position (x, y), the current velocity (vx, vy), the distance between its current position and *pbest* and the distance between its current position and *gbest* as shown below:

$$v_i^{k+1} = w_i\, v_i^k + c_1\, rand_1 \times (pbest_i - X_i^k)$$
$$+ c_2\, rand_2 \times (gbest - X_i^k) \qquad (9)$$

Where,

v_i^kvelocity of agent i at iteration k,

$w_i$inertia weight for velocity of agent i,

rand random number between 0 and 1,

c_1 individual learning rate,

$c_2$social learning rate,

s_i^kposition of agent i at iteration k,

$pbest_i$*pbest* of agent i,

gbest gbest of the group.

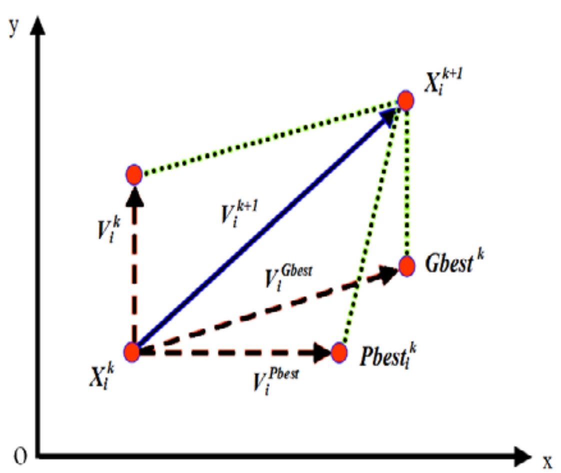

Fig. 1: Convergence of a new searching point.

X_i^kcurrent position in search space,
X_i^{k+1}modified position in search space,
V_i^k current velocity of agent,
V_i^{k+1}modified velocity of agent,
V_i^{pbest} modified velocity based on pbest,
V_i^{gbest} modified velocity based on gbest.

Using the equation (9), a particle's velocity that gradually converges towards *pbest* and *gbest* can be calculated. The current searching point in the solution space can be updated as follows:

$$X_i^{k+1} = X_i^k + v_i^{k+1} \qquad (10)$$

Fig. 1 shows the above concept of convergence of searching points graphically.

The RHS of the equation (9) have three terms. The first term is inertia (previous velocity) of agent, makes the particle move in the same direction with same velocity. The second term influences the agent personally and makes the particle return to a previous position, better than the current while; the third term has social influence and makes the particle follow the best neighbor's direction.

4. ADAPTIVE PARTICLE SWARM OPTIMIZATION

In the optimization of multi objective problem, PSO algorithm usually suffers from stagnation, which occurs because of non optimal swarm have a tendency to move near the location of *gbest*, preventing further exploration of new search area. The main reason of trapping in local optima is that agents (with lack of diversity), which lies on the line between *gbest* and *pbest* position use to converge to a single point (local optimal).

In APSO, different agents are allocated with different tasks. In this technique we can vary the inertia weight according to the performance or assigned task of agents that can increase the diversity among them and escaping from the local optima. By the variation inweight, a large inertia weight is responsible for a global exploration while a small inertia weight is responsible for a local search. To achieve a balance between global and local search the inertia weightis updated, which speed up the convergence to the real optimum as follow:

$$w^k = w_{max} - (w_{max} - w_{min}) \times \frac{(k-1)}{(m-1)} \qquad (11)$$

Where,
w^k inertia weight at iteration k,
w_{max} initial weight,
w_{min} final weight,
k current iteration number,
m swarm (population) size.

At the starting of the run PSO tends to have more global search while having more local search ability near the end of the run. To overcome this problem in APSO, acceleration constantalso updated after every iteration as follows:

$$c_{1i} = c_{2i} = \frac{wk+1+2\times\sqrt{wk}}{2} \qquad (12)$$

c_{1i}andc_{2i} determine the step size of the agent'smovements through the *pbest* and *gbest*, respectively and also help in fasting the convergence.

5. RPO ALGORITHM USING APSO

The proposed algorithm using APSO can be expressed as follows:

Step 1: **Initialization**: Initialize the searching points and velocities of agents from the solution space randomly.
Step 2: The objective function for each agent is calculated using the load flow analysis. If the constraints limits are violated, the penalty is added to the loss.
Step 3: *pbest* is set to each initial searching point in space. The initial best value among *pbest* is set to *gbest*.
Step 4: **Velocity update**: Particle velocity is updated using *pbest* and *gbest* according to (9).
Step 5: **Position update**: Based on the updated velocity, new searching points are calculated using (10).
Step 6: The objective function to the new searching points and the evaluation values are calculated. If the evaluation valueof each agent is better than the previous *pbest*, thevalue is set to *pbest*. If the best *pbest* is better than *gbest*, thevalue is set to *gbest*. All of *gbests*are stored as candidates for the final control strategy.
Step 7: **Weight update**: Update the weight w^kaccording to the update equation (11).
Step 8: **Acceleration constant update**:Update the acceleration constant$c_{1i}$and c_{2i}according to the equation (12).
Step 9: If one of the stopping criterion is met, then go to Step 10.Otherwise, go to Step 4.
Step 10: **Update the optimal value**: If the MW margin is satisfied, then set the target as the final solution.

6. NUMERICAL EXAMPLES

The proposed APSO algorithm for solving the RPO problem on the standard IEEE 30-bus power system has been applied and the effectiveness of the results is compared with the existing PSO algorithm.

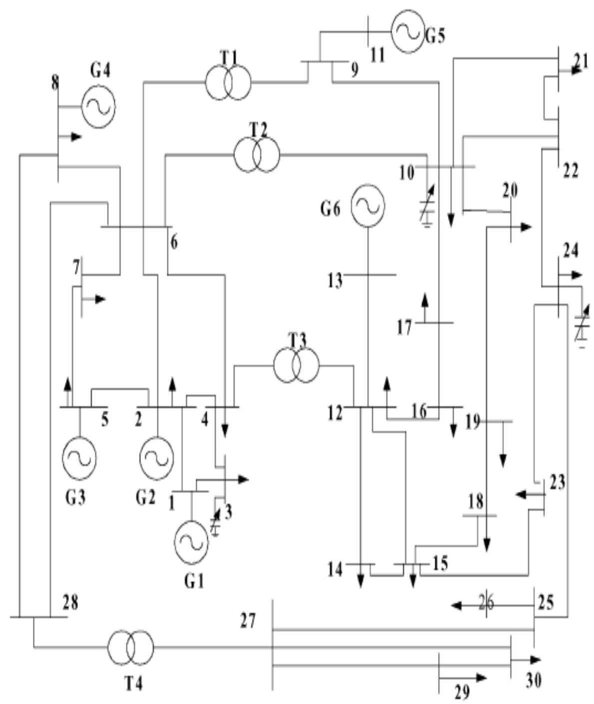

Fig. 2: A modified IEEE 30 bus system.

7. IEEE 30 BUS SYSTEM

1) *Simulation Condition:* A modified IEEE 30 bus systemis as shown in Fig. 2. The system contains 13 control variables in which there are 6 generators, 4 transformers and 3VAR compensators.Four branches (4, 12), (6, 9), (6, 10) and (27, 28) are under load tap setting transformer branches. TheVAR compensators are installed at buses 3, 10 and 24. Bus 1 is considered as theslack bus; the buses 2, 5, 8, 11, and 13 are taken as generator (PV)-buses whose voltages are required to be maintained, within the range of 0.90-1.1 p.u and the remaining buses are takenas load (PQ) –buses, whose voltages need to maintain within the range of 0.94-1.06 p.u.System MVA base is taken as 100.

8. PARAMETERS SELECTION

The branch parameters and operating condition of IEEE 30 bus system is taken from [16]-[18]. The inertia weight for the PSO is set to the following equation:

$$w^k = w_{max} - (w_{max} - w_{min}) \times \frac{k}{kmax} \qquad (13)$$

Where,

k current iteration number,

k_{max} maximum iteration number,

w_{max} and w_{min} are taken as 0.9 and 0.4 respectively. Swarm size for the simulation using PSO and APSO are taken as50 and the results are compared with 200 searching iterations.

9. SIMULATION RESULTS

Table 1 shows the best results obtained by the proposed method (APSO) in 200 numbers of iterations and compared with the result obtained by PSO and NR load flow analysis. Table 2 shows the total active power losses obtained using different optimization technique. The proposed APSO gives lesser loss values than other computation techniques, which can be verified from the repeated trial runs.Fig. 3 shows the convergence characteristics for IEEE 30 bus system. From figure it is inferred that PSO converges to the optimum solution quickly at the first few iterations. On the other hand, APSO converges up to last iterations gradually and improves the quality solutions in lesser computation time.

TABLE 1: Comparison of best result for IEEE 30 bus system

Sr. No.	Opt. Method / Cont. Variables	APSO	PSO
1	AVR 1 (pu)	1.1026	1.0909
2	AVR 2	1.0731	1.0600
3	AVR 5	1.0325	1.0088
4	AVR 8	1.0235	1.0105
5	AVR 11	1.0384	1.1025
6	AVR 13	0.9988	0.9943
7	Tap 4-12	0.9892	0.9745
8	Tap 6-9	0.9730	1.0167
9	Tap 6-10	1.0319	1.0021
10	Tap 27-28	0.9907	0.9768
11	SC 3 (MVAR)	18.8559	19.1231
12	SC 10	1.5542	1.1444
13	SC 24	14.4223	16.5134

TABLE 2: Comparison of Ploss for IEEE 30 bus system

Sr. No.		Losses before optimization	Losses after optimization using PSO	Losses after optimization using APSO
1	Active power losses (Ploss) MW	17.068	16.9914	16.6151

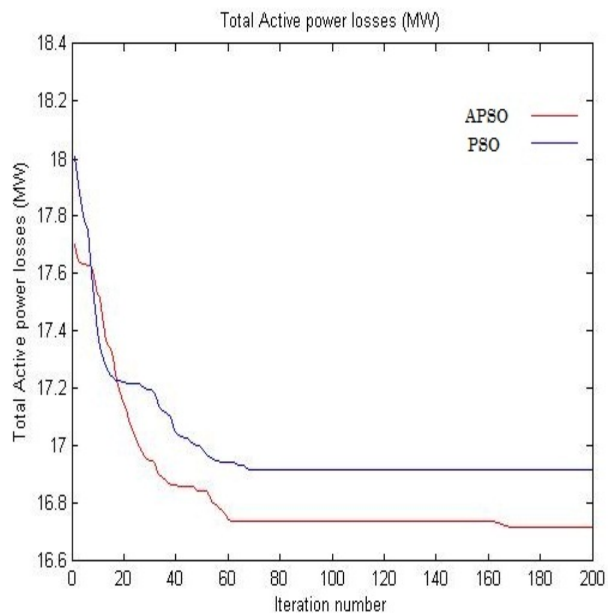

Fig. 3: Convergence characteristics by APSO and PSO for IEEE 30 bus system.

10. CONCLUSION

Adaptive PSO technique is proposed for reactive power optimization (RPO) problem for voltage control. Using this method RPO problem is formulated as mixed-integer/non-linear optimization problem (MINLOP) and gives the high quality solution with continuous as well as discrete state variables.

In this paper multi-objective RPO problem is consideredwith three objectives such as active power loss minimization, voltage profile improvement at load buses and voltage stabilityimprovement. The robustness of the result is verified on employing the proposed method to solve RPO problem on IEEE 30-bus system. From the simulation results, it has been concluded that APSO requires very few parameters tuning and especially, it converges to sub-optimal solutions within 80 iterations even for very large power system. Fast convergence to optimal solution and lesser computation time requirement are the advantages of APSO over conventional PSO and other optimization techniques.

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