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REDUCTION OF REAL POWER LOSS BY ADVANCED PARTICLE SWARM OPTIMIZATION ALGORITHM

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Abstract

This paper presents Advanced Particle Swarm Optimization (APSO) algorithm for solving optimal reactive power problem. In this work Biological Particle swarm Optimization algorithm utilized to solve the problem by eliminating inferior population & keeping superior population, to make full use of population resources and speed up the algorithm convergence. Projected Advanced Particle Swarm Optimization (APSO) algorithm has been tested on standard IEEE 30 bus test system and simulation results shows clearly about the superior performance of the proposed Advanced Particle Swarm Optimization (APSO) algorithm in reducing the real power loss and static voltage stability margin (SVSM) Index has been enhanced.

Keywords: Biological Particle Swarm; Reactive Power Optimization; Transmission Loss.

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1. Introduction

Main objective of the Optimal reactive power dispatch (ORPD) problem is to minimize the real power loss and to enhance the voltage stability index. A variety ofnumerical techniqueslike the gradient method [1-2], Newton method [3] and linear programming [4-7] have been adopted to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods has the complexity in controlling inequality constraints. If linear programming is applied, then the input- output function has to be articulated as a set of linear functions which predominantly lead to loss of accuracy. Thedifficulty of voltage stability and fall down, play a major role in power system planning and operation [8]. Global optimization has received wide-ranging research responsiveness, and enormousnumber of methods has been applied to solve this problem. Evolutionary algorithms such as genetic algorithm have been already proposed to solve the reactive power flow problem [9,10].Evolutionary algorithm is a heuristic approach used for minimization problems by utilizing nonlinear and non-differentiable incessant space functions. In [11], Genetic algorithm has been used to solve optimal reactive power flow problem. In [12], Hybrid differential evolution algorithm is proposed to perk up the voltage stability index. In

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[13],Biogeography Based algorithm is planned to solve the reactive power dispatch problem. In [14], afuzzy based method is used to solve the optimal reactive power scheduling method. In [15],an improved evolutionary programming is used to solvethe optimal reactive power dispatch problem. In [16], the optimal reactive power flow problem is solved by integrating a genetic algorithm with a nonlinearinterior point method. In [17], apattern algorithm is used to solve ac-dc optimal reactive powerflow model with the generator capability limits. In [18], proposes a two-step approach to evaluate Reactive power reserves with respect to operating constraints and voltage stability. In [19], a programming based proposed approach used to solve the optimal reactive power dispatch problem. In [20], presents aprobabilistic algorithm for optimal reactive power requirementin hybrid electricity markets with uncertain loads. This paper presents Advanced Particle Swarm Optimization (APSO) algorithm for solving optimal reactive power problem. In this work Biological Particle swarm Optimization algorithm utilized to solve the problem by eliminating inferior population & keeping superior population, to make full use of population resources and speed up the algorithm convergence. The proposed algorithm has four phases of migration, selection, elimination and reproduction, evolution. Using searching optimal model of PSO in the migration phase; introducing LEVEL SET theory dividing population to be able to facilitate the selection operation in the selection phase; speeding up the algorithm convergence by abandoning the inferior population, reproducing superior population and making full use of population resource in the phase of elimination and reproduction; creating new population to keep the diversity to avoid monotone of the algorithm in the last evolutionary phase. Projected Advanced Particle Swarm Optimization (APSO) algorithm has been tested on standard IEEE 30 bus test system and simulation results shows clearly about the superior performance of the proposed Advanced Particle Swarm Optimization (APSO) algorithm in reducing the real power loss and static voltage stability margin (SVSM) Index has been enhanced.

2. Voltage Stability Evaluation

2.1. Modal Analysis for Voltage Stability Evaluation

Modal analysis is one among best methods for voltage stability enhancement in power systems. The steady state system power flow equations are given by.

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_{p\theta} & J_{pv} \\ J_{q\theta} & J_{QV} \end{bmatrix} \begin{bmatrix} \Delta\theta \\ \Delta V \end{bmatrix} \quad (1)$$

Where
ΔP = Incremental change in bus real power.
ΔQ = Incremental change in bus reactive Power injection
$\Delta\theta$ = incremental change in bus voltage angle.
ΔV = Incremental change in bus voltage Magnitude
$J_{p\theta}$, J_{PV} , $J_{Q\theta}$, J_{QV} jacobian matrix are the sub-matrixes of the System voltage stability is affected by both P and Q.
To reduce (1), let $\Delta P = 0$, then.

$$\Delta Q = \left[J_{QV} - J_{Q\theta} J_{P\theta^{-1}} J_{PV}\right]\Delta V = J_R \Delta V \quad (2)$$

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$$\Delta V = J^{-1} - \Delta Q \tag{3}$$

Where

$$J_R = \left(J_{QV} - J_{Q\theta} J_{P\theta^{-1}} JPV\right) \tag{4}$$

J_R is called the reduced Jacobian matrix of the system.

2.2. Modes of Voltage instability

Voltage Stability characteristics of the system have been identified by computing the Eigen values and Eigen vectors.
Let

$$J_R = \xi \wedge \eta \tag{5}$$

Where,
ξ = right eigenvector matrix of JR
η = left eigenvector matrix of JR
∧ = diagonal eigenvalue matrix of JR and

$$J_{R^{-1}} = \xi \wedge^{-1} \eta \tag{6}$$

From (5) and (8), we have

$$\Delta V = \xi \wedge^{-1} \eta \Delta Q \tag{7}$$

Or

$$\Delta V = \sum_I \frac{\xi_i \eta_i}{\lambda_i} \Delta Q \tag{8}$$

Where ξi is the ith column right eigenvector and η the ith row left eigenvector of JR.
λi is the ith Eigen value of JR.
The ith modal reactive power variation is,

$$\Delta Q_{mi} = K_i \xi_i \tag{9}$$

where,

$$K_i = \sum_j \xi_{ij^2} - 1 \tag{10}$$

Where
ξji is the jth element of ξi
The corresponding ith modal voltage variation is

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$$\Delta V_{mi} = [1/\lambda_i]\Delta Q_{mi} \tag{11}$$

If | λi | =0 then the ith modal voltage will collapse.

In (10), let ΔQ = ek where ek has all its elements zero except the kth one being 1. Then,

$$\Delta V = \sum_i \frac{\eta_{1k}\ \xi_1}{\lambda_1} \tag{12}$$

η_{1k} k th element of η_1
V –Q sensitivity at bus k

$$\frac{\partial V_K}{\partial Q_K} = \sum_i \frac{\eta_{1k}\ \xi_1}{\lambda_1} = \sum_i \frac{P_{ki}}{\lambda_1} \tag{13}$$

3. Problem Formulation

The objectives of the reactive power dispatch problem is to minimize the system real power loss and maximize the static voltage stability margins (SVSM).

3.1. Minimization of Real Power Loss

Minimization of the real power loss (Ploss) in transmission lines is mathematically stated as follows.

$$P_{loss=} \sum_{\substack{k=1 \\ k=(i,j)}}^{n} g_{k(V_i^2+V_j^2-2V_i\,V_j\,\cos\theta_{ij})} \tag{14}$$

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

3.2. Minimization of Voltage Deviation

Minimization of the voltage deviation magnitudes (VD) at load buses is mathematically stated as follows.

$$\text{Minimize VD} = \sum_{k=1}^{nl} |V_k - 1.0| \tag{15}$$

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

3.3. System Constraints

Objective functions are subjected to these constraints shown below.
Load flow equality constraints:

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$$P_{Gi} - P_{Di} - V_{i\sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, i = 1,2 \ldots., nb \quad (16)$$

$$Q_{Gi} - Q_{Di} - V_{i\sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \sin\theta_{ij} \\ +B_{ij} & \cos\theta_{ij} \end{bmatrix} = 0, i = 1,2 \ldots., nb \quad (17)$$

where, nb is the number of buses, PG and QG are the real and reactive power of the generator, PD and QD are the real and reactive load of the generator, and Gij and Bij are the mutual conductance and susceptance between bus i and bus j.

Generator bus voltage (VGi) inequality constraint:

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max}, i \in ng \quad (18)$$

Load bus voltage (VLi) inequality constraint:

$$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max}, i \in nl \quad (19)$$

Switchable reactive power compensations (QCi) inequality constraint:

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max}, i \in nc \quad (20)$$

Reactive power generation (QGi) inequality constraint:

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}, i \in ng \quad (21)$$

Transformers tap setting (Ti) inequality constraint:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in nt \quad (22)$$

Transmission line flow (SLi) inequality constraint:

$$S_{Li}^{min} \leq S_{Li}^{max}, i \in nl \quad (23)$$

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

4. Particle Swarm Optimization Algorithm

Particle Swarm Optimization (PSO) is a population-based optimization algorithm inspired by the behaviour of flocks of birds. The standard approach [21-22] is composed by a swarm of particles, where each one has a position within the search space $\overrightarrow{x_i}$ and each position represents a solution for the problem. The particles fly through the search space of the problem searching for the best solution, according to the current velocity $\overrightarrow{v_i}$ the best position found by the particle itself

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$(\overrightarrow{P_{best\iota}})$ and the best position found by the entire swarm during the search so far$(\overrightarrow{G_{best\iota}})$. According to this approach the velocity of a particle i is evaluated at each iteration of the algorithm by using the following equation:

$$\vec{v_i}\,(t+1) = \omega\vec{v_i}(t) + r_1c_1\left|\overrightarrow{P_{best_\iota}} - \vec{x_\iota}(t)\right| + r_2c_2\left|\overrightarrow{G_{best_\iota}} - \vec{x_\iota}(t)\right|, \tag{24}$$

Where r_1 and r_2 are numbers randomly generated in the interval [0, 1]. The inertia weight (ω) controls the influence of the previous velocity and balances the exploration-exploitation behaviour along the process. It generally decreases from 0.9 to 0.4 during the algorithm execution. c_1 and c_2 are called cognitive and social acceleration constants, respectively, and weights the influence of the memory of the particle and the information acquired from the neighbourhood. The position of each particle is updated based on the velocity of the particle, according to the following equation:

$$\vec{x_\iota}\,(t+1) = \vec{x_\iota}\,(t) + \vec{v_\iota}\,(t+1) \tag{25}$$

The communication topology defines the neighbourhood of the particles and, as a consequence, the flow of information through the particles. There are two basic topologies: global and local. In the former, each particle shares and acquires information directly from all other particles, *i.e.* all particles use the same social memory, called G_{best}. In the local topology, each particle only shares information with two neighbours and the social memory is not the same within the whole swarm. This approach, called L_{best}, helps to avoid a premature attraction of all particles to a single spot point in the search space.

4.1. Shortcomings of Conventional PSO Algorithm

As shown in Fig. 1, each particle of PSO closes to historical optimal location and global optimal location. This makes PSO algorithms have many advantages, such as that their computational complexity doesn't increase with the rising of the dimension of the problem, and rapid convergent speed, etc. However, they still have some shortcomings, which are listed as follows:

Shortcoming 1: When the conventional PSO searches, the particles tend to get close to the better particles. This property would make the algorithm find out the optimal solution as soon as possible, however, this property is also a flaw that could result in premature convergence. That is, when all the particles constantly get close to the better ones, all the particles in the system would be probably concentrated in a local optimal solution. At this situation, it is a pity that all the particles cannot jump out of the local optimal solution they have approached. From Fig. 2, it can be seen clearly that particles don't find the global optimal solution but concentrate to a local optimal solution. At this time, they no longer have the abilities to get rid of the attraction of the local optimal solution and result in premature convergence.

Shortcoming 2: The speeds of particles are too great. When particles are located in some local, the objective function is quite sensitive to the slight changes of particles. Thus, at this time, too great speed of the particle is not suitable; meanwhile, too little speed would influence the speed of convergence. We can see from Fig. 3 that though particle is attracted by the optimal solution,

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and motion toward the optimal solution. Nevertheless, because the speed of particle is too great, it would easily miss the optimal solution.

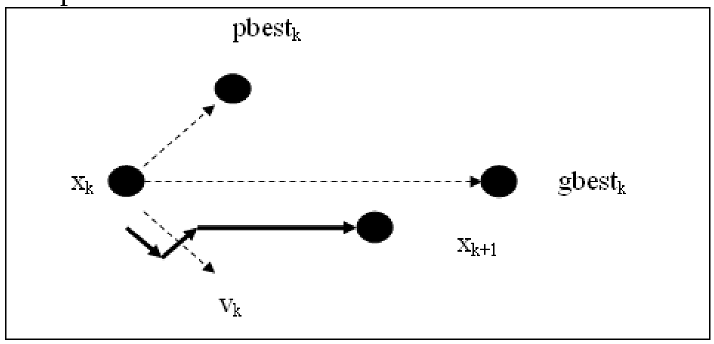

Figure 1: Sport of the particle

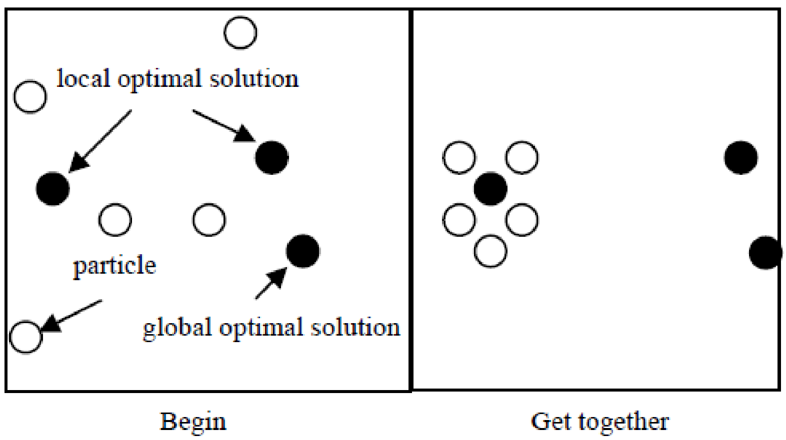

Figure 2: Particle gets together

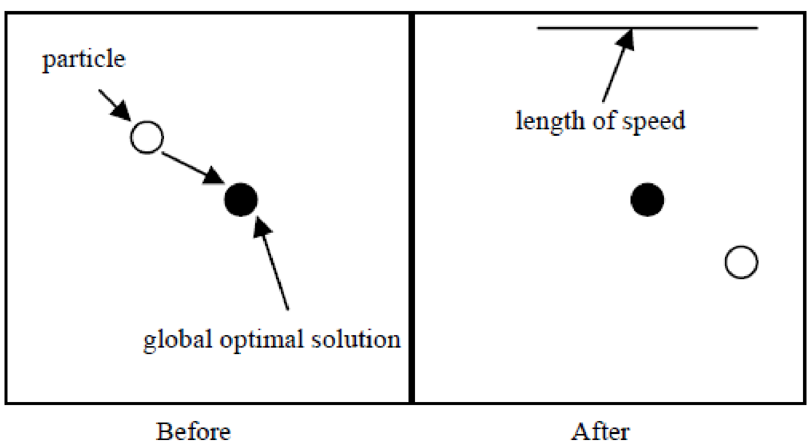

Figure 3: Particle moves to the best position

5. PSO Algorithm Based on Biological Population Multiplication

In nature, each population will search food in order to multiply. As we all know that the rule of survival of the fittest, original but effective, exits in the process of searching food. In this paper,

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we introduced this rule to PSO algorithm eliminating inferior population and keeping superior population. It is helpful to make full use of population resources and speed up the algorithm convergence. In the selection phase, classifying successfully by using LEVEL SET theory make the algorithm accord with the principle of survival of the fittest. At the same time, we also take into account the evolution of population to keep the diversity of the population which can prevent the monotone and prematurity of the algorithm. Finally, the algorithm is applied to some test functions to verify its feasibility and effectiveness.

5.1. Biological Population Multiplication

In nature, populations search food in order to multiply. As we all know the rule of survival of the fittest, original but effective, exits in the process of searching food. First of all, we assume that some biomes are dotted in a region. Each of them migrates to search food as well as a more suitable place for survival. In the Fig. 4, this article assumes that there are four communities, p1, p2, p3, p4, in a region, Because of the need looking for food, community migration is called respectively: P1, P2, P3, and P4. And after that, the survival of the fittest begins. Among them, P3 and P4 successfully accepted the test to continue to survive, besides P3 takes further reproduction to extend the community due to good environment; P1, tortured by the nature, evolves eventually to become P1’ adapting to the environment; but P2 has to be eliminated because it is hard to find suitable places to survive. This mode of biomes multiplication not only washes out the inferior population and keeps the superior ones, but also stimulates the evolution of population to adapt to the survival environment. For this right mode, hundreds of thousands of biological communities could survive and continue.

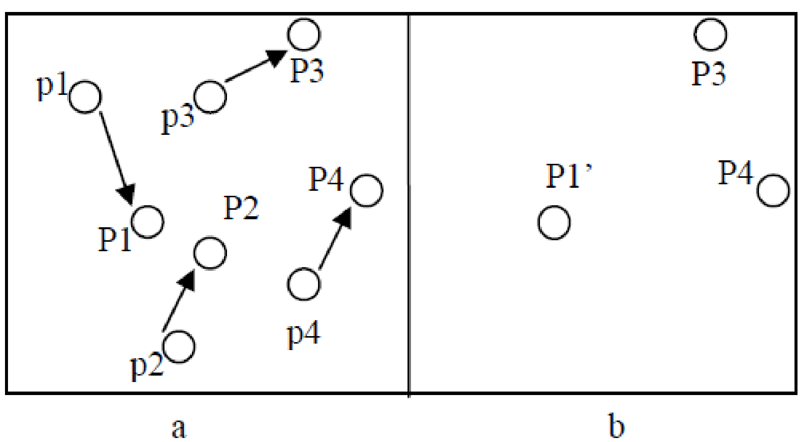

Figure 4: Particle survival

5.2. Improved PSO Algorithm Based on the Population

5.2.1. Multiplication

We know that in PSO algorithm, each particle moves towards the global optimal location and the optimal location of individual history as a criterion to find a better location for survival. This model allows algorithm has a good convergence, but also maintains a good searching performance. In Fig. 5, after a round of movement, the particles all have new locations A1, B1,

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C1, D1, E1 and F1. However, each new particle continues to search optimization directly without the process of survival of the fittest in the next movements, illustrated as shown in Fig. 6. However, this movement in PSO makes some inferior particles continue to reproduce to become inferior communities unable to be eliminated which affects the algorithm convergence rate. At the same time the resource of particle swam cannot be fully utilized. That is because the quantity of particles affects the algorithm efficiency while the quality of particles does the same. In order to overcome this disadvantage, the paper presented an improved PSO algorithm with the principles of biologic population multiplication. The algorithm is divided into four phases: migration, selection, elimination and reproduction, evolution.

5.2.2. Migration

We introduce the concept of migration to the new algorithm. The population migration is similar to the changes of the particles location in PSO, one change for the survival of population while the other is for a better location. And the migration of population is also affected by two factors: history experience and communication experience. The history experience just means searching the optimal location of individual and communication experience is for the global optimal location in PSO.

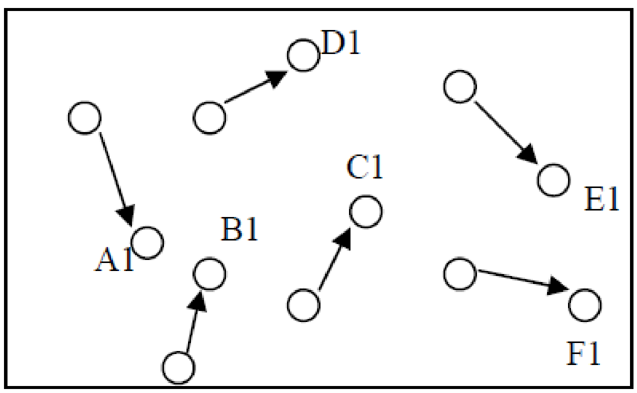

Figure 5: The movement of first generation particles, each of them moves to search a better place

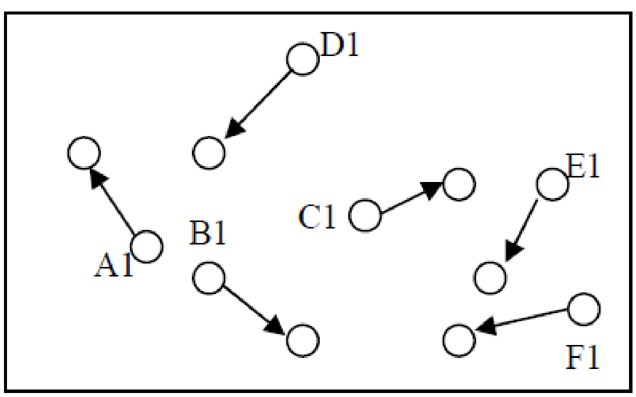

Figure 6: Traditional PSO algorithm: Each particle gets location of the next particle after the previous round and continues to move

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So at this phase, the new algorithm and PSO algorithm look like the same (maybe only the name is different). We will still use the speed changing (24) and location changing (25) of PSO. In the (24), the value w is fixed. w, set a litter larger, is suit to a wide range of exploration to solution space while smaller is suit to a small range. At the early convergence, the larger w can speed up the convergence, while in the latter the smaller w can improve the capacity of searching optimization. Therefore, this paper defines the w as follow:

$$w(i) = w_{max} - i(w_{max} - w_{min})/N \tag{26}$$

Here, $w(i)$ is alterable (maybe degressive more exactly),$w_{max}, w_{min} \in (0,1)$

5.2.3. Selection

At selection phase, we need to judge which population will be eliminated and reproduce and how much they reproduce. This requires that all population should be divided into two parts: the superior ones and the inferior ones. LEVEL SET theory is introduced here. For the tth-generation P(t) = (P1, P2, ..., Pn), n denotes the number of particles, the fitness function of particles is set to fi(x), order

$$Ft = \sum_{i=1}^{n} \frac{f(x_i)}{n} \tag{27}$$

$$HFt = \{x_i \in P(t) | f(x_i) \leq \dot{f}t \,, 1,2,..,n\} \tag{28}$$

Where t denotes t^{th}-generation ft, H is called the level set about f relative to P(t). After that the population of each generation can be divided two parts.
Selection steps are as follows:
a) Set the initial population for X = (X1, X2, ..., Xn);
b) Calculate the fitness of each population;
c) Calculate the mean of fitness
d) According to the method of Step c), Xb is divided into Xc and Xd, between them Xc stands for the better population, and Xd for the poorer population.
e) The population number in Xd is nd. So we select randomly nd-pm in Xa+Xb+Xc for reproducing. pm is the number of evolution population discussed below.

5.2.4. Elimination and Reproduction

When population arrives in a new environment, which is too bad to adapt to, the entire population has to be extinct which is called elimination. However, when they arrive an eminent environment, they will be developed and reproduce. This concept introduced in new algorithm is completely different with the PSO algorithm. Fig. 9 has illustrated the particle change of PSO algorithm, changes of the improved PSO algorithm is as follows in Fig. 7:

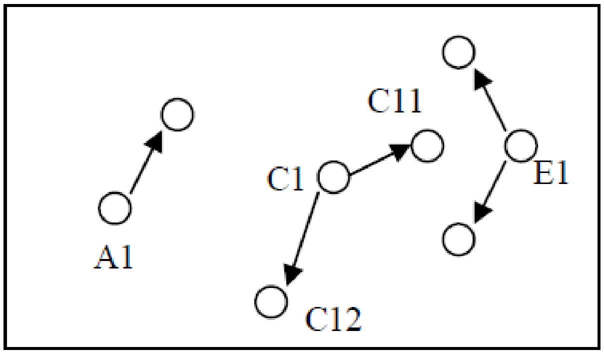

Figure 7: Particle movement in the Biological PSO

The difference between Fig. 9 and Fig.10 is B1, D1, and F1 are all eliminated and disappear while A1, C1, and E1 take a further reproduction because of good environment and continue to the next migration. At the reproduction phase, combining the merits of PSO algorithm (memory individual information) and the characteristics of biomes multiplication (population reproduction) makes the post-breeding population memory the mother possible. For example C1 reproduces two populations: C1' and C1", both of them will inherit the memory of C1 (memory includes the individual optimal location and current location of C1), and then migrate respectively to get C11 and C12.

5.2.5. Evolution

The reason why biological population is able to keep balance is not only the extinction of population but also the evolution of population. This constant evolution creates a lot of new population, which makes the whole system keep balance. This evolution is worth thinking, the phase of that is also contained in our algorithm. It makes the number of population hold the line, of course, more important; it will not become the monotonous population. Mentioned above, it is said that there are pm populations to evolve, that is to say, it will creates pm new populations. However, we know that only the location can distinguish the differences in solution space. So pm populations evolve means generating randomly pm new solutions.

Advanced Particle Swarm Optimization (APSO) algorithm for solving reactive power problem

- Initialize parameters and set the number of evolution population for pm;
- Initialize population X = (X1, X2,…, Xn);
- Calculate the fitness of each population;
- Selection operation;
- Reproduction and elimination operation;
- Evolution operation;
- Migration operation;
- End if the migration algebra arrived; otherwise go to c.

Step 1. Initial searching points and velocities of agents are generated.
Step 2. Ploss to the searching points for each agent is calculated using the load flow calculation. If the constraints are violated, the penalty is added to the loss (evaluation value of agent).

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Step 3. Pbest is set to each initial searching point. The initial best evaluated value (loss with penalty) among pbests is set to gbest.
Step 4. New velocities are calculated .
Step 5. Update the velocity from previous velocity to the new velocity .
Step 6. To new function applied.

1) setdirection
2) calculateDiversity to control swarm.

Step 7. Ploss to the new searching points and the evaluation values are calculated.
Step 8. If the evaluation value of each agent is better than the previous pbest, the value is set to pbest. If the best pbest is better than gbest, the value is set to gbest. All of gbests are stored as candidates for the final control strategy.
Step 9. If the iteration number reaches the maximum iteration number, then stop. Otherwise, go to Step 4. If the voltage and power flow constraints are violated, the absolute violated value from the maximum and minimum boundaries is largely weighted and added to the objective function as a penalty term. The maximum iteration number should be determined by pre-simulation.

6. Simulation Results

The efficiency of the proposed Advanced Particle Swarm Optimization (APSO) algorithm is demonstrated by testing it on standard IEEE-30 bus system. The IEEE-30 bus system has 6 generator buses, 24 load buses and 41 transmission lines of which four branches are (6-9), (6-10) , (4-12) and (28-27) - are with the tap setting transformers. The lower voltage magnitude limits at all buses are 0.95 p.u. and the upper limits are 1.1 for all the PV buses and 1.05 p.u. for all the PQ buses and the reference bus. The simulation results have been presented in Tables 1, 2, 3 &4. And in the Table 5 shows the proposed algorithm powerfully reduces the real power losses when compared to other given algorithms. The optimal values of the control variables along with the minimum loss obtained are given in Table 1. Corresponding to this control variable setting, it was found that there are no limit violations in any of the state variables.

Table 1: Results of APSO – ORPD optimal control variables

Control variables	**Variable setting**
V1	1.040
V2	1.039
V5	1.041
V8	1.030
V11	1.000
V13	1.030
T11	1.00
T12	1.00
T15	1.00
T36	1.01
Qc10	2
Qc12	2
Qc15	2
Qc17	0
Qc20	2

Qc23	2
Qc24	3
Qc29	2
Real power loss	4.2642
SVSM	0.2470

Optimal Reactive Power Dispatch (ORPD) problem together with voltage stability constraint problem was handled in this case as a multi-objective optimization problem where both power loss and maximum voltage stability margin of the system were optimized simultaneously. Table 2 indicates the optimal values of these control variables. Also it is found that there are no limit violations of the state variables. It indicates the voltage stability index has increased from 0.2470 to 0.2482, an advance in the system voltage stability. To determine the voltage security of the system, contingency analysis was conducted using the control variable setting obtained in case 1 and case 2. The Eigen values equivalents to the four critical contingencies are given in Table 3. From this result it is observed that the Eigen value has been improved considerably for all contingencies in the second case.

Table 2: Results of APSO -Voltage Stability Control Reactive Power Dispatch (VSCRPD) Optimal Control Variables

Control Variables	**Variable Setting**
V1	1.045
V2	1.047
V5	1.044
V8	1.033
V11	1.004
V13	1.032
T11	0.090
T12	0.090
T15	0.090
T36	0.090
Qc10	3
Qc12	2
Qc15	2
Qc17	3
Qc20	0
Qc23	2
Qc24	2
Qc29	3
Real power loss	4.9894
SVSM	0.2482

Table 3: Voltage Stability under Contingency State

Sl.No	**Contingency**	**ORPD Setting**	**VSCRPD Setting**
1	28-27	0.1419	0.1434
2	4-12	0.1642	0.1650
3	1-3	0.1761	0.1772

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4	2-4	0.2022	0.2043

Table 4: Limit Violation Checking Of State Variables

State variables	**limits**		**ORPD**	**VSCRPD**
	Lower	**upper**		
Q1	-20	152	1.3422	-1.3269
Q2	-20	61	8.9900	9.8232
Q5	-15	49.92	25.920	26.001
Q8	-10	63.52	38.8200	40.802
Q11	-15	42	2.9300	5.002
Q13	-15	48	8.1025	6.033
V3	0.95	1.05	1.0372	1.0392
V4	0.95	1.05	1.0307	1.0328
V6	0.95	1.05	1.0282	1.0298
V7	0.95	1.05	1.0101	1.0152
V9	0.95	1.05	1.0462	1.0412
V10	0.95	1.05	1.0482	1.0498
V12	0.95	1.05	1.0400	1.0466
V14	0.95	1.05	1.0474	1.0443
V15	0.95	1.05	1.0457	1.0413
V16	0.95	1.05	1.0426	1.0405
V17	0.95	1.05	1.0382	1.0396
V18	0.95	1.05	1.0392	1.0400
V19	0.95	1.05	1.0381	1.0394
V20	0.95	1.05	1.0112	1.0194
V21	0.95	1.05	1.0435	1.0243
V22	0.95	1.05	1.0448	1.0396
V23	0.95	1.05	1.0472	1.0372
V24	0.95	1.05	1.0484	1.0372
V25	0.95	1.05	1.0142	1.0192
V26	0.95	1.05	1.0494	1.0422
V27	0.95	1.05	1.0472	1.0452
V28	0.95	1.05	1.0243	1.0283
V29	0.95	1.05	1.0439	1.0419
V30	0.95	1.05	1.0418	1.0397

Table 5: Comparison of Real Power Loss

Method	**Minimum loss**
Evolutionary programming [29]	5.0159
Genetic algorithm [30]	4.665
Real coded GA with Lindex as SVSM [31]	4.568
Real coded genetic algorithm [32]	4.5015
Proposed APSO method	4.2642

7. Conclusion

In this paper Advanced Particle Swarm Optimization (APSO) algorithm successfully solved optimal reactive power problem. In this work Biological Particle swarm Optimization algorithm utilized to solve the problem by eliminating inferior population & keeping superior population, to make full use of population resources and speed up the algorithm convergence. Projected Advanced Particle Swarm Optimization (APSO) algorithm has been tested on standard IEEE 30 bus test system and simulation results shows clearly about the superior performance of the proposed Advanced Particle Swarm Optimization (APSO) algorithm in reducing the real power loss and static voltage stability margin (SVSM) Index has been enhanced.

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