PSC2009
24th International Power System Conference
09-E-PSS-0247
بيست و چهارمين
كنفرانس بين المللى برق

Reactive /Voltage control by A Multi-agent based PSO approach considering voltage stability

A .H . Khazali , M. Kalantar

**Center of Excellence for Power System Automation and Operation,
Iran university of science & Technology
Tehran, Iran**

Keywords : Optimal reactive power dispatch; Multiagent based PSO; Optimization; Loss minimization

Abstract :
This paper presents a Multiagent based particle swarm optimization (MAPSO) for optimal reactive & voltage control. Optimal reactive/voltage control is a mixed integer, nonlinear optimization problem which includes both continuous and discrete control variables. The proposed algorithm is used to find the settings of control variables such as generator voltages, tap positions of tap changing transformers and the amount of reactive compensation devices to optimize a certain objective. The objectives are power transmission loss, voltage stability and voltage profile which are optimized separately. In the presented method , the inequality constraints are handled by penalty coefficients. The study is implemented on IEEE 30 system and the results are compared with other evolutionary programs such as simple genetic algorithm (SGA) and particle swarm optimization (PSO).

1. Introduction

The Optimal Reactive power dispatch problem is affective on secure and economic operation of power systems. This problem denotes optimal settings of control variables such as generator voltages, tap ratios of transformers and reactive compensation devices to minimize a certain object While satisfying equality and inequality constraints. Transformer tap settings and reactive compensation devices are discrete values while bus voltage magnitudes and reactive power outputs of generators are continuous variables so the ORPD problem can be modeled using mixed integer nonlinear programming.

Up to now a number of mathematical programming approaches have been implemented to the ORPD problem. In [1-4] gradient based optimization algorithms have been used to solve the ORPD problem.

Recently interior-point methods have been implemented to the ORPD and the OPF problem. Interior-point linear programming [5] was used by Granville. Quadratic programming [6] was also implemented by momeh. These methods are incapable in handling nonlinear, discontinuous functions and constraints, and problems having multiple local minima. In all these techniques simplifications have been done to overcome the limitations. In [7] Aoki handled discrete variables by an approximation–search method and Bakirtziss in [8] represented a linear-programming to handle the shunt reactive compensation devices .

Recently, stochastic search methods have been used widely for the global optimization problem. In [9] an Evolutionary Programming (EP) is applied by Wu for global optimization of a power system to accomplish optimal reactive power dispatch and voltage control. Lai in [10] showed EP is more capable of handling non-continuous and non- smooth functions comparing nonlinear programming. In [11] Lee used simple genetic algorithm (SGA) combined with successive linear programming to solve reactive power operational problem. Particle swarm optimization (PSO) was applied by Yoshida in [13] for reactive power and voltage control considering voltage security assessment. [14] proposed a multi-agent based PSO by Zhao for the ORPD problem. In [15] Zhang used a fuzzy adaptive PSO for reactive power and voltage control.

In the few years many evolutionary optimization methods have been implemented to the reactive/ voltage control problem such as genetic algorithm (GA) and particle swarm optimization (PSO). PSO is developed on the base of a social system and is capable of handling nonlinearities and discrete variables in optimization problems [16]. PSO takes shorter time for finding sufficient solutions while showing high convergence qualities comparing with other stochastic algorithms.

Recently agent-based computation has been investigated in the field of artificial intelligence [17]. Problem solving is an area that multi-agent systems have many applications.

In this paper a novel approach by the combination of PSO and multi-agent systems has been used to optimize the reactive/voltage control problem. In this solution every the agents are solutions that are organized in a lattice-like environment while each of these agents represents a particle to the PSO. For finding the optimum solution these agents compete and cooperate with each other and their information are updated by PSO at each iteration.

2. Problem formulation

The proposed algorithm is tested and compared with other conventional algorithms on optimal performance in terms of minimization of a) Power losing transmission lines. b) Sum of voltage deviations on load busses. c) Voltage stability. The function is optimized while satisfying equality and inequality constraints. The first objective is to minimize the real power losses that could be expressed as:

$$F_1 = P_{Loss}(\mathbf{x}, \mathbf{u}) = \sum_{L=1}^{Nl} P_L \qquad (1)$$

Where **x** is the vector of dependent variables, **u** is the vector of control variables, P_L is the real power losses at line-L and Nl is the number of transmission lines.

The second object is the voltage deviation at load buses and can be expressed as :

$$F_2 = VD(\mathbf{x}, \mathbf{u}) = \sum_{i=1}^{Nd} \left| V_i - V_i^{sp} \right| \qquad (2)$$

Where V_i is the voltage at load bus-i, which is usually set to 1.0 pu and Nd is the number of load buses.

Reliable assessment of voltage stability of an electric power system is essential for its operation and control. To accommodate the need for accurate analysis of voltage stability a number of methods have been developed. In one of these approaches a index is introduced to evaluate the voltage stability of the system[18]. The voltage stability index is

based on the hybrid matrix of circuit theory. It is assumed are divided in to generator nodes(indicated by index G) and load nodes(indicated by index L).
The transmission system is written as:

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = [H]\begin{bmatrix} I_L \\ V_G \end{bmatrix} = \begin{bmatrix} Z_{LL} & F_{LG} \\ K_{GL} & Y_{GG} \end{bmatrix}\begin{bmatrix} I_L \\ V_G \end{bmatrix} \quad (3)$$

Where:
H: hybrid matrix
$V_L\,(I_L)$: Voltage(Current) at load node
$V_G\,(I_G)$: Voltage(Current) at generator node

The voltage stability index at load node j may be written as:

$$L_j = \left| 1 + \frac{V_{oj}}{V_j} \right| \quad (4)$$

Where $V_{oj} = -\sum_i F_{ji} V_i$

i indicates the generator buses.

Therefore, the voltage stability index for the whole network may be expressed as:

$$L = \mathrm{Max}\, L_j \quad (5)$$

Index L varies between 0 and 1 where 0 means a power network without load and L=1 shows a voltage collapse. Hence the introduced index allows the operator to estimate a margin to voltage instability.
The third objective which is minimized is the L voltage stability index. This index is calculated for all load buses and the maximum amount of all buses is the objective. It can be expressed as:

$$F_3 = VD(\mathbf{x}, \mathbf{u}) = L_{max} \quad (3)$$

In all of the problems the dependent vector is considered as:

$$x^T = [[V_L]^T, [Q_G]^T, [S_L]^T] \quad (4)$$

Where **x** is the vector of dependent variables, $[V_L]$ is the vector of load bus voltages, $[Q_G]$ is the vector of generator reactive power outputs and $[S_L]$ is the transmission line loadings.
The vector of control variables is presented as below.

$$u^T = [[V_G]^T, [t]^T, [Q_c]^T] \quad (5)$$

$[V_G]$ is the vector of generator bus voltages, $[t]$ is the vector of transformer taps and $[Q_C]$ is the vector of reactive compensation devices.
The equality constraints are the load flow equations as:

$$P_{Gi} - P_{Di} = V_i \sum_{j \in N_i} V_j (G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) \quad (6)$$

$$Q_{Gi} - Q_{Di} = V_i \sum_{j \in N_i} V_j (G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) \quad (7)$$

The inequality constraints in all of the problems represent the system operating constraints:

Generator constraints: Generator voltages V_G and reactive power outputs are restricted by their limits as follows:

$$V_{G_i}^{min} \le V_{G_i} \le V_{G_i}^{max} \qquad i = 1,2,\ldots, NG, \quad (8)$$

$$Q_{G_i}^{min} \le Q_{G_i} \le Q_{G_i}^{max} \qquad i = 1,2,\ldots, NG, \quad (9)$$

Where NG is the number of generators.

Reactive compensation sources: These devices are limited as follows:

$$Q_{c_i}^{min} \le Q_{c_i} \le Q_{c_i}^{max} \qquad i = 1,2,\ldots, NC \quad (10)$$

Where NC is the number of reactive compensation devices.
Transformer constraints: Tap settings are restricted as:

$$t_i^{min} \le t_i \le t_i^{max} \quad i = 1,2,\ldots, NT \quad (11)$$

Where NT is the number of transformers.
Operating constraints: Which are the constraints of voltage load buses and line loadings.

$$V_{L_i}^{min} \le V_{L_i} \le V_{L_i}^{max} \quad i = 1,2,..., Nd \qquad (12)$$

$$S_{L_i} \le S_{L_i}^{max} \quad i = 1,2,..., Nd \qquad (13)$$

The inequality constraints are considered in the objective function by penalty coefficients.

3. Multi-agent based PSO

Multi-agent systems are computational systems which several agents cooperate with each other to accomplish a certain goal. In the lattice environment each agent has the below properties:

Agent lives and acts in an environment.
Agents are able to cooperate with other agents .
agents try to accomplish a certain goal.
Agents are able to respond to changes that occur based on their learning ability.
Multi-agent systems can be used for optimizing complicated problems[17].

3.1 PSO

In the recent years Particle Swarm Optimization (PSO) is one the evolutionary algorithms that has been proposed by Eberhart [16] for solving optimization problems. The algorithm uses a number of particles (solutions) in the search space to find the optimum. During the search each particle modifies its position by using the information gathered by itself and the other particles. In each step the particles update their position by the modified velocity.
We assume that the position of each particle is x and its velocity is v. The best previous answer of each particle is denoted as $pBest$ and the best answer among all particles is represented as $gBest$. The modification of velocity and position of each particle can be obtained by the below relations:

$$v_{d+1} = k * (w * v_d + \varphi_1 .rand.(pBest - x_d) + \varphi_2 .rand.(gBest - x_d) \qquad (14)$$

$$x_{d+1} = x_d + v_{d+1} \qquad (15)$$

Where d is the iteration number, x_d is the current position at the dth iteration, v_d is the velocity of each particle at each iteration. w is the weight factor and φ_1 and φ_2 are acceleration constants, rand is a random number between 0 and 1 and k is the constriction factor which is a function of φ_1 and φ_2 and is represented as :

$$k = 2 / \left| 2 - \varphi - \sqrt{\varphi^2 - 4\varphi} \right| \qquad (16)$$

Where $\varphi = \varphi_1 + \varphi_2$ and $\varphi > 4$

In the above relations the particle velocity is limited by some maximum value. The maximum value should be set at 10%-20% of the dynamic range of the variable on each dimension.

3.2 MAPSO

In this paper, MAS and PSO are combined to optimize the reactive/voltage control problem. In the MAPSO in addition that each solution is an agent at the multi-agent system it is also a swarm for the PSO.
The agents are organized in a lattice like environment. For finding the optimal solution each agent competes and cooperates with its neighbors.
When MAPSO is used the below elements should be defined:

Purpose of each agent: Each agent represents a solution which has an fitness value to the optimization problem. In this study the object functions are power line loss, voltage stability and voltage deviation.

Definition of an environment: In MAS all agents compete and cooperate in an environment. In this study the environment is a lattice like environment as Fig. 1 which each agent is fixed on a lattice point. As each agent represents a particle to PSO each agent contains two variables which consists the current position and the velocity. The size of the lattice is $L_{max} \times L_{max}$ where L_{max} is an integer.

Definition of the local environment: Each agent only competes and cooperates with its local environment. In this paper the local environment is the neighbors of each agent. The agent α located at (i,j) is represented as $\alpha_{i,j}, i, j = 1,2,...., L_{size}$. The neighbors of $\alpha_{i,j}$ are $N_{i,j}$ and are defined as :

$$N_{i,j} = \{\alpha_{i^1,j}, \alpha_{i,j^1}, \alpha_{i^2,j}, \alpha_{i,j^2}\} \qquad (17)$$

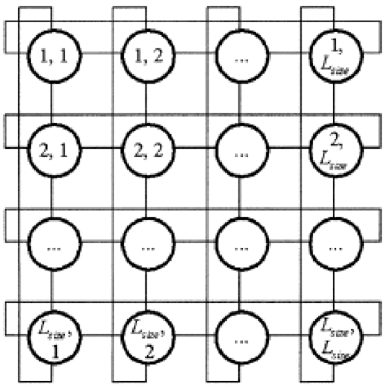

Fig. 1. A lattice like environment

Where

$$i^1 = \begin{cases} i-1 & i \neq 1 \\ L_{size} & i = 1 \end{cases}$$

$$i^2 = \begin{cases} i+1 & i \neq L_{size} \\ 1 & i = L_{size} \end{cases}$$

$$j^1 = \begin{cases} j-1 & j \neq 1 \\ L_{size} & j = 1 \end{cases}$$

$$j^2 = \begin{cases} j+1 & j \neq L_{size} \\ 1 & j = Lsize \end{cases}$$

From the above relations each agent has fours neighbors which it competes and cooperates with and forms a local environment.

4. Behavioral strategies for agents: For achieving the certain goals each agent competes and cooperates with its local environment to exchange its information and diffuse the useful information to the whole environment. Also PSO is implemented to speed up diffusing the useful information in the whole environment. Hence, three operator is implemented to each agent which come in the following:

Competition and cooperation operator : Assume that the operators implemented to the agent α located at (i,j) and the agent represents a solution vector in the search space. Suppose that $m = MinN_{i,j} = (m_1, m_2, ..., m_n)$ is the agent with minimum fitness value among all of neighbors. If the specified agent satisfies the below relation it is a winner otherwise it is a loser:

$$f(\alpha_{i,j}) \leq f(m)$$

If the agent is a winner it will stay in the lattice and its location will not change. If it is a loser it is replaced by a new agent $New_{i,j}$.

The new agent is generated as following:

$$\alpha'_k = m_k + rand(0,1) * (m_k - a_k) \qquad (18)$$

Where rand is a random number between 0 and 1. If any variable passes the specified upper limit the amount of that variable will be the upper limit. Also is the same for crossing the lower limit.

PSO operator: After the competition and cooperation operator the PSO operator is implemented to all agents. As each agent only exchanges information with its neighbors the diffusion of information in the whole environment is very slow. Using the PSO operator consequences to a faster information distribution in the whole lattice.

Self learning operator: In this stage each operatoruses its own information to improve the ability to solve the problem.
The sell learning operator of the agent first constructs a lattice like environment sL. The size of the environment is $sL_{size} \times sL_{size}$ and all new agents are generated in this new environment as :

$$s\alpha_{i',j'} = \begin{cases} \alpha_{i,j} & i' = 1, j' = 1 \\ New\ \alpha_{i',j'} & otherwise \end{cases} \qquad (19)$$

Where $\text{New}\ \alpha_{i',j'}$ is determined as below:

$$\text{New}\ \alpha_{i',j'} = \alpha_k * \text{rand}\,(1 - sR, 1 + sR) \qquad (20)$$

Where sR represents the search radius and is between 0 and 1. After that the PSO operator is performed on sL. Finally, the agent in the L lattice is replaced by the agent with minimum fitness function in the sL environment.

4. Simulation results

The MAPSO has been implemented to IEEE 30-bus and the results are compared with SGA and PSO algorithms. All of the three algorithms are used to minimize three objective functions separately which are: (1) real power losses in transmission lines (2) voltage stability index and (3) sum of voltage deviations.

4.1 Case study

The IEEE 30-bus network used in this study consists of 6 generators, 41 lines, 4 transformers which are placed in lines 6-9, 4-12, 9-12 and 27-28. The network also includes 3 reactive compensation devices which are placed in buses 3, 10 and 24. Tap settings are in the range of [0.95,1.1]. The reactive compensation devices are considered within the interval [-12,30]Mvar also generator voltages are limited to [0.9,1.1]p.u. In this case the optimization problem has 13 control variables. The variable limits are presented in Table 1. Transformer taps and reactive compensation devices are discrete variables with the changes step of 0.01p.u.

To expose the profit of MAPSO, simulation results have been compared other techniques such as standard genetic algorithm (SGA) and PSO method. The initial conditions for all the methods are same and are given as :

$$P_{load} = 2.832\ \text{p.u.} \qquad Q_{load} = 1.262\ \text{p.u.}$$

When the generator bus voltages and transformer taps are set to 1p.u. the total generations and power losses are as :

$$\sum P_G = 2.893\ \text{p.u.} \qquad \sum Q_G = 0.980199\ \text{p.u.}$$

$$P_{loss} = 0.059879$$

The bus which there voltages are outside the specified range are:

$$V_{26} = 0.932 \quad V_{29} = 0.940 \quad V_{30} = 0.928$$

4.2 Results

After implementing the MAPSO to the ORPD problem for different objective functions the results are presented. Table 2 compares optimal transmission loss for the 30-bus IEEE network for different methods after ten runs for each method. The table also shows percentage of power loss decrease with respect to the case that all generator voltages and transformer taps are set to 1 p.u. and reactive compensation devices are set to zero.

Table 1 Variable Limits (p.u.)

Reactive Power Generation Limits						
Bus	1	2	5	8	11	13
Q_G^{max}	0.596	0.48	0.6	0.53	0.15	0.155
Q_G^{min}	-0.298	-0.24	-0.3	-0.265	-0.075	-0.078
Voltage And Tap-Setting Limits						
V_G^{max}	V_G^{min}	V_{load}^{max}	V_{load}^{max}	T_K^{max}	T_K^{max}	
1.1	0.9	1.05	0.95	1.05	0.95	
Reactive Compensation Devices And Voltage Limits						
Q_c^{max}	Q_c^{max}	V_{load}^{max}	V_{load}^{max}			
0.36	-0.12	1.05	0.95			

These results show that the MAPSO leads to a better solution than the other two solutions. Also the proposed method keeps all of the dependent variables within their limits. The transmission loss is reduced from 0.05934 p.u. (In the base case) to 0.049008 by the MAPSO.

Also the amount of control variables come in Table. 4. for the transmission loss optimization.

Table. 2. Results of transmission loss for different methods in the IEEE 30-bus system

Compared item	SGA	PSO	MAPSO
Best P_{loss} (MW)	4.9408	4.9239	4.9008
Worst P_{loss} (MW)	5.1651	5.0576	5.02
Average P_{loss} (MW)	5.0378	4.9720	4.9254
P_{save} (%)	16.07%	17.02%	18.15%

Table. 4. represents the results for the voltage stability objective function. The results show that MAPSO improves the voltage stability better than the other two methods. By the MAPSO maximum value of the L index has reduced from 0.1579 to 0.1191 and as a consequence the voltage stability margin has increased. Also the control values for this optimization is exhibited Table. 5.

Also the results for voltage deviation as the objective function is exposed in Table.6. while the control

Table. 3 Values of control variables after power loss optimization by SGA, PSO and MAPSO

Bus	SGA	PSO	MAPSO
V_1	1.0512	1.0313	1.0725
V_2	1.0421	1.0114	1.0636
V_5	1.0322	1.0221	1.0411
V_8	0.9815	1.0031	1.0416
V_{11}	0.9766	0.9744	1.0092
V_{13}	1.1	0.9987	1.0684
T_1	0.95	0.97	1.05
T_2	0.98	1.02	0.9804
T_3	1.04	1.01	0.9962
T_4	1.02	0.99	0.9709
Q_1	0.12	0.17	-0.0682
Q_2	-0.1	0.13	0.2349
Q_3	0.3	0.23	0.0693

Table. 4. Results of voltage stability for different methods for the IEEE 30-bus system

Compared item	SGA	PSO	MAPSO
Best L_{max}	0.1230	0.1217	0.1191
Worst L_{max}	0.1560	0.1327	0.1241
Average L_{max}	0.1347	0.1264	0.1205

Table. 5 Values of control variables after voltage stability optimization by SGA, PSO and MAPSO

Bus	SGA	PSO	MAPSO
V_1	1.0512	1.0313	1.0501
V_2	1.0421	1.0114	1.0434
V_5	1.0322	1.0221	1.0218
V_8	0.9815	1.0031	1.0322
V_{11}	0.9766	0.9744	1.0219
V_{13}	1.1	0.9987	0.9932
T_1	0.95	0.97	1.0069
T_2	0.98	1.02	1.0223
T_3	1.04	1.01	1.0321
T_4	1.02	0.99	0.9694
Q_1	0.12	0.17	-0.0426
Q_2	-0.1	0.13	0.2690
Q_3	0.3	0.23	0.2715

variables for this optimization is presented in Table. 7.

The results show that The MAPSO decreases the voltage deviation more than SGA and PSO.

Using the MAPSO voltage deviation has decreased from 0.1579 in the base case to 0.1238 in the base case.

Table. 6 Results of voltage deviation for different methods for the IEEE 30 bus system

Compared item	SGA	PSO	MAPSO
Best deviation	0.1578	0.1508	0.1236
Worst deviation	0.1921	0.1903	0.1526
Average deviation	0.1832	0.1801	0.13306

Table. 5 Values of control variables after voltage deviation optimization by SGA, PSO and MAPSO

Bus	SGA	PSO	MAPSO
V_1	1.0512	1.0313	1.0251
V_2	1.0421	1.0114	1.0216
V_5	1.0322	1.0221	1.0172
V_8	0.9815	1.0031	1.0021
V_{11}	0.9766	0.9744	1.0001
V_{13}	1.1	0.9987	1.0254
T_1	0.95	0.97	1.013
T_2	0.98	1.02	0.9764
T_3	1.04	1.01	0.9688
T_4	1.02	0.99	0.9505
Q_1	0.12	0.17	-0.12
Q_2	-0.1	0.13	0.0312
Q_3	0.3	0.23	0.1028

5. Conclusions and future research

In this study MAPSO has been implemented to the ORPD problem for determination of the global or near global optimum solution. Comparing the proposed algorithm with two other techniques (SGA & PSO) shows the advantage of this algorithm in decreasing transmission loss, voltage deviation and increasing voltage stability margin.

In this paper MAPSO parameters are constant. An improved MAPSO could be implemented to the ORPD with adaptive parameters to find better solutions. Also multi-objective studies can be done by the proposed algorithm to enhance power transmission loss, voltage stability and voltage deviation together.

Also it should be noticed that for large scale applications the algorithms its abilities better comparing with the other two algoritms.

References

[1] K. Y. Lee, Y. M. park, J. L. Ortiz, "A united approach to optimal real and reactive power dispatch," IEEE Trans. Power Syst., vol. 1, no. 2, pp. 1147-1153, may 1985.

[2] Y. Y. Hong, D. I. Sun, S. Y. Lin,, C. J. Lin, " Multi-year multi-case optimal AVR planning," IEEE trans. Power syst., vol. 5, no. 4,pp. 1294-1301, Nov 1990.

[3] N. Deeb, and S. M. Shahedipour, "Linear reactive power optimization in a large power network using the decomposition approach," IEEE Trans. Power Syst , vol. 5 , no. 2, pp. 428-435, May 1990

[4] J. R. S. Manlovani and A. V. Garcia , " A heuristic model for reactive power planning," IEEE trans. Power Syst., vol. 11, no. 1, pp. 68-74 Feb. 1995.

[5] S. Granville, " Optimal reactive dispatch through interior point methods," IEEE Trans. Power Syst., vol. 9, no. 1, pp. 136-146, Feb. 1994.

[6] J. A. momeh, S. X. Guo, E. C. Oghuobiri, R Adapa, " The quadratic interior point method solving power system optimization problems," IEEE Trans. Power syst. , vol. 9, no. 3, pp. 1327-1336, Aug. 1994.

[7] K. Aoki, M. Fan, and A. Nishikori, "Optimal var planning by approximation method for recursive mixed integer =linear programming, " IEEE Trans. Power Syst., vol. 3, no. 4, pp-1741-1747, Nov 1998.

[8] A. G. Bakirtzis and A. P. Meliopous, "Incorporation of switching operations in power system corrective control computation," IEEE Trans. Power syst., vol. 2, no. 3, pp 669-676, Aug. 1987

[9] Wu QH, Ma JT, " Power system optimal reactive power dispatch using evolutionary programming," IEEE Trans Power Syst 1995, vol.10 no. 3 1995

[10] Lai LL, Ma Jt, " Application of evolutionary programming to reactive power planning – comparison with nonlinear programming approach, " IEEE Trans Power Syst vol. 12, no. 1 pp. 198-206, 1997.

[11] Lee KY, Bai X, Park YM.Optimization method for reactive power planning by using a modified simple genetic algorithm. IEEE Trans Power Syst. , vol. 10, no. 4, pp 1843-1850, 1995

[12] Chebbo AM, Irving MR, " Combined active and reactive dispatch-Part 1: Problem formulation and solution algorithm ," IEEE Proc Generat Transmission Distribut 142 (4) :pp 393-400.

[13] Yoshida H, Fukuyama Y, Kawata K, Takayama S, Nakanishi Y, " A particle swarm optimization for reactive power and voltage control
considering voltage security assessment. IEEE Trans Power Syst 2001; 15 (4): 1232-9

[14] B, Zhao, C. X. Guo, and Y, J, Cao " A miltiagent-based particle swarm optimization approach for optimal reactive power dispatch, " IEEE Trans on Power Systems, vol. 20, no. 2, May 2005

[15] Wen Zhang, Yutian Liu, " Multi-objective reactive power and voltage control based on fuzzy optimization strategy and fuzzy adaptive particle swarm,:" Electrical Power and Energy systems 30 (2008) 525-532

[16] J. Kennedy and R. Eberhart, "Particle swarm optimization," in Proc.
IEEE Int. Conf. Neural Netw., vol. 4, Nov. 1995, pp. 1942–1948.

[17] J. Liu, Autonomous Agents and Multiagent Systems:Explorationsin Learning Self-Organization, and Adaptive Computation, Singapore:World Scientific, 2001.

[18] P. Kessel and H. Glavitsch, "Estimating the Voltage Stability of Power System," *IEEE Trans. Power Delivery*, Vol. PWRD-1, No. 3, pp. 346-354, July 1986