International Journal of Soft Computing 8 (6): 393-399, 2013
ISSN: 1816-9503

Optimal Reactive Power Dispatch for Real Power Loss Minimization and Voltage Stability Enhancement Using Gravitational Search Algorithm

[1]M. Ettappan and [2]M. Rajaram
[1]Department of Electrical and Electronics Engineering,
Sardar Raja College of Engineering, Tamilnadu, India
[2]Anna University, Chennai, Tamilnadu, India

Abstract: Reactive power plays crucial roles in power systems reliability and security. This study proposes the gravitational search algorithm is applied to Optimal Reactive Power Dispatch (ORPD) problem for real power loss minimization, voltage deviation minimization and voltage stability enhancement. ORPD is a mixed integer, non-linear 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 reactive power output of the compensating devices. The proposed algorithm is evaluated on an IEEE 30-Bus Power System, simulation results show that the proposed approach converges to better solutions much faster than the earlier reported approaches in the literature.

Key words: Reactive power dispatch, gravitational search algorithm, power loss, minimization, IEEE

INTRODUCTION

Reactive power dispatch for improving economy and security of power system operation has received much attention at present. The main objective of optimal reactive power dispatch is to improve the voltage profile and minimizing system real power losses via redistribution of reactive power in the system. In addition, the voltage stability can be enhanced by reallocating reactive power generations. Therefore, the problem of the RPD can be optimized to enhance the voltage stability to improve voltage profile and to minimize the system losses as well. The reactive power dispatch problem has a significant influence on secure and economic operation of power system. Reactive power optimization is a sub problem of the Optimal Power-Flow (OPF) calculation which determines reactive power outputs of generators, control voltages of PV-buses and tap settings of the under-load tap changing transformers to minimize network power loss. Solving these problems is subject to a number of constraints such as limits on bus voltages, tap settings of transformers, number of control variables, etc.

Up to now, a number of techniques ranging from classical techniques like gradient-based optimization algorithms to various mathematical programming techniques have been applied to solve this problem (Lee *et al*., 1985; Hong *et al*., 1990; Manlovani and Garcia, 1995). Recently, due to the basic efficiency of interior-point methods which offer fast convergence and convenience in handling inequality constraints in comparison with other methods, interior-point linear programming (Granville, 1994), quadratic programming (Momoh *et al*., 1994) and Non-Linear Programming Methods have been widely used to solve the ORPD problem of large-scale power systems. However, these techniques have severe limitations in handling non-linear, discontinuous functions and constraints and function having multiple local minima. Unfortunately, the original reactive power problem does have these properties. In all these efforts some of the other simplification has been done to get over the inherent limitations of the solution technique.

Recently, agent-based computation has been studied in the field of distributed artificial intelligence (Liu, 2001) and has been widely used in other branches of computer science. Problem solving is an area that many multiagent-based applications are concerned with introduced an application of distributed techniques for solving constraint satisfaction problem (Liu *et al*., 2002). In the last decades, computational intelligence-based techniques have been proposed for the application of reactive power optimization problem. Ant colony optimization (Slimani and Bouktir, 2006) Differential Evolutionary algorithm (Varadarajan and Swarup, 2008), Seeker optimization algorithm (Dai *et al*., 2009), genetic algorithm (Devaraj and Roselyn, 2010), comprehensive

Corresponding Author: M. Ettappan, Department of Electrical and Electronics Engineering, Sardar Raja College of Engineering, Tamilnadu, India

learning particle swarm optimization (Mahadevan and Kannan, 2010), harmony search algorithm (Khazali and Kalantar, 2011). Since, transformer tap ratios and outputs of shunt capacitors/reactors have a discrete nature while reactive power outputs of generators and static VAR compensators, bus-voltage magnitudes and angles are on the other hand.

In this study, the reactive power optimization problem can be exactly formulated using a gravitational search algorithm, i.e., cast as a nonlinear optimization problem with a mixture of discrete and continuous variables.

MATERIALS AND METHODS

Problem formulation: In this study, the objective of reactive power dispatch problem is to minimize the real power losses and voltage deviation and voltage stability enhancement while satisfying equality and inequality constraints.

Real power loss minimization: The main objective of the reactive power dispatch is to minimize the active power loss in the transmission network which can be described as follows:

$$f_Q = \sum_{k \in N_E} P_{kloss} = \sum_{k \in N_E} g_k \; (V_i^2 + V_j^2 - 2V_i V_j \cos\theta_{ij}) \qquad (1)$$

Where:

$k = (i, j)$; $i \in N_B$;

$j \in N_i$, N_E = The set of numbers of network branches

P_{kloss} = The active power loss in branch k

g_k = The conductance of branch k

V_i and V_j = The voltage magnitude of bus i and j

θ_{ij} = Voltage angle difference between buses i and j

Voltage deviation minimization: Voltage profile is improved by minimizing the deviation of the load bus voltage. Bus voltage magnitude should be maintained with in the allowable range to ensure quality service:

$$VD = \sum_{i \in NL} \left| V_i - Vref_i \right| \qquad (2)$$

Where:

NL = The number of load buses in the power system

$Vref_i$ = The reference value of the voltage magnitude of the ith bus which is equal to 1.0 p.u.

Voltage stability enhancement: Voltage stability is interested with the ability of a power system to maintain constantly acceptable bus voltage at each bus in the power system under nominal operating conditions. A system experiences a state of voltage instability when the system is being subjected to a disturbance, rise in load demand, change in system configuration may lead to progressive and uncontrollable reduce in voltage. Consequently, enhancement of voltage stability of a system is a significant parameter of power system operation and planning. Voltage stability enhancement can be done by minimizing the voltage stability indicator L-index values at every bus of the network and consequently the global power system L-index. L-index which is in the interval [0-1], defines a scalar number for each load bus and uses information on a normal power flow. The L-index of a bus specifies the proximity of voltage collapse condition of that bus. L-index L_j of the jth bus is defined as follows:

$$L_j = \left| 1 - \sum_{i=1}^{NPV} F_{ji} \frac{V_i}{V_j} \right| \qquad (3)$$

$$\text{Where } j = 1, 2, \ldots, NPQ$$

$$F_{ji} = -\left[Y_1\right]^{-1}\left[Y_2\right] \qquad (4)$$

Where:

NPV = The number of PV bus

NPQ = The number of load bus

Y_1 and Y_2 are the sub-matrices of the system YBUS obtained after separating the PQ and PV bus bar parameters.

Constraints: The minimization problem is subject to the following equality and inequality constraints.

Equality constraints:

$$P_{Gi} - P_{Di} - V_i \sum_{j \in N_i} V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) = 0 \quad i \in N_O \qquad (5)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j \in N_i} V_j (G_{ij} \sin\theta_{ij} + B_{ij} \cos\theta_{ij}) = 0 \quad i \in N_{PQ} \qquad (6)$$

Inequality constraints:

$$V_i^{min} \le V_i \le V_i^{max} \quad i \in N_B \qquad (7)$$

$$T_k^{min} \le T_k \le T_k^{max} \quad k \in N_T \qquad (8)$$

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max} \quad i \in N_G \qquad (9)$$

$$Q_{Ci}^{min} \le Q_{Ci} \le Q_{Ci}^{max} \quad i \in N_C \tag{10}$$

$$S_l \le S_l^{max} \quad l \in N_l \tag{11}$$

where power flow equations are used as equality constraints, reactive power source installation restrictions, reactive generation restrictions, transformer tap-setting restrictions, bus voltage restrictions and power flow of each branch are used as inequality constraints.

In the most of the non-linear optimization problems, the constraints are considered by generalizing the objective function using penalty terms. In the reactive power dispatch problem, the generator bus voltages V_{PV} and V_S, the tap position of transformer T and the amount of the reactive power source installation Q_C are control variables which are self-constrained. Voltages of PQ bus V_{PQ} and injected reactive power of PV bus Q_G are constrained by adding them as penalty terms to the objective function (1). The above problem is generalized as follows:

$$F_Q = f_Q + \sum_{i \in N_V^{lim}} \lambda_{Vi}(V_i - V_i^{lim})^2 + \sum_{i \in N_Q^{lim}} \lambda_{Gi}(Q_{Gi} - Q_{Gi}^{lim})^2 \tag{12}$$

where, λ_{Vi} and λ_{Gi} are the penalty factors and both penalty factors are large positive constants V_i^{lim} and Q_{Gi}^{lim} are defined as:

$$V_i^{lim} = \begin{cases} V_i^{max} & V_i > V_i^{max} \\ V_i^{min} & V_i < V_i^{min} \end{cases} \tag{13}$$

$$Q_{Gi}^{lim} = \begin{cases} Q_{Gi}^{max} & Q_{Gi} > Q_{Gi}^{max} \\ Q_{Gi}^{min} & Q_{Gi} < Q_{Gi}^{min} \end{cases} \tag{14}$$

Gravitational search algorithm: This algorithm is introduced based on Newton's law of gravity and law of motion. The law of gravity states that every particle attracts every other particle and the gravitational force between two particles is directly proportional to the product of their masses and inversely proportional to the square of the distance between them. According to the proposed algorithm, agents are assumed to be objects, the performances of which are measured by means of masses. Hence, all these objects attract each other by a gravity force and this force causes a global movement of all objects towards the objects with heavier masses. Since, the heavier masses have higher fitness values they describe good optimal solution to the problem and they move more slowly than lighter ones representing worse solutions. In GSA, each mass has four particulars: its position, its inertial mass, its active gravitational mass and passive gravitational mass. The position of the mass equaled to a solution of the problem and its gravitational and inertial masses are specified by using a fitness function. In other words, each mass performs a solution and the algorithm is navigated by appropriately adjusting the gravitational and inertia masses. It is assumed that given a system with N agents, the position of the ith agent in search space represents a solution to the problem. Agent is described as follows:

$$X_i = (x_i^1, .., x_i^d, ..., x_i^n) \text{ for } i = 1, 2, ..., N \tag{15}$$

Where:

n = The space dimension of the problem

x_i^d = The position of the ith agent in the dth dimension

Initially, the agents of the solution are described randomly and according to Newton gravitation theory, a gravitational force from mass j acts mass i at the time t is specified as follows:

$$F_{ij}^d(t) = G(t) \frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t) + \varepsilon} \left(x_j^d(t) - x_i^d(t) \right) \tag{16}$$

Where:

M_{pi} = The passive gravitational mass of the agent i

M_{aj} = The active gravitational mass of the agent j

G(t) = The gravitational constant at time t

ε = A small constant

$R_{ij}(t)$ = The Euclidian distance between i and j agents defined as follows:

$$R_{ij}(t) = \| X_i(t), X_j(t) \| \tag{17}$$

The total force acting on agent i in a dimension d is a randomly weighted sum of the forces exerted from other agents:

$$F_i^d(t) = \sum_{j=1 j \ne i}^{m} rand_j F_{ij}^d(t) \tag{18}$$

where, $rand_j$ is a random number in interval [0, 1]. In order to find the acceleration of the ith agent, at t time in the dth dimension on law of motion is used directly to calculate. In accordance with this law, it is proportional to the force acting on that agent and inversely proportional to the mass of the agent. $\alpha_i^d(t)$ is given as follows:

$$\alpha_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \tag{19}$$

Moreover, the searching strategy can be defined to find the next velocity and next position of an agent. Next velocity of an agent is defined as a function of its current velocity added to its current acceleration. Also, the next position function is the sum of the current position and next velocity of that agent. The next position and next velocity of an agent can be defined as follows:

$$v_i^d(t+1) = rand_i \times v_i^d(t) + \alpha_i^d(t) \quad (20)$$

$$x_i^d\ (t+1) = x_i^d\ (t) + v_i^d\ (t+1) \quad (21)$$

Where:

$v_i^d(t)$ and $x_i^d(t)$ = The velocity and position of an agent at t time in d dimension, respectively
$rand_i$ = A random number in the interval [0, 1]

It gives a randomized feature to the search. The gravitational constant, G which is initialized randomly at the starting will decrease according to time to control the search accuracy. In this, G is a function of the initial value (G_0) and time (t):

$$G(t) = G(G_0, t) \quad (22)$$

$$G(t) = G_0 e^{-\alpha\left(\frac{t}{T}\right)} \quad (23)$$

Where:

α = A user-specified constant
t = The current iteration
T = The total number of iterations

The masses of the agents are calculated using fitness evaluation. The heavier mass of an agent, the more influential is that agent, concerning the solution it represents. It is notable that as Newton's law of gravity and law of motion refer, a heavy mass has a higher pull on power and moves slower. The masses are updated as follows:

$$M_{ai} = M_{pi} = M_{ii} = M_i,\ \ i = 1, 2, ..., N \quad (24)$$

$$m_i(t) = \frac{fit_i(t)\text{-}worst(t)}{best(t)\text{-}worst(t)} \quad (25)$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \quad (26)$$

where, $fit_i(t)$ represents the fitness value of the agent i at time t and the best(t) and worst(t) in the population, respectively specify the strongest and the weakest agent with regard to their fitness route. For a minimization problem:

$$best(t) = \min_{j\in\{1,...,m\}} fit_j(t) \quad (27)$$

$$worst(t) = \max_{j\in\{1,...,m\}} fit_j(t) \quad (28)$$

For a maximization problem:

$$best(t) = \max_{j\in\{1,...,m\}} fit_j(t) \quad (27)$$

$$worst(t) = \min_{j\in\{1,...,m\}} fit_j(t) \quad (28)$$

In order to solve optimization problem with GSA at the beginning of the algorithm every agent is placed at a certain point of the search space that specifies a solution to the problem at every unit of time. Then, according to Eq. 20 and 21, the agents are evaluated and their next positions are computed. Other parameters of the algorithm such as the gravitational constant G, masses M and acceleration a are computed via Eq. 22, 23, 25, 26 and 19, respectively and are updated at every cycle of time. The flow diagram of the GSA is shown in Fig. 1.

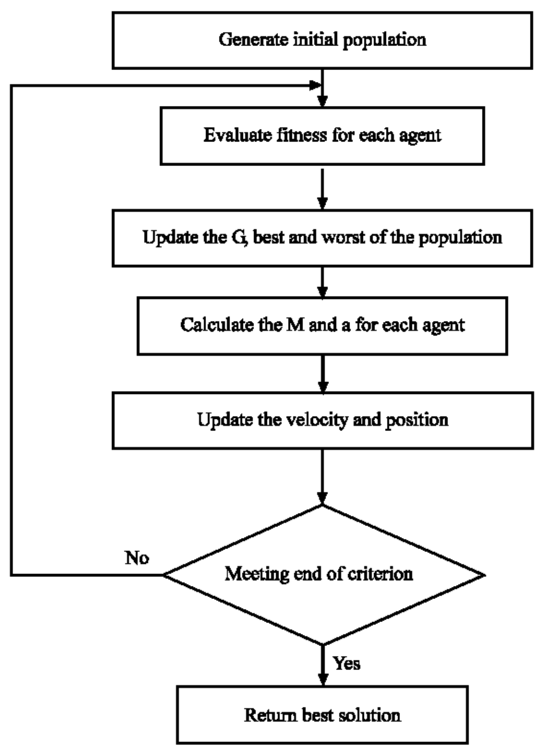

Fig. 1: Flow chart of the GSA

Application of GSA for optimal RPD problem: A new Heuristic Method to perform the GSA algorithm will be explained for solving the optimal RPD problem in this study. Especially, a proposal will be about how to deal with the equality and inequality constraints of the optimal RPD problems by adapting each agent's search point in the GSA algorithm. The process of GSA algorithm can be demonstrated as follows.

Step 1 (Initialization): Determine the lower and upper bounds of independent variables which contain generator voltages, transformer tap settings and shunt VAR compensations. When it is assumed that there is a system with N (dimension of the search space) masses, position of the ith mass (control variable) is described in a feasible numerical range as follows:

$$X_i = X_i^L + \text{rand} \times (X_i^U - X_i^L) \quad (29)$$

where, rand is a uniformly distributed random number between 0 and 1.

Step 2 (Fitness evaluation of all agents): After controlling lower and upper bounds of each control variable, the fitness function value is calculated according to Eq. 12. If output of the ith control variable $U_i > U_i^{max}$:

$$U_i = U_i^{max}$$

If output of the ith control variable $U_i > U_i^{min}$:

$$U_i = U_i^{min}$$

If output of ith control variable, U_i, is within its maximum and minimum operation limits:

$$U_i = U_i$$

Step 3 (Determination of gravitational constant, best and worst fitnesses): For all agents, best and worst fitnesses are determined at each iteration described as in Eq. 27 and 28. The gravitational constant at t time is determined according to in Eq. 22 and 23. Gravitational constant adjusts the accuracy of the search and gravitational constant reduces in time.

Step 4 (Update the gravitational and inertial masses): In this step, the gravitational and inertial masses are updated as in Eq. 24-26.

Step 5 (Calculate the total force): At the specific t time, the gravitational force and total force are described according to Eq. 16 and 18.

Step 6 (Calculate the acceleration and update velocity): In this step, the acceleration ($a_i^d(t)$) and updating velocity (v_i^d (t+1)) of the ith agent at t time in dth dimension are calculated in Eq. 19 and 20.

Step 7 (Update the position of the agents): In this step, the next position of the ith agents in dth (X_i^d (t = 1)) dimension is updated according to Eq. 21.

Step 8 (Repeat): In this stage, steps 2-7 are repeated until the maximum iteration is reached at the stopping criteria. In the final iteration, the algorithm returns the value of positions of the corresponding agent at specified dimensions. This value is the best solution of the optimization problem.

RESULTS AND DISCUSSION

To verify the effectiveness and efficiency of the proposed gravitational search algorithm based reactive power optimization approach, the IEEE 30-Bus Power System is used as the test system. The GSA has been implemented in MATLAB 7.11.0.584 programming language and numerical tests are carried on a Intel (R) Core (TM) 2 Duo @ 2.20 GHz, 3 GB RAM computer.

The IEEE 30-Bus System consists of 48 branches, six generator-buses and 22 load-buses. Four branches (6, 9), (6, 10), (4, 12) and (27, 28) are under load tap setting transformer branches. The possible reactive power source installation buses are 3, 10 and 24. Six buses are selected as PV-buses and Vθ-buses as follows; PV-buses: bus 2, 5, 8, 11, 13, Vθ bus: bus 1. The others are PQ-buses. The transformer taps and the reactive power source installation are discrete variables with the changes step of 0.01 p.u.

After implementing the GSA algorithm to the ORPD problem for different objective functions the results are presented. Figure 1 shows the flowchart for the gravitational search algorithm. Figure 2-4 show the output of power loss minimization, voltage deviation minimization and voltage stability enhancement. Table 1 shows the optimized values of control variables and Table 2 compares optimal transmission loss for the IEEE 30-Bus System for different methods.

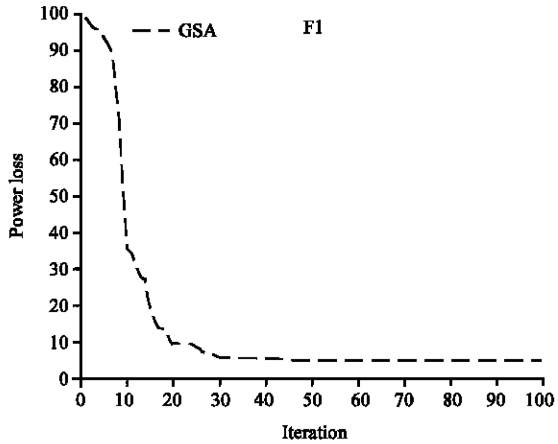

Fig. 2: Minimization of real power losses

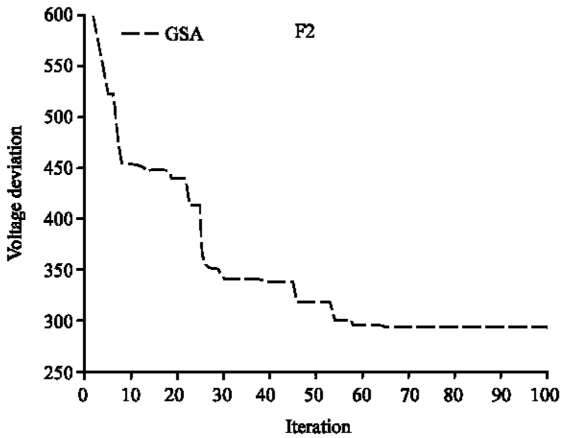

Fig. 3: Minimization of voltage deviation

Table 1: Values of control variables after optimization by HSA, SGA, PSO and GSA

Control devices	HSA	SGA	PSO	GSA
V_1	1.0726	1.0512	1.0313	1.0310
V_2	1.0625	1.0421	1.0114	1.0106
V_5	1.0399	1.0322	1.0221	1.0205
V_8	1.0422	0.9815	1.0031	1.0004
V_{11}	1.0318	0.9766	0.9744	0.9656
V_{13}	1.0681	1.1000	0.9987	0.9897
T_1	1.0100	0.9500	0.9700	0.9600
T_2	1.0000	0.9800	1.0200	1.0600
T_3	0.9900	1.0400	1.0100	1.0300
T_4	-0.0500	1.0200	0.9900	0.7800
Q_1	0.3400	0.1200	0.1700	0.1600
Q_2	0.1200	-0.1000	0.1300	-0.0700
Q_3	0.1000	0.3000	0.2300	0.1500

The results obtained from GSA for power loss reduction is compared with other algorithms such as HSA, CLPSO and PSO. In all of these references some of the constraints and initial settings of the problem are different with the assumed values and constraints.

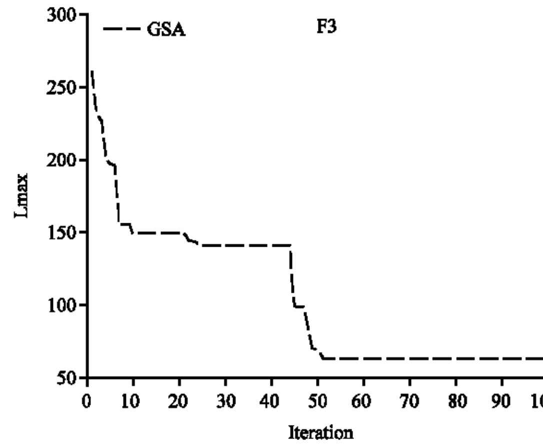

Fig. 4: Enhancement of voltage stability

Table 2: Comparison of transmission loss for different methods in the IEEE 30-Bus System

Methods	Power loss (MW)
LP	5.9880
EP	4.9630
CGA	4.9800
AGA	4.9260
PSO	4.8136
CLPSO	4.7208
HSA	4.7624
DEGL	4.7038
GSA	4.6926

CONCLUSION

In this study, the gravitational search algorithm has been proposed and successfully applied to solve Optimal Reactive Power Dispatch (ORPD) problem. The ORPD problem has been formulated as a constrained optimization problem where several objective functions have been considered to minimize power losses to improve the voltage profile and to enhance the voltage stability. The proposed approach has been tested and examined on the standard IEEE 30-Bus Test System. The simulation results shows that the effectiveness and robustness of the proposed algorithm to solve ORPD problem. The results of the proposed GSA have been compared to other techniques PSO, CLPSO, SOA and HSA those reported in the literature. The comparison confirms the effectiveness and the superiority of the proposed GSA approach.

REFERENCES

Dai, C., W. Chen, Y. Zhu and X. Zhang, 2009. Seeker optimization algorithm for optimal reactive power dispatch. IEEE Trans. Power Syst., 24: 1218-1231.

Devaraj, D. and J.P. Roselyn, 2010. Genetic algorithm based reactive power dispatch for voltage stability improvement. Electr. Power Energy Syst., 32: 1151-1156.

Granville, S., 1994. Optimal reactive dispatch through interior point methods. IEEE Trans. Power Syst., 9: 136-146.

Hong, Y.Y., D.I. Sun, S.Y. Lin and C.J. Lin, 1990. Multi-year multi-case optimal AVR planning. IEEE Trans. Power Syst., 5: 1294-1301.

Khazali, A.H. and M. Kalantar, 2011. Optimal reactive power dispatch based on harmony search algorithm. Int. J. Electr. Power Energy Syst., 33: 684-692.

Lee, K.Y., Y.M. Park and J.L. Ortiz, 1985. A united approach to optimal real and reactive power dispatch. IEEE Trans. Power Apparatus Syst., 104: 1147-1153.

Liu, J., 2001. Autonomous Agents and Multi Agent Systems: Explorations in Learning, Self Organization and Adaptive Computation. World Scientific Publishers, Singapore, ISBN-13: 9789812811844, Pages: 280.

Liu, J., H. Jing and Y.Y. Tang, 2002. Multi-agent oriented constraint satisfaction. Artif. Intell., 136: 101-144.

Mahadevan, K. and P.S. Kannan, 2010. Comprehensive learning particle swarm optimization for reactive power dispatch. Applied Soft Comput., 10: 641-652.

Manlovani, J.R.S. and A.V. Garcia, 1995. A heuristic method for reactive power planning. IEEE Trans. Power Syst., 11: 68-74.

Momoh, J.A., S.X. Guo, E.C. Ogbuobiri and R. Adapa, 1994. The quadratic interior point method solving power system optimization problems. IEEE Trans. Power Syst., 9: 1327-1336.

Slimani, L. and T. Bouktir, 2006. An ant colony optimization for solving the optimal power flow problem in medium-scale electrical network. IEEE Trans. Ind. Electr Power Syst., 6: 10-15.

Varadarajan, M. and K.S. Swarup, 2008. Differential evolutionary algorithm for optimal reactive power dispatch. Int. J. Electr. Power Energy Syst., 30: 435-441.