Particle Sharing Based Particle Swarm Frog Leaping Hybrid Optimization Algorithm for Solving Optimal Reactive Power Dispatch Problem

K. Lenin, B. Ravindranath Reddy, and M. Surya Kalavathi
Jawaharlal Nehru Technological University Kukatpally, Hyderabad 500 085, India
Email: gklenin@gmail.com, {bumanapalli-brreddy, munagala12}@yahoo.co.in

***Abstract*—This paper presents an algorithm for solving the multi-objective reactive power dispatch problem in power system. Modal analysis of the system is used for static voltage stability assessment. Loss minimization and maximization of voltage stability margin are taken as the objectives. Generator terminal voltages, reactive power generation of the capacitor banks and tap changing transformer setting are taken as the optimization variables. A particle sharing based particle swarm frog leaping hybrid optimization algorithm (PSFLH) is used to solve the reactive power dispatch problem. The algorithm uses the good global search capability of particle swarm and the strong local search ability of shuffled frog leaping algorithm, and overcomes the shortcomings of swarm intelligence algorithms to fall into local optimum at later stage and "premature" convergence. Simulation results show that this algorithm has better coverage optimization results. In order to evaluate the proposed algorithm, it has been tested on IEEE 30 bus system and compared to other algorithms and simulation results show that (PSFLH) is more efficient than other algorithms for solution of single-objective ORPD problem.**

***Index Terms*—shuffled frog leaping algorithm, particle swarm optimization, optimal reactive power, transmission loss**

I. Introduction

Optimal reactive power dispatch problem is one of the difficult optimization problems in power systems. The sources of the reactive power are the generators, synchronous condensers, capacitors, static compensators and tap changing transformers. The problem that has to be solved in a reactive power optimization is to determine the required reactive generation at various locations so as to optimize the objective function. Here the reactive power dispatch problem involves best utilization of the existing generator bus voltage magnitudes, transformer tap setting and the output of reactive power sources so as to minimize the loss and to enhance the voltage stability of the system. It involves a non linear optimization problem. Various mathematical techniques have been adopted to solve this optimal reactive power dispatch problem. These include the gradient method [1], [2], Newton method [3] and linear programming [4]-[7]. The gradient and Newton methods suffer from the difficulty in handling inequality constraints. To apply linear programming, the input-output function is to be expressed as a set of linear functions which may lead to loss of accuracy. Recently, global optimization techniques such as genetic algorithms have been proposed to solve the reactive power flow problem [8], [9]. In recent years, the problem of voltage stability and voltage collapse has become a major concern in power system planning and operation. To enhance the voltage stability, voltage magnitudes alone will not be a reliable indicator of how far an operating point is from the collapse point [10]. The reactive power support and voltage problems are intrinsically related. Hence, this paper formulates the reactive power dispatch as a multi-objective optimization problem with loss minimization and maximization of static voltage stability margin (SVSM) as the objectives. Voltage stability evaluation using modal analysis [10] is used as the indicator of voltage stability. Particle Swarm Optimization (PSO) algorithm was originally an evolutionary computation technique proposed by Kennedy and Eberhart [11] in 1995, from observation and study of the predatory behaviour of birds. Later Shi and Eberhart [12] introduced the inertia weight to balance global search and convergence rate, forming the current standard PSO. Shuffled Frog Leaping Algorithm (SFLA) is swarm intelligence based sub-heuristic computation optimization algorithm proposed in 2003 by Muzaffar Eusuff and Kevin Lansey [13], to solve discrete combinatorial optimization problem. The two algorithms are simple in concept, have less parameter, fast calculation speed, global search capability, and are easy to implement. In just more than a decade, they have gained great development, made good applications in some areas, and become a research hotspot in the field of intelligent computing [14]. Using the good global search capability of particle swarm and the strong local search ability of shuffled frog leaping algorithm, we combine particle swarm and shuffled frog leaping algorithm, proposes a particle sharing based particle swarm frog leaping hybrid optimization algorithm, and applies it to reactive power optimization problem. The performance of (PSFLH) has been evaluated in standard IEEE 30 bus test system and the results analysis shows that our proposed approach outperforms all approaches investigated in this paper.

Manuscript received December 2, 2013; revised March 21, 2014.

doi: 10.12720/ijoee.2.2.172-177

II. Voltage Stability Evaluation

A. Modal Analysis for Voltage Stability Evaluation

Modal analysis is one of the methods for voltage stability enhancement in power systems. In this method, voltage stability analysis is done by computing eigen values and right and left eigen vectors of a jacobian matrix. It identifies the critical areas of voltage stability and provides information about the best actions to be taken for the improvement of system stability enhancements. The linearized steady state system power flow equations are given by.

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

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}, $J_{Q\theta}$ and J_{QV} jacobian matrix are the sub-matrixes of the System voltage stability is affected by both P and Q. However at each operating point we keep P constant and evaluate voltage stability by considering incremental relationship between Q and V.

To reduce (1), let ΔP=0, then

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

$$\Delta V=J^{-1}\text{-}\Delta Q \quad (3)$$

where

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

J_R is called the reduced Jacobian matrix of the system.

B. Modes of Voltage Instability

Voltage Stability characteristics of the system can be identified by computing the eigen values and eigen vectors. Let

$$J_R=\xi\wedge\eta \quad (5)$$

where

ξ=right eigenvector matrix of J_R

η=left eigenvector matrix of J_R

$\wedge$=diagonal eigenvalue matrix of J_R and

$$J_{R^{-1}}=\xi\wedge^{-1}\eta \quad (6)$$

From (3) and (6), we have

$$\Delta V=\xi\wedge^{-1}\eta\Delta Q \quad (7)$$

or

$$\Delta V=\sum_I\frac{\xi_i\eta_i}{\lambda_i}\Delta Q \quad (8)$$

where ξ_i is the ith column right eigenvector, η the ith row left eigenvector of J_R, and λ_i is the ith eigen value of J_R.

The ith modal reactive power variation is,

$$\Delta Q_{mi}=K_i\xi_i \quad (9)$$

where

$$K_i=\sum_j \xi_{ij^2}\text{-}1 \quad (10)$$

where ξ_{ji} is the jth element of ξ_i

The corresponding ith modal voltage variation is

$$\Delta V_{mi}=[1/\lambda_i]\Delta Q_{mi} \quad (11)$$

It is seen that, when the reactive power variation is along the direction of ξ_i the corresponding voltage variation is also along the same direction and magnitude is amplified by a factor which is equal to the magnitude of the inverse of the ith eigenvalue. In this sense, the magnitude of each eigenvalue λ_i determines the weakness of the corresponding modal voltage. The smaller the magnitude of λ_i, the weaker will be the corresponding modal voltage. If $|\lambda_i|$=0, the ith modal voltage will collapse because any change in that modal reactive power will cause infinite modal voltage variation.

In (8), let $\Delta Q=e_k$ where e_k has all its elements zero except the kth one being 1. Then

$$\Delta V= \sum_i\frac{\eta_{1k}\ \xi_1}{\lambda_1} \quad (12)$$

η_{1k} kth element of η_1

V-Q sensitivity at bus k

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

III. Problem Formulation

The objectives of the reactive power dispatch problem considered here is to minimize the system real power loss and maximize the static voltage stability margins (SVSM). This objective is achieved by proper adjustment of reactive power variables like generator voltage magnitude (gi) V, reactive power generation of capacitor bank (Qci), and transformer tap setting (tk). Power flow equations are the equality constraints of the problems, while the inequality constraints include the limits on real and reactive power generation, bus voltage magnitudes, transformer tap positions and line flows.

A. Minimization of Real Power Loss

It is aimed in this objective that minimizing of the real power loss (P_{loss}) in transmission lines of a power system. This is mathematically stated as follows.

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

where n is the number of transmission lines, g_k is the conductance of branch k, V_i and V_j are voltage magnitude at bus i and bus j, and θ_{ij} is the voltage angle difference between bus i and bus j.

B. Minimization of Voltage Deviation

It is aimed in this objective that minimizing of the Deviations in voltage magnitudes (*VD*) at load buses. This is mathematically stated as follows.

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

where nl is the number of load busses and V_k is the voltage magnitude at bus k.

C. System Constraints

In the minimization process of objective functions, some problem constraints which one is equality and others are inequality had to be met. Objective functions are subjected to these constraints shown below.

Load flow equality constraints:

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

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

where, nb is the number of buses, P_G and Q_G are the real and reactive power of the generator, P_D and Q_D are the real and reactive load of the generator, and G_{ij} and B_{ij} are the mutual conductance and susceptance between bus i and bus j. Generator bus voltage (V_{Gi}) inequality constraint:

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

Load bus voltage (*VLi*) inequality constraint:

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

Switchable reactive power compensations (*QCi*) inequality constraint:

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

Reactive power generation (*QGi*) inequality constraint:

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

Transformers tap setting (T_i) inequality constraint:

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

Transmission line flow (S_{Li}) inequality constraint:

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

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

IV. Particle Sharing Based Particle Swarm Frog Leaping Hybrid Optimization Algorithm

A. Particle Swarm Optimization Algorithm

Particle swarm optimization algorithm [15]-[21] is an optimization algorithm based on group and fitness. The system initializes particles (representing potential solutions) as a set of random solutions, which has two features of position and velocity. The fitness values of particles are decided by particle positions. Particles move in the solution space; the moving direction and distance are determined by the speed vector and new speed, position are updated from personal best position pbest, global best position gbest and the current particle velocity; particles search and pursue the optimal particle based on fitness values in the solution space, and gradually converge to the optimal solution. Assuming in a d-dimensional search space, there is a group composed of n particles, where of generation t particle i (i = 1, 2, ..., n), position coordinates $x_i^t=(x_{i1}, x_{i2}, ..., x_{id})$, velocity $v_i^t=(v_{i1}, v_{i2}, \ldots, v_{id})$ personal best position $p_i^t=(p_{i1}, p_{i2}, \ldots, p_{id})$ and global best position $p_g^t=(p_{g1}, p_{g2}, ..., p_{gd})$. For particle i dimension d generation t, its iterative formula can be expressed as:

$$v_{id}^{t+1} = \omega \vartheta_{id}^{t} + c_1 r_1 (p_{id}^t \text{-} x_{id}^t) + c_2 r_2 (p_{gd}^t \text{-} x_{id}^t) \quad (24)$$

$$x_{id}^{t+1} = x_{id}^t + \vartheta_{id}^{t+1} \quad (25)$$

where

ϑ_{id}^{t} - Current velocity,

ϑ_{id}^{t+1} - New speed of particle *r* after iteration *t*,

ω - Inertia weight,

c_1, c_2 - Acceleration (learning) factors,

r_1, r_2 - Uniformly distributed random numbers between 0 and 1,

x_{id}^{t} - Current position of particle *i*,

x_{id}^{t+1} -new position of particle *i* after iteration *t*.

B. Shuffled Frog Leaping Algorithm

Shuffled frog leaping algorithm is a biological evolution algorithm based on swarm intelligence. The algorithm simulates a group of frogs in the wetland passing thought and foraging by classification of ethnic groups. In the execution of the algorithm, F frogs are generated at first to form a group, for N-dimensional optimization problem, frog i of the group is represented as $(x_i^1, x_i^2, \ldots, x_i^N)$ then individual frogs in the group are sorted in descending order according to fitness values, to find the global best solution P_x. The group is divided into m ethnic groups, each ethnic group including n frogs, satisfying the relation F=m×n. The rule of ethnic group division is: the first frog into the first sub-group, the second frog into the second sub-group, frog m into sub-group m, frog m+1 into the first sub-group again, frog m+2 into the second sub-group, and so on, until all the frogs are divided, then find the best frog in each sub-group, denoted by P_b; get a worst frog correspondingly, denoted by P_w. Its iterative formula can be expressed as:

$$D = rand\,()^* (P_b \text{-} P_\omega) \quad (26)$$

$$P_{new\ \text{-}\omega} = P_\omega + D_i,\ \text{-}D_{max} \le D_i \le D_{max} \quad (27)$$

where *rand* ( ) represents a random number between 0 and 1,
P_b represents the position of the best frog,
P_w represents the position of the worst frog,
D represents the distance moved by the worst frog,
$P_{new\text{-}w}$ is the improved position of the frog,
D_{max} represents the step length of frog leaping.

In the execution of the algorithm, if the updated $P_{new\text{-}w}$ is in the feasible solution space, calculate the corresponding fitness value of $P_{new\text{-}w}$, if the corresponding fitness value of $P_{new\text{-}w}$ is worse than the corresponding fitness value of P_w, then use P_w to replace P_b in equation (26) and re-update $P_{new\text{-}w}$; if there is still no improvement, then randomly generate a new frog to replace P_w; repeat the update process until satisfying stop conditions.

V. The Particle Sharing Based Particle Swarm Frog Leaping Hybrid Optimization Algorithm for RPO Problem

A. Algorithm Idea

Exploration and exploitation has been a contradiction in the search process of swarm intelligence algorithms. Exploration stresses searching for a new search region in the global range, and exploitation is focused on fine search in local search area. Although particle swarm optimization algorithm is simple and its optimization performance is good, in the entire iterative process, exploration capability is strong and exploitation capability is weak in early period, at this time if particles fall on the neighbourhood of the best particle, they may flee the neighbourhood of the best particle, due to too strong exploration capability; exploration capability is weak and exploitation capability is strong in later period, at this time if particles encounter local optima, the speed of all particles may be rapidly reduced to zero instead of flying, leading to convergence of particle swarm to local optima; the iterative mechanism and ethnic group division lead to strong exploitation and weak exploration in early period, and strong exploration and weak exploitation in later period. Based on the above analysis, in the update process of the algorithm, in order to ensure the diversity of particles, particle swarm and frog group sharing part of the particles, we propose particle sharing based particle swarm frog leaping hybrid optimization algorithm. The idea is as follows: divide the total number of particles N into two sub-groups of numbers N1 and N2, where the first sub-group uses shuffled frog leaping algorithm to optimize, the second sub-group uses the standard particle swarm optimization algorithm to optimize, and N, N1 and N2 satisfy N≤N1+N2, so the number of shared particles is N1+N2－N.

B. Algorithm Process

(1) Initialize groups and parameters. Initialize group total number of particles N, total number of frogs N1, number of sub-groups m, number of frogs in each sub-group n (parameters satisfying N_1=m×n), number of updates It within frog group sub-group, number of particles N_2 of particle swarm (parameters satisfying N≤N1+N2), inertia weight ω, acceleration factor c_1, deceleration factor c_2, the maximum number of iterations Iter Max and other parameters.

(2) Evaluate the initial fitness values of the particles, save the initial best positions and the initial best fitness values, and sort all N particles in ascending order according to fitness values; N_1 particles counted from front to back belong to the frog group, and N_2 particles counted from back to front belong to the particle swarm.

(3) Sort N_1 frogs in ascending order and divide them into sub-groups according to the sub-group division rule.

(4) Determine the best fitness individual P_b and the worst fitness individual P_w of each subgroup in frog group, and the group best individual P_x, improve the worst solution within a specified number of iterations It according to equations (26) and (27).

(5) Sort particles of the group in ascending order according to fitness values, re-mix the particles to form a new group, and sort the N particles in ascending order according to fitness values; N_1 particles counted from front to back belong to the frog group, and N2 particles counted from back to front belong to the particle swarm. Calculate the new speed of each particle according to equation (24), calculate the new position of each particle according to equation (25), limiting the maximum values of the new speed and position of each particle; update each particle's personal best fitness value and personal best position; update the global best fitness value and the global best position.

(6) Sort particles of the group in ascending order according to fitness values, and re-mix the particles to form a new group.

(7) If stop conditions are satisfied (the number of iterations exceeds the maximum allowable number of iterations or the optimal solution is obtained), the search stops, and output the position and fitness value of the first particle of the group; otherwise, return to step (3) to continue the search.

VI. Simulation Results

The validity of the proposed Algorithm technique is demonstrated on 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 0.95p.u. and the upper limits are 1.1 for all the PV buses and 1.05p.u. for all the PQ buses and the reference bus. Table I shows the volatge stability levels at contingency state and Table II shows values for limit checking violation checking of state variables. Table III shows the comparison of the real power loss and clearly proposed approach out performs other algorithms given in Table III.

TABLE I. Voltage Stability under Contingency State

Sl. No	Contigency	ORPD Setting	VSCRPD Setting
1	28-27	0.1400	0.1422
2	4-12	0.1658	0.1662
3	1-3	0.1784	0.1754
4	2-4	0.2012	0.2032

TABLE II. 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 III. COMPARISON OF REAL POWER LOSS

Method	Minimum loss
Evolutionary programming[22]	5.0159
Genetic algorithm[23]	4.665
Real coded GA with Lindex as SVSM[24]	4.568
Real coded genetic algorithm[25]	4.5015
Proposed PSFLH method	4.2103

VII. CONCLUSION

In this paper a novel approach PSFLH algorithm used to solve optimal reactive power dispatch problem. The performance of the proposed algorithm demonstrated through its voltage stability assessment by modal analysis and is effective at various instants following system contingencies. Also this method has a better performance in voltage stability Enhancement and reducing the real power loss. The effectiveness of the proposed method is demonstrated on IEEE 30-bus system.

REFERENCES

[1] O. Alsac and B. Scott, "Optimal load flow with steady state security," *IEEE Transaction on Power Apparatus and Systems*, vol. PAS-93, no. 3, pp. 745-751, 1973.

[2] K. Y. Lee, Y. M. Park, and J. L. Oritz, "A united approach to optimal real and reactive power dispatch," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-104, no. 5, pp. 1147-1153, 1985.

[3] A. Monticelli, M. V. F. Pereira, and S. Granville, "Security constrained optimal power flow with post contingency corrective rescheduling," *IEEE Transactions on Power Systems*, vol. 2, no. 1, pp. 175-180, 1987.

[4] N. Deeb and S. M. Shahidehpur, "Linear reactive power optimization in a large power network using the decomposition approach," *IEEE Transactions on Power Systems*, vol. 5, no. 2, pp. 428-438, 1990.

[5] E. Hobson, "Network constrained reactive power control using linear programming," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-99, no. 3, pp. 868-877, 1980

[6] K. Y. Lee, Y. M. Park, and J. L. Oritz, "Fuel-Cost minimisation for both real- and reactive-power dispatches," *IEE Proceedings C*, vol. 131, no. 3, pp. 85-93, 1984.

[7] M. K. Mangoli and K. Y. Lee, "Optimal real and reactive power control using linear programming," *Electric Power Systems Research*, vol. 26, pp. 1-10, 1993.

[8] S. R. Paranjothi and K. Anburaja, "Optimal power flow using refined genetic algorithm," *Electric Power Components and Systems*, vol. 30, pp. 1055-1063, 2002.

[9] D. Devaraj and B. Yeganarayana, "Genetic algorithm based optimal power flow for security enhancement," *IEE proceedings-Generation, Transmission and Distribution*, vol. 152, no. 6, pp. 899-905, 2005.

[10] C. A. Canizares, A. C. Z. de Souza, and V. H. Quintana, "Comparison of performance indices for detection of proximity to voltage collapse," *IEEE Transactions on Power Systems*, vol. 11. no. 3, pp. 1441-1450, 1996.

[11] J. Kennedy and R C. Eberhart, "Particle swarm optimization," in *Proc. IEEE International Conference on Neural Network*, 1995, pp. 1942-1948.

[12] Y. Shi and R Eberhart, "A modified particle swarm optimizer," in *Proc. IEEE International Conference on Evolutionary Computation*, 1998, pp. 69-73.

[13] M. M. Eusuff and K. E. Lansey, "Optimization of water distribution network design using shuffled frog leaping algorithm," *Journal of Water Resources Planning and Management*, vol. 129, no. 3, pp. 210-225, 2003.

[14] Y. H. Chi, F. C. Sun, W. J. Wang, S. X. Wang, and C. M. Yu, "Improved particle swarm optimization based on boundary condition and its application for task scheduling on grid," *Journal of Computational Information Systems*, vol. 6, no. 2, pp. 321-329, 2010.

[15] Z. B. Feng, H. G. Huang, and Y. Li, "Improved particle swarm optimization based WSN coverage optimization strategy," *Computer Applications Research*, vol. 28, no. 4, pp. 1272-1275, 2011.

[16] L. Zhang, D. Lu, D. C. Dong, and L. Chen, "A wireless sensor network coverage particle swarm optimization," *Journal of Tongji University (Natural Science Edition)*, vol. 37, no. 2, pp. 262-266, 2009.

[17] W. Qu, J. K. Wang, X. Zhao, and Z. G. Liu, "Genetic algorithm based wireless sensor network coverage control optimization strategy," *Systems Engineering and Electronics*, vol. 32, no. 11, pp. 2476-2479, 2010.

[18] M. Y. Liang, L. Li, and K. Chen, "Ant colony algorithm based underground wireless sensor network node localization research," *Mining Machinery*, vol. 31, no. 12, pp. 48-50, 2010.

[19] L. Y. Wu, H. Sun, and M. M. Bai, "Two sub-swarm exchange particle swarm optimization based on different evolutionary models," *Journal of Nanchang Institute of Technology*, vol. 4, pp. 1-4, 2008.

[20] J. Zhao and H. Sun, "Multi-Stage multi-model improved particle swarm optimization algorithm," *Computer Engineering and Applications*, vol. 46, no. 33, pp. 32-35, 2010.

[21] W. T. Liu and Z. Y. Fan, "Chaotic particle swarm optimization based wireless sensor network coverage optimization," *Computer Applications*, vol. 31, no. 2, pp. 338-340, 2011.

[22] Q. H. Wu and J. T. Ma, "Power system optimal reactive power dispatch using evolutionary programming," *IEEE Transactions on Power Systems*, vol. 10, no. 3, pp. 1243-1248, 1995.

[23] S. Durairaj, D. Devaraj, and P. S. Kannan, "Genetic algorithm applications to optimal reactive power dispatch with voltage stability enhancement," *Journal-Institution of Engineers India Part El Electrical Engineering Division*, vol. 87, 2006.

[24] D. Devaraj, "Improved genetic algorithm for multi-objective reactive power dispatch problem," *European Transactions on Electrical Power*, vol. 17, pp. 569-581, 2007.

[25] P. A. Jeyanthy and .D. Devaraj, "Optimal reactive power dispatch for voltage stability enhancement using real coded genetic algorithm," *International Journal of Computer and Electrical Engineering*, vol. 2, no. 4, pp. 1793-8163, 2010.

K. Lenin has received his B.E. Degree Electrical and Electronics Engineering in 1999 from university of madras, Chennai, India and M.E. Degree in Power Systems in 2000 from Annamalai University, TamilNadu, India. At present pursuing Ph.D. degree at JNTU, Hyderabad, India.

Bhumanapally Ravindhranath Reddy, Born on 3rd September, 1969. Got his B.Tech in Electrical & Electronics Engineering from the J.N.T.U. College of Engg., Anantapur in the year 1991. Completed his M.Tech in Energy Systems in IPGSR of J.N.T. University Hyderabad in the year 1997. Obtained his doctoral degree from JNTUA, Anantapur University in the field of Electrical Power Systems. Published 12 research papers and presently guiding 6 Ph.D. scholars. He was specialized in power systems, high voltage engineering and control systems. His research interests include simulation studies on transients of different power system equipment.

M. Surya Kalavathi has received her B.Tech. Electrical and Electronics Engineering from SVU, Andhra Pradesh, India and M.Tech, power system operation and control from SVU, Andhra Pradesh, India. she received her Phd. Degree from JNTU, hyderabad and Post doc. From CMU-USA. Currently she is Professor and Head of the electrical and electronics engineering department in JNTU, Hyderabad, India and she has published 16 research papers and presently guiding 5 Ph.D. scholars. She has specialised in power systems, high voltage engineering and control systems. Her research interests include simulation studies on transients of different power system equipment. She has 18 years of experience. She has invited for various lectures in institutes.