

Hybrid - Invasive Weed Optimization Particle Swarm Optimization Algorithm For Solving Optimal Reactive Power Dispatch Problem

K. Lenin, ¹Dr.B.Ravindranath Reddy, ²Dr.M.Surya Kalavathi

¹Research Scholar, Jawaharlal Nehru Technological University, Kukatpally, Hyderabad, India.

²Deputy executive Engineer, Jawaharlal Nehru Technological University, Kukatpally, Hyderabad, India.

³Professor of Electrical and Electronics Engineering, Jawaharlal Nehru Technological University, Kukatpally, Hyderabad, India.

Abstract

This paper presents a hybrid optimization algorithm which originates from Invasive Weed Optimization (IWO) and Particle Swarm Optimization (PSO). Based on the novel and distinct qualifications of IWO and PSO, we introduce HIWOPSO algorithm and try to combine their excellent features in this extended algorithm. It is applied to solve the optimal reactive power dispatch (ORPD) problem. The ORPD problem is formulated as a nonlinear constrained single-objective optimization problem where the real power loss and the bus voltage deviations are to be minimized separately. In order to evaluate the proposed algorithm, it has been tested on IEEE 30 bus system consisting 6 generator and compared other algorithms reported those before in literature. Results show that HIWOPSO is more efficient than others for solution of single-objective ORPD problem.

Keywords

Evolutionary Algorithms, Invasive weed optimization, optimal reactive Power dispatch, power system.

I. Introduction

In recent years the optimal reactive power dispatch (ORPD) problem has received great attention as a result of the improvement on economy and security of power system operation. Solutions of ORPD problem aim to minimize object functions such as fuel cost, power system losses, etc. while satisfying a number of constraints like limits of bus voltages, tap settings of transformers, reactive and active power of power resources and transmission lines and a number of controllable Variables [1, 2]. In the literature, many methods for solving the ORPD problem have been done up to now. At the beginning, several classical methods such as gradient based [3], interior point [4], linear programming [5] and quadratic programming [6] have been successfully used in order to solve the ORPD problem. However, these methods have some disadvantages in the Process of solving the complex ORPD problem. Drawbacks of these algorithms can be declared insecure convergence properties, long execution time, and algorithmic complexity. Besides, the solution can be trapped in local minima [1, 7]. In order to overcome these disadvantages, researches have successfully applied evolutionary and heuristic algorithms such as Genetic Algorithm (GA) [2], Differential Evolution (DE) [8] and Particle Swarm Optimization (PSO) [9]. It is reported in those that evolutionary or heuristic algorithms are more efficient than classical algorithms for solving the RPD problem. Recently there has been considerable amount of attention devoted to bioinspiration and biomimicry, for solving computational problems and constructing intelligent systems, including autonomous robots [12],[13], automated fabrication devices, smart structures, and also developing intelligent control strategies like distributed and cooperative control [14], [15], formation control for multi-agent systems [16], [17], and attention control [18]. Reviewing these achievements in the scope of computational intelligence suggests that there seems to be at least six main domains of intelligence in biological systems and wild life: swarming, Communication and collaboration, Reproduction and Colonization, Learning and

Experience, Competition, Evolution. There are many evidences of intelligence for the posed domains in animals, plants, and generally living systems. For example, ants foraging, birds flocking, fish schooling, bacterial chemotactics are some of the well-known examples in category of swarming [19-25]. Communication is present among most animals and plants. For example, the way honey bees share their information about the quality of nutrients makes one of the fastest mediums of communication in collective systems [26, 27]. Reproduction is also existed in all the creatures; However, some show an intellectual mechanism for breeding or reproducing like making fruiting body in some kinds of bacteria [28]. In plants and trees, roots and branches have deliberate and intelligent attitude toward colonization. Generally speaking, where the resources are abundant, branching increases and bushy structures are constructed, and where the nutrients are insufficient, growth is accelerated and branching decreases, so the density in the rich places becomes larger [29]. The same process is available in weeds accompanied by r and k selection approach [30, 31]. Competition is mostly a result of deficiency and can be seen in all species whether in the form of intraspecific or interspecific competition. Human beings and some other creatures are capable of cognitive learning and experience recording. For example, in lack of nutrients, a kind of bacteria is producing extra copies of itself as memento to remember the situation; thus, if shortage recurs later, the bacterium is better prepared [32]. Finally, we can see numerous evidences of evolution in nature that has made our present universe. In this paper, we aim to merge the idea of intelligent swarming, social cooperation, competition, and reproduction in an optimization meta-algorithm.

Particle Swarm Optimization is inspired from flocking birds (swarming and collaborative communication) and has been used in a large number of applications like neural network training [33], data mining [34], web content organizing [35], computing Nash equilibria in strategic games [36], etc. Invasive Weed Optimization is a novel ecologically inspired algorithm that

mimics the process of weeds colonization and distribution. Despite its recent development, it has shown successful results in a number of practical applications like optimization, optimal positioning of piezoelectric actuators [37], developing a recommender system [38], antenna configuration [39], analysis of electricity markets dynamics [40], etc. The proposed Algorithm is tested on IEEE30-bus system for evolution of effectiveness of it. Results obtained from HIWOPSO is compared results reported those in [1]. Results show that proposed algorithm is more effective and powerful than other algorithms in solution of ORPD problem.

II. Formulation of ORPD Problem

The objective of the ORPD problem is to minimize one or more objective functions while satisfying a number of constraints such as load flow, generator bus voltages, load bus voltages, switchable reactive power compensations, reactive power generation, transformer tap setting and transmission line flow.

A. Minimization of Real Power Loss

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

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

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.

$$\text{Minimize VD} = \sum_{k=1}^{nl} |V_k - 1.0| \tag{2}$$

Where n_l 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:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{nb} v_j \begin{bmatrix} G_{ij} & \cos \theta_{ij} \\ +B_{ij} & \sin \theta_{ij} \end{bmatrix} = 0, i = 1, 2, \dots, nb \tag{3}$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{nb} v_j \begin{bmatrix} G_{ij} & \cos \theta_{ij} \\ +B_{ij} & \sin \theta_{ij} \end{bmatrix} = 0, i = 1, 2, \dots, nb \tag{4}$$

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:

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max}, i \in ng \tag{18}$$

Load bus voltage (VLi) inequality constraint:

$$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max}, i \in nl \tag{19}$$

Switchable reactive power compensations (QCi) inequality constraint:

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max}, i \in nc \tag{20}$$

Reactive power generation (QGi) inequality constraint:

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}, i \in ng \tag{21}$$

Transformers tap setting (Ti) inequality constraint:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in nt \tag{22}$$

Transmission line flow (SLi) inequality constraint:

$$S_{Li}^{min} \leq S_{Li} \leq S_{Li}^{max}, i \in nl \tag{23}$$

Where, nc, ng and nt are numbers of the switchable reactive power sources, generators and transformers. During the simulation process, all constraints satisfied as explained [10].

III. Algorithm Design

A. Particle Swarm Optimization

PSO was developed by Kennedy and Eberhart in 1995 [41]. This algorithm aims to mimic foraging trend and communication behavior in flocks of birds when they are flying. Contrary to traditional evolutionary algorithms which only keep track of position, PSO maintains information regarding position and velocity [41]. The equations for calculating the next particle velocity and position are presented in (1) and (2).

$$V_i(t+1) = \omega V_i(t) + c_1 * \varphi_1 * (P_i(t) - X_i(t)) + c_2 * \varphi_2 * (P_g(t) - X_i(t))$$

$$X_i(t+1) = X_i(t) + V_i(t+1)$$

P_i is the best previous position for that particle, and P_g is the position of the best particle in the whole swarm up to that iteration. c_1 and c_2 called learning factors, are constants that determine the balance between acceleration toward local best (individual's experience, cognition, exploration) or global best (social collaboration or interaction, exploitation). φ_1 and φ_2 are uniform random numbers in the range of [0, 1]. ω is an inertia weight which determines the influence of velocity memory and is employed on the favour of global or local search [42]. It is also suggested to restrict the velocity to a specified range $[-V_{max}, V_{max}]$ [43]. Until now, numerous versions of PSO with selection, reproduction, recombination, and mutation operators have been developed and the way on the improvement of PSO and generally swarm intelligence seems to be continued.

B. Invasive Weed Optimization

Invasive weed optimization was developed by Mehrabian and Lucas in 2006 [30]. IWO algorithm is a bioinspired numerical optimization algorithm that simply simulates natural behaviour of weeds in colonizing and finding suitable place for growth and reproduction. Some of the distinctive properties of IWO in comparison with other evolutionary algorithms are the way of reproduction, spatial dispersal, and competitive exclusion [30]. In Invasive Weed Optimization algorithm, the process begins with initializing a population. It means that a population of initial solutions is randomly generated over the problem space. Then members of the population produce seeds depending on their relative fitness in the population. In other words, the number of seeds for each member is beginning with the value of S_{min} for the worst member and increases linearly to S_{max} for the best

member. For the third step, these seeds are randomly scattered over the search space by normally distributed random numbers with mean equal to zero and an adaptive standard deviation. The equation for determining the standard deviation (SD) for each generation is presented in (3).

$$\sigma_{iter} = \frac{(iter_{max} - iter)^n}{(iter_{max})^n} (\sigma_{initial} - \sigma_{final}) + \sigma_{final}$$

Where $iter_{max}$ is the maximum number of iterations, σ_{iter} is the SD at the current iteration and n is the nonlinear modulation index. The produced seeds, accompanied by their parents are considered as the potential solutions for the next generation. Finally, a competitive exclusion is conducted in the algorithm,

i.e., after a number of iterations the population reaches its maximum, and an elimination mechanism should be employed. To this end, the seeds and their parents are ranked together and those with better fitness survive and become reproductive.

C. The Hybrid IWOPSO Algorithm

From the two previous sections it can be concluded that IWO and PSO have two different approaches for optimization. IWO offers good exploration and diversity, while PSO is an algorithm with fairly deliberate and to the point movements in each iteration. In this section, we mix the two algorithms and present a hybrid algorithm. In hybrid IWO/PSO algorithm, colonization is beginning in the same way as IWO, however, the seeds are located like the equations in PSO for flying particles. It means that after reproducing the seeds, the velocity is updated with (4), and temporary position of seeds is estimated by (5), and finally these seeds are randomly distributed the same as the process used in IWO to construct the next population.

$$V_{i,s}(t + 1) = \omega V_i(t) + c_1 * \varphi_{1,s} * (P_i(t) - X_i(t)) + c_2 * \varphi_{2,s} * (P_g(t) - X_i(t))$$

$$X_{i,s}(t + 1) = X_i(t) + V_{i,s}(t + 1)$$

$V_{i,s}$ and $X_{i,s}$ are the velocity and position for the sth seed of the ith member.

HIWOPSO algorithm for solving reactive power dispatch problem

1. Generate random population of N_0 solutions;
2. For iter = 1 to the maximum number of generations;
 - a. Calculate fitness for each individual;
 - b. Compute maximum and minimum fitness in the colony;
 - c. Set P_g as the best position of all individuals;
 - d. For each individual $w \in W$;

- i. Set P_i as the best position of individual w in comparison with its predecessors;
 - ii. Compute number of seeds of w , corresponding to its fitness;
 - iii. For each seed s ;
 - 1) Calculate the velocity according to (4);
 - 2) Update the position according to (5);
 - iv. Randomly distribute generated seeds over the search space with normal distribution around the parent plant (w);
 - v. Add the generated seeds to the solution set, W ;
 - e. If $(|w|=N) > P_{max}$;
 - i. Sort the population W in descending order of their fitness;
 - ii. Truncate population of weeds with smaller fitness until $N=P_{max}$
3. Next iter :

IV. Simulation Results

Proposed approach has been applied to solve ORPD problem. In order to demonstrate the efficiency and robustness of proposed HGIWO which is tested on standard IEEE30-bus test system. The test system has six generators at the buses 1, 2, 5, 8, 11 and 13 and four transformers with off-nominal tap ratio at lines 6-9, 6-10, 4-12, and 28-27 and, hence, the number of the optimized control variables is 10 in this problem.

Table 1: Best Control Variables Settings for Different Test Cases of Proposed Approach

Control Variables setting	Case 1: Power Loss	Case 2: Voltage Deviations
VG1	1.03	0.98
VG2	1.01	0.92
VG5	1.01	1.00
VG8	1.02	1.01
VG11	1.01	1.02
VG13	0.90	1.03
VG6-9	1.00	0.90
VG6-10	1.06	1.01
VG4-12	1.75	1.00
VG27-28	1.00	0.90
Power Loss (Mw)	3.74110	3.664
Voltage deviations	0.6841	0.1699

Table 2: Comparison of The Simulation Results for Power Loss

Control Variables Setting	HGIWO	GSA [11]	Individual Optimizations [1]	Multi Objective Ea [1]	As Single Objective [1]
VG1	1.03	1.049998	1.050	1.050	1.045
VG2	1.01	1.024637	1.041	1.045	1.042
VG5	1.01	1.025120	1.018	1.024	1.020
VG8	1.02	1.026482	1.017	1.025	1.022
VG11	1.01	1.037116	1.084	1.073	1.057
VG13	0.90	0.985646	1.079	1.088	1.061
T6-9	1.00	1.063478	1.002	1.053	1.074

T6-10	1.06	1.083046	0.951	0.921	0.931
T4-12	1.75	1.100000	0.990	1.014	1.019
T27-28	1.00	1.039730	0.940	0.964	0.966
Power Loss (Mw)	3.74110	4.616657	5.1167	5.1168	5.1630
Voltage Deviations	0.6841	0.836338	0.7438	0.6291	0.3142

V. Conclusion

In this paper, one of the recently developed stochastic algorithms HIWOPSO has been demonstrated and applied to solve optimal reactive power dispatch problem. The problem has been formulated as a constrained optimization problem. Different objective functions have been considered to minimize real power loss, to enhance the voltage profile. The proposed approach is applied to optimal reactive power dispatch problem on the IEEE 30-bus power system. The simulation results indicate the effectiveness and robustness of the proposed algorithm to solve optimal reactive power dispatch problem in test system. The HIWOPSO approach can reveal higher quality solution for the different objective functions in this paper.

References

- [1] M. A. Abido, J. M. Bakhshwain, "A novel multiobjective evolutionary algorithm for optimal reactive power dispatch problem," in *proc. Electronics, Circuits and Systems conf.*, vol. 3, pp. 1054-1057, 2003.
- [2] W. N. W. Abdullah, H. Saibon, A. A. M. Zain, K. L. Lo, "Genetic Algorithm for Optimal Reactive Power Dispatch," in *proc. Energy Management and Power Delivery conf.*, vol. 1, pp. 160-164, 1998.
- [3] K. Y. Lee, Y. M. Park, J. L. Ortiz, "Fuel-cost minimisation for both real and reactive-power dispatches," in *proc. Generation, Transmission and Distribution conf.*, vol. 131, pp. 85-93, 1984.
- [4] S. Granville, "Optimal Reactive Dispatch Through Interior Point Methods," *IEEE Trans. on Power Systems*, vol. 9, pp. 136-146, 1994.
- [5] N. I. Deeb, S. M. Shahidehpour, "An Efficient Technique for Reactive Power Dispatch Using a Revised Linear Programming Approach," *Electric Power System Research*, vol. 15, pp. 121-134, 1988.
- [6] N. Grudin, "Reactive Power Optimization Using Successive Quadratic Programming Method," *IEEE Trans. on Power Systems*, vol. 13, pp. 1219-1225, 1998.
- [7] M. A. Abido, "Optimal Power Flow Using Particle Swarm Optimization," *Electrical Power and Energy Systems*, vol. 24, pp. 563-571, 2002.
- [8] A. A. Abou El Ela, M. A. Abido, S. R. Spea, "Differential Evolution Algorithm for Optimal Reactive Power Dispatch," *Electric Power Systems Research*, vol. 81, pp. 458-464, 2011.
- [9] V. Miranda, N. Fonseca, "EPSO-Evolutionary Particle Swarm Optimization, A New Algorithm with Applications in Power Systems," in *Proc. of Transmission and Distribution conf.*, vol. 2, pp. 745-750, 2002.
- [10] S. Durairaj, P. S. Kannan, D. Devaraj, "Application of Genetic Algorithm to Optimal Reactive Power Dispatch Including Voltage Stability Constraint," *Journal of Energy & Environment*, vol. 4, pp. 63-73, 2005.
- [11] S. Duman, Y. Sonmez, U. Guvenc, N. Yorukeran, "application of gravitational search algorithm for optimal reactive power dispatch problem" in *IEEE trans on power system* pp 519-523, 2011.
- [12] I. Suzuki and M. Yamashita, "Distributed anonymous mobile robots: formation of geometric patterns," *SIAM J. Comput.*, vol. 28, no. 4, pp. 1347-1363, 1999.
- [13] B. W. Andrews, K. M. Passino, and T. A. Waite, "Foraging Theory for Autonomous Vehicle Decisionmaking System Design," *J. of Intelligent Robot Syst.*, vol. 49, pp. 39-65, Mar. 2007.
- [14] I. Suzuki and M. Yamashita, "Distributed anonymous mobile robots: formation of geometric patterns," *SIAM J. Comput.*, vol. 28, no. 4, pp. 1347-1363, 1999.
- [15] N. Quijano, A. E. Gil, and K. M. Passino, "Experiments for dynamic resource allocation, scheduling, and control," *IEEE Control Syst. Mag.*, vol. 25, no. 1, pp. 63-79, 2005.
- [16] F. Giuliatti, L. Pollini, and M. Innocenti, "Autonomous formation flight," *IEEE Control Syst. Mag.*, vol. 20, pp. 34-44, Dec. 2000.
- [17] T. Balch and R. C. Arkin, "Behavior-based formation control for multirobot teams," *IEEE Trans. Robot. Automat.*, vol. 14, pp. 926-939, Dec. 1998.
- [18] H. Fatemi Shariatpanahi and M. Nili Ahmadabadi, "Biologically Inspired Framework for Learning and Abstract Representation of Attention Control," in *Proc. 4th International Workshop on Attention in Cognitive Systems*, Hyderabad, India, 2007, pp. 63-80.
- [19] K. M. Passino, "Biomimicry of Bacterial Foraging for Distributed Optimization and Control," *IEEE Control Systems Magazine*, vol. 22, no. 3, pp. 52-67, June 2002.
- [20] E. Bonabeau, M. Dorigo, and G. Theraulaz, *Swarm Intelligence: From Natural to Artificial Systems*. New York: Oxford Univ. Press, 1999.
- [21] A. Okubo, "Dynamical aspects of animal grouping: swarms, schools, flocks, and herds," *Adv. Biophys.*, vol. 22, pp. 1-94, 1986.
- [22] S. Gueron and S. A. Levin, "The dynamics of group formation," *Math Biosci.*, vol. 128, pp. 243-264, 1995.
- [23] E. Ben-Jacob, "Bacterial self-organization: coenhancement of complexification and adaptability in a dynamic environment," *Phil. Trans. R. Soc. Lond. A*, vol. 361, pp. 1283-1312, May 2003.
- [24] E. Ben-Jacob and H. Levine, "Self-engineering capabilities of bacteria," *Journal of The Royal Society Interface*, 3 (6), pp. 197-214, 2006.
- [25] E. Ben-Jacob, I. Becker, Y. Shapira, and H. Levine, "Bacterial linguistic communication and social intelligence," *TRENDS in Microbiology*, vol. 12 no. 8 August 2004.
- [26] A. Trewavas, "Aspects of Plant Intelligence," *Annals of Botany*, vol. 92, pp. 1-20, 2003.
- [27] K. M. Passino, and T. D. Seeley, "Modeling and Analysis of Nest-Site Selection by Honey Bee Swarms: The Speed and Accuracy Trade-off," *Behavioral Ecology and Sociobiology*, vol. 59, no. 3, pp. 427-442, Jan. 2006.
- [28] N. F. Britton, N. R. Franks, S. C. Pratt, and T. D. Seeley, "Deciding on a new home: how do honey bees agree?" in *Proc. Roy. Soc. Lond. (B)*, vol. 269, pp. 1383-1388, 2002.

- 2002.
- [29] A. Stevens, "A stochastic cellular automaton, modeling gliding and aggregation of myxobacteria," *SIAM J. Appl. Math.*, vol. 61, no. 1, pp. 172–182, 2000.
- [30] A. R. Mehrabian and C. Lucas, "A novel numerical optimization algorithm inspired from weed colonization," *Ecological Informatics*, vol. 1, pp. 355–366, 2006.
- [31] R. Dawkins, *The extended phenotype: the long reach of the gene*. Oxford University Press, Oxford, 1999 (First edition, 1982), pp. 156–164.
- [32] S. M. Hoffer, H. V. Westerhoff, K. J. Hellingwerf, P. W. Postma, and J. Tommassen, "Autoamplification of a Two-Component Regulatory System Results in Learning Behavior," *J. of Bacteriology*, vol. 183, no. 16, pp. 4914–4917, Aug. 2001.
- [33] R. C. Eberhart. and Y. Shi, "Evolving artificial neural networks," in *Proc. the 1998 International Conference on Neural Networks and Brain*, Beijing, China, 1998, pp. 5–13.
- [34] Q. Y. Li, Z. P. Shi, J. Shi, and Z. Z. Shi, "Swarm intelligence clustering algorithm based on attractor," *LNCS 3612*, Changsha, China, 2005, pp. 496–504.
- [35] S. Hassas, "Using swarm intelligence for dynamic web content organizing," in *Proc. the 2003 IEEE Swarm Intelligence Symposium*, Indianapolis, USA, 2003, pp. 19–25.
- [36] N.G. Pavlidis, K.E. Parsopoulos, and M.N. Vrahatis, "Computing Nash equilibria through computational intelligence methods," *J. of Computational and Applied Mathematics*, vol. 175, no. 1, pp. 113–136, 2005.
- [37] A. R. Mehrabian and A. Yousefi-Koma, "Optimal positioning of piezoelectric actuators of smart fin using bio-inspired algorithms," *Aerospace Science and Technology*, vol. 11, pp. 174–182, 2007.
- [38] H. Sepeshri-Rad and C. Lucas, "A recommender system based on invasive weed optimization algorithm," in *Proc. IEEE Congress on Evolutionary Computation*, 2007, pp. 4297–4304.
- [39] B. Dadalipour, A. R. Mallahzadeh, Z. Davoodi-Rad, "Application of the invasive weed optimization technique for antenna configurations," in *Proc. Loughborough Antennas and Propagation Conf.*, Loughborough, pp. 425–428, Mar. 2008.
- [40] M. Sahraei-Ardakani, M. Roshanaei, A. Rahimi-Kian, C. Lucas, "A Study of Electricity Market Dynamics Using Invasive Weed Optimization," in *Proc. IEEE Symposium on Computational Intelligence and Games*, Perth, Australia, Dec. 2008.
- [41] J. Kennedy and R.C. Eberhart, "Particle swarm optimization," in *Proc. IEEE Int. Conference on Neural Networks*, Piscataway, NJ, pp. 1942–1948, 1995.
- [42] Y. Shi and R. C. Eberhart, "A modified particle swarm optimizer," in *Proc. IEEE Int. Conference on Evolutionary Computation*, Piscataway, NJ, pp 69–73, 1998.
- [43] R.C. Eberhart, P. Simpson, and R. Dobbins, *Computational intelligence PC tools*. Academic Press Professional, San Diego, CA, 1996, pp. 212–226.



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. Now pursuing Ph.D., degree at JNTU, Hyderabad, India.



Bhmanapally. 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.