International Journal of Computer & Information Technologies (IJOCIT)
www.ijocit.org & www.ijocit.ir
ISSN=2345-3877

Improved Teaching Learning Based Optimization (ITLBO) Algorithm For Solving Optimal Reactive Power Dispatch Problem

K. Lenin [1], Dr.B.Ravindranath Reddy [2] ,Dr.M.Surya Kalavathi[3]
Jawaharlal Nehru technological university Kukatpally,
Hyderabad , India
gklenin@gmail.com

Abstract: This paper presents an algorithm for solving the multi-objective reactive power dispatch problem in a 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. This paper introduces a new search model Teaching-Learning-Based Optimization (TLBO), it is recently being used as a new, reliable, accurate and robust optimization technique scheme for global optimization over continuous spaces .This paper presents an, improved version of TLBO algorithm, called the improved Teaching-Learning-Based Optimization (ITLBO). This algorithm uses a parameter in TLBO algorithm to increase convergence rate. In order to evaluate the proposed algorithm, it has been tested on IEEE 30 bus system and compared to other algorithms reported those before in literature. Results show that TLBO is more efficient than others for solution of single-objective ORPD problem.

Keywords: Modal analysis, optimal reactive power, Transmission loss, teaching learning, Meta-heuristic.

International Journal of Computer & Information Technologies (IJOCIT)
www.ijocit.org & www.ijocit.ir
ISSN=2345-3877

1. 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 which 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 [11]. 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 [12] is used as the indicator of voltage stability. During the last decades a lot of population-based meta-heuristic algorithms were proposed. One population-based category is the evolutionary based algorithms including Genetic Programming, Evolutionary Programming, Evolutionary Strategies, Genetic Algorithms, Differential Evolution, Harmony Search algorithm, etc. Other category is the swarm based algorithms including Ant Colony Optimization, Particle Swarm Optimization, Bees Algorithms, Honey Bee Mating Optimization, etc. In evolutionary algorithms the convergence rate of the algorithm is given prime importance for solving an optimization problem. The ability of the algorithm to obtain the global optima value is one aspect and the faster convergence is the other aspect. It is studied in the evolutionary techniques literature that there are few good techniques, often achieve global optima results but at the cost of the convergence speed. Those algorithms are good candidates for use in the areas where the main focus is on the quality of results rather than the convergence speed. In real world applications, the faster computation of ac- curate results is the ultimate aim. In recent time, a new optimization technique called Teaching learning based optimization [17] is gaining popularity [18-25] due to its ability to achieve better results in comparatively faster convergence time to techniques like Genetic Algorithms, Particle swarm Optimizations, Differential Evolution .The main reason for TLBO being faster to all other contemporary evolutionary techniques is it has no parameters to tune. However, in evolutionary computation re- search there has been always attempts to improve any given findings further and further. This work is an attempt to improve the convergence characteristics of TLBO further without sacrificing the accuracies obtained in TLBO and in some occasions trying to even better the accuracies. In our proposed work, the attempt is made to include a parameter called as "weight" in the basic TLBO equations. Our proposed algorithm is known as improved TLBO (ITLBO). The inclusion of this parameter is found not only be bettering the convergence speed of TLBO, even providing better results for the problem. The performance of ITLBO 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.

2. Voltage Stability Evaluation

2.1. 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} , $J_{Q\theta}$, 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 $\Delta P = 0$, then.

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

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

Where

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

J_R is called the reduced Jacobian matrix of the system.

2.2. Modes of Voltage instability

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

Let

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

Where,

ξ = right eigenvector matrix of J_R

η = left eigenvector matrix of J_R

Λ = diagonal eigenvalue matrix of J_R and

$J_R^{-1} = \xi \wedge^{-1} \eta$ (6)

From (3) and (6), we have

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

or

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

Where ξ_i is the i^{th} column right eigenvector and η the i^{th} row left eigenvector of J_R.

λ_i is the ith eigen value of J_R.

The i^{th} modal reactive power variation is,

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

where,

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

Where

ξ_{ji} is the j^{th} element of ξ_i

The corresponding i^{th} modal voltage variation is

$\Delta V_{mi} = [1/\lambda_i] \Delta Q_{mi}$ (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 i^{th} 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 i^{th} 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

International Journal of Computer & Information Technologies (IJOCIT)
Corresponding Author: K. Lenin
August 23, 2013 Volume 1, Issue 1

zero except the k^{th} one being 1. Then,

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

η_{1k} k th element of η_1

$V - Q$ sensitivity at bus k

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

3. 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 $(g_i)\ V$, reactive power generation of capacitor bank (Q_{ci}), and transformer tap setting (t_k).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.

3.1. 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.

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

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.

3.2. 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.

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

Where n_l is the number of load busses and V_k

is the voltage magnitude at bus ***k***.

3.3. 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:

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

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

where, n_b 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 (V_{Li}) inequality constraint:

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

Switchable reactive power compensations (Q_{Ci}) inequality constraint:

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

Reactive power generation (Q_{Gi}) 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 n_c, n_g and n_t are numbers of the switchable reactive power sources, generators and transformers. During the simulation process, all constraints satisfied as explained below [15].

International Journal of Computer & Information Technologies (IJOCIT)
Corresponding Author: K. Lenin
August 23, 2013 Volume 1, Issue 1

4. Teaching & Learning Based Optimization

This optimization method is based on the effect of the influence of a teacher on the output of learners in a class. It is a population based method and like other population based methods it uses a population of solutions to proceed to the global solution. A group of learner's constitutes population in TLBO. In any optimization algorithms there are numbers of different design variables. The different design variables in TLBO are analogous to different subjects offered to learners and the learners' result is analogous to the "fitness", as in other population-based optimization techniques. As the teacher is considered the most learned person in the society, the best solution so far is analogous to Teacher in TLBO. The process of TLBO is divided into two parts. The first part consists of the "Teacher Phase" and the second part consists of the "Learner Phase". The "Teacher Phase" means learning from the teacher and the "Learner Phase" means learning through the interaction between learners. In the sub-sections below, we briefly discuss the implementation of TLBO.

4.1. Initialization

Following are the notations used for describing the TLBO:

N: number of learners in a class i.e. "class size";

D: number of courses offered to the learners;

MAXIT: maximum number of allowable iterations.

The population ***X*** is randomly initialized by a search space bounded by matrix of ***N*** rows and ***D*** columns. The j^{th} parameter of the i^{th} learner is assigned values randomly using the equation

$$x^0_{(i,j)} = x_j^{min} + rand \times (x_j^{max} - x_j^{min}) \quad (24)$$

Where rand represents a uniformly distributed random variable within the range (0, 1) , X_j^{max} and X_j^{min} represent the minimum and maximum value for j^{th} parameter. The parameters of the i^{th} learner for the generation g are given by

$$X^g_{(i)} = \left[x^g_{(i,1)}, x^g_{(i,2)}, x^g_{(i,3)}, \ldots, x^g_{(i,j)}, \ldots, x^g_{(i,D)}\right] \quad (25)$$

4.2. Teacher Phase

The mean parameter M_g of each subject of the learners in the class at generation g is given as

$$M^g = [m_1^g, m_2^g, \dots, m_j^g, \dots, m_D^g] \quad (26)$$

The learner with the minimum objective function value is considered as the teacher $X^g_{Teacher}$ for respective iteration. The Teacher phase makes the algorithm proceed by shifting the mean of the learners towards its teacher. To obtain a new set of improved learners a random weighted differential vector is formed from the current mean and the desired mean parameters and added to the existing population of learners.

$$Xnew^g_{(i)} = X^g_{(i)} + rand \times (X^g_{Teacher} - T_F M^g) \quad (27)$$

T_F is the teaching factor which decides the value of mean to be changed. Value of T_F can be either 1 or 2. The value of T_F is decided randomly with equal probability as,

$$T_F = round\,[1 + rand\,(0.1)\,\{2-1\}] \quad (28)$$

Where T_F is not a parameter of the TLBO algorithm. The value of T_F is not given as an input to the algorithm and its value is randomly decided by the algorithm using Equation (28). After conducting a number of experiments on many benchmark functions it is concluded that the algorithm performs better if the value of T_F is between 1 and 2. However, the algorithm is found to perform much better if the value of T_F is either 1 or 2 and hence to simplify the algorithm, the teaching factor is suggested to take either 1 or 2 depending on the rounding up criteria given by Equation (28). If $X^g_{(i)}$ is found to be a superior learner than $Xnew^g_{(i)}$ in generation g, than it replaces inferior learner in the matrix.

4.3. Learner Phase

In this phase the interaction of learners with one another takes place. The process of mutual interaction tends to increase the knowledge of the learner. The random inter- action among learners improves his or her knowledge. For a

International Journal of Computer & Information Technologies (IJOCIT)
Corresponding Author: K. Lenin
August 23, 2013 Volume 1, Issue 1

given learner $X^g_{(i)}$ another learner $X^g_{(r)}$ is randomly selected $(i \neq r)$. The $\boldsymbol{i^{th}}$ parameter of the matrix $\boldsymbol{X_{new}}$ in the learner phase is given as

$$X^g_{(i)} = \begin{cases} X^g_{(i)} + rand \times \left(X^g_{(i)} - X^g_{(r)}\right) \\ if\ f\left(X^g_{(i)}\right) < f\left(X^g_{(r)}\right) \\ X^g_{(i)} + rand \times \left(X^g_{(r)} - X^g_{(i)}\right) otherwise \end{cases} \quad (29)$$

4.4. Algorithm Termination

The algorithm is terminated after MAXIT iterations are completed. Details of TLBO can be refereed in [17].

5. Proposed Improved Teaching-Learning Based Optimizer (ITLBO)

Since the original TLBO is based on the principles of teaching-learning approach, we can always draw analogy with the real class room or learning scenario while designing TLBO algorithm. Although, a teacher always wishes that his/her student should achieve the knowledge equal to him in fast possible time but at times it becomes difficult for a student due to his/her forgetting characteristics. Teaching-learning process is an iterative process wherein the continuous interaction takes place for the transfer of knowledge. Every time a teacher interacts with a student he/she finds that the student is able to recall part of the lessons learnt from the last session. This is mainly due to the physiological phenomena of neurons in the brain. In this work we have considered this as our motivation to include a parameter known as "weight" in the Equations (27) and (29) of original TLBO. In contrast to the original TLBO, in our approach while computing the new learner value the part of its previous value is considered and that is decided by a weight factor *w*. It is generally believed to be a good idea to encourage the individuals to sample diverse zones of the search space during the early stages of the search. During the later stages it is important to adjust the movements of trial solutions finely so that they can explore the interior of a relatively small space in which the

International Journal of Computer & Information Technologies (IJOCIT)
Corresponding Author: K. Lenin
August 23, 2013 Volume 1, Issue 1

suspected global optimum lies. To meet this objective we reduce the value of the weight factor linearly with time from a (predetermined) maximum to a (predetermined) minimum value:

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{\max iteration}\right) * i \quad (30)$$

Where w_{max} and w_{min} are the maximum and minimum values of weight factor *w*, *i* iteration is the current iteration number and maxiteration is the maximum number of allowable iterations. w_{max} and w_{min} are selected to be 0.9 and 0.1, respectively. Hence, in the teacher phase the new set of improved learners can be

$$Xnew_{(i)}^{g} = w * X_{(i)}^{g} + rand * \left(X_{Teacher}^{g} - T_F M^{g}\right) \quad (31)$$

and a set of improved learners in learner phase as

$$Xnew_{(i)}^{g} = \begin{cases} w * X_{(i)}^{g} + rand \times \left(X_{(i)}^{g} - X_{(r)}^{g}\right) \\ if\ f\left(X_{(i)}^{g}\right) < f\left(X_{(r)}^{g}\right) \\ w * X_{(i)}^{g} + rand \times \left(X_{(r)}^{g} - X_{(i)}^{g}\right) otherwise \end{cases} \quad (32)$$

6. 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 real power settings are taken from [1]. The lower voltage magnitude limits at all buses are 0.95 p.u. and the upper limits are 1.1 for all the ***PV*** buses and 1.05 p.u. for all the ***PQ*** buses and the reference bus.

Table 1: 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 2: 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 3: Comparison of Real Power Loss

Method	***Minimum loss***
Evolutionary programming[13]	5.0159
Genetic algorithm[14]	4.665
Real coded GA with Lindex as SVSM[15]	4.568
Real coded genetic algorithm[16]	4.5015
Proposed ITLBO method	4.3189

7. Conclusion

In this paper a novel approach ITLBO algorithm used to solve optimal reactive power dispatch problem, considering various generator constraints, has been successfully applied.The performance of the proposed algorithm demonstrated through its voltage stability assessment by modal analysis is effective at various instants following system contingencies. Also this method has a good performance for voltage stability Enhancement of large, complex power system networks. 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. PAS -1973, pp. 745-751.

[2] Lee K Y ,Paru Y M , Oritz J L –A united approach to optimal real and reactive power dispatch , IEEE Transactions on power Apparatus and systems 1985: PAS-104 : 1147-1153

[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 :PWRS-2, No. 1, pp.175-182.,1987.

[4] Deeb N ,Shahidehpur S.M ,Linear reactive power optimization in a large power network using the decomposition approach. IEEE Transactions on power system 1990: 5(2) : 428-435

[5] E. Hobson ,'Network consrained reactive power control using linear programming, ' IEEE Transactions on power systems PAS -99 (4) ,pp 868=877, 1980

[6] K.Y Lee ,Y.M Park , and J.L Oritz, "Fuel –cost optimization for both real and reactive power dispatches" , IEE Proc; 131C,(3), pp.85-93.

[7] M.K. Mangoli, and K.Y. Lee, "Optimal real and reactive power control using linear programming" , Electr.Power Syst.Res, Vol.26, pp.1-10,1993.

[8] S.R.Paranjothi ,and K.Anburaja, "Optimal power flow using refined genetic algorithm", Electr.Power Compon.Syst , Vol. 30, 1055-1063,2002.

[9] D. Devaraj, and B. Yeganarayana, "Genetic algorithm based optimal power flow for security enhancement", IEE proc-Generation.Transmission and. Distribution; 152, 6 November 2005.

[10] Luo, F.F., Chen, G.L., Guo, W.Z.: An improved 'fish-search' algorithm for information retrieval. In: Proceedings of IEEE International Conference on Natural Language, Processing and Knowledge Engineering (NLP-KE 2005), Wuhan, China, pp. 523–528 (2005).

[11] Carmelo J.A.Bastos Filho , Fernando B. de Lima Neto , Anthony J.C.C.Lins , Antonio I.S. Nascimento , Marilia P.Lima , Fish school search nature – inspired algorithms for optimization studies in computational intelligence vol 193 , 2009 , pp 261-277.

[12] C.A. Canizares , A.C.Z.de Souza and V.H. Quintana , " Comparison of performance indices for detection of proximity to voltage collapse ,'' vol. 11. no.3 , pp.1441-1450, Aug 1996 .

[13] Wu Q H, Ma J T. Power system optimal reactive power dispatch using evolutionary programming. IEEE Transactions on power systems 1995; 10(3): 1243-1248 .

[14] S.Durairaj, D.Devaraj, P.S.Kannan ,' Genetic algorithm applications to optimal reactive power dispatch with voltage stability enhancement' , IE(I) Journal-EL Vol 87,September 2006.

[15] D.Devaraj ,' Improved genetic algorithm for multi – objective reactive power dispatch problem' European Transactions on electrical power 2007 ; 17: 569-581.

[16] P. Aruna Jeyanthy and Dr. 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, August, 2010 1793-8163.

[17] R. V. Rao, V. J. Savsani and D. P. Vakharia, "Teaching- Learning-Based Optimization: A Novel Method for Con- strained Mechanical Design Optimization Problems," Computer-Aided Design, Vol. 43, No. 1, 2011, pp. 303- 315. doi:10.1016/j.cad.2010.12.015 .

[18] R. V. Rao, V. J. Savsani and D. P. Vakharia, "Teach- ing-Learning-Based Optimization: An Optimization Me- thod for Continuous Non-Linear Large Scale Problems," INS 9211 No. of Pages 15, Model 3G 26 August 2011.

[19] R. V. Rao, V. J. Savsani and J. Balic, "Teaching Learning Based Optimization Algorithm for Constrained and Un- constrained Real Parameter Optimization Problems," En- gineering Optimization, Vol. 44, No. 12, 2012, pp. 1447- 1462. doi:10.1080/0305215X.2011.652103.

[20] R. V. Rao and V. K. Patel, "Multi-Objective Optimization of Combined Brayton and Inverse Brayton Cycles Using Advanced Optimization Algorithms," Engineering Opti- mization, Vol. 44,

No. 8, 2012, pp. 965-983. doi:10.1080/0305215X.2011.624183 .

[21] R. V. Rao and V. J. Savsani, "Mechanical Design Opti- mization Using Advanced Optimization Techniques," Springer-Verlag, London, 2012. doi:10.1007/978-1-4471-2748-2

[22] V. Toğan, "Design of Planar Steel Frames Using Teach- ing-Learning Based Optimization," Engineering Struc- tures, Vol. 34, 2012, pp. 225-232. doi:10.1016/j.engstruct.2011.08.035

[23] R. V. Rao and V. D. Kalyankar, "Parameter Optimization of Machining Processes Using a New Optimization Algo- rithm," Materials and Manufacturing Processes, Vol. 27, No. 9, 2011, pp. 978-985. doi:10.1080/10426914.2011.602792.

[25]S. C. Satapathy and A. Naik, "Data Clustering Based on Teaching-Learning-Based Optimization. Swarm, Evolu- tionary, and Memetic Computing," Lecture Notes in Com- puter Science, Vol. 7077, 2011, pp. 148-156, doi:10.1007/978-3-642-27242-4_18 .

Authors Profile

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. Working as asst prof in sree sastha college of engineering & at present pursuing Ph.D., degree at JNTU, Hyderabad,India.

****

DR. Bhumanapally. Ravindhranath Reddy, 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.

****

Dr. 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.