

A novel methodology for maximization of Reactive Reserve using Teaching-Learning-Based Algorithm

Ankita Tiwari¹, S.C.Choube²

¹University Institute of Technology, RGPV, Bhopal, MP 462 033, India

²Department of Electrical and Electronics Engg. UIT-RGPV, Bhopal, MP 462 033, India

Abstract : *This paper presents a new algorithm to optimize the reactive reserve. As the amount of reactive reserves at generating station is a measure of voltage stability. A new approach for scheduling of reactive power control variables for voltage stability enhancement using teaching-learning-based optimization (TLBO) has been developed. An objective function selected for maximization of reactive reserve for maintaining the voltage stability. A Sensitivity inequality relation analysis based proximity indicator has been selected for obtaining desired stability margin whose value along with reactive power reserve maximization assures desired static voltage stability margin. TLBO has been selected because this is an efficient optimization method for large scale non linear optimization problems for finding global solutions. It is basically based on the influence of a teacher on an output of learners in a class. Developed algorithm has been implemented on 6-bus standard test systems.*

Keywords: *Voltage stability, Reactive power reserve, Generation participation factor, Proximity indicator, Teaching-learning-Based-Optimization algorithm.*

I. INTRODUCTION

The problem of reactive power optimization has played an important role in the reliable and optimum operation of power system. Reactive power reserve optimization (RPRO) has complex and non-linear characteristic with large number of equality and inequality constraints [1]. The reactive power optimization problem is a nonlinear combinational and computational optimization problem and during last two decades there are many efforts has been devoted to the development are done by using different mathematical methods known as optimization techniques for solving the reactive power optimization problems.

Primarily the conventional optimization techniques such as linear programming and non linear programming are in practice with the advantage of computational speed and convergence with the objective function of continuous and differentiable value. These are so named as conventional optimization techniques because they cannot handle the large and discrete-continuous problems such as reactive power optimization. So recently, computational intelligence based optimization techniques are in practice and have been proposed in the application of reactive power optimization such as genetic algorithm (GA), Tabu search, simulation annealing, particle swarm optimization(PSO), differential evolution(DE) and most recent one is teaching-learning-based-optimization (TLBO).these all are consider as most practical, user friendly and powerful scheme to obtain the global optimum solution for different optimization problems[2].

All these optimization techniques are used for solving this reactive reserve optimization problem but teaching-learning-based optimization (TLBO) gives high quality solution within short calculation time with high value of performance. Wu et al.[3] proposed optimal reactive power dispatch using an adaptive genetic algorithm (GA).Yoshida et al.[4] proposed a modified PSO to control reactive power flow through the system and also improved the voltage limit violation. Zhang and Liu [5] present a modified PSO algorithm to deal with multi-objective reactive power optimization. Varadarajan and Swarup [6] proposed differential evolution algorithm approach for optimal reactive power dispatch. Zhang et al. [7] have presented dynamic multi-group self adaptive differential evolution algorithm for reactive power optimization problem. The problem was a mixed-integer, non-linear optimization problem with inequality constraints. The available reactive power at sources and network transfer capability are two important aspects, which are necessary to be considered while rescheduling of reactive power control variables.

A hierarchical optimization scheme has been introduced by Vaahedi et al. [8], which optimized a set of control variables such that the solution satisfied a specified voltage stability margin. Menezes et al. [9] proposed a methodology for rescheduling reactive power generation of plants and synchronous condenser for maintaining desired level of stability margin. Dong et al. [10] developed an optimized reactive reserve management scheme using Bender's decomposition technique.

The voltage and reactive power management has been an important concern for power system operators, especially after restructuring of the power industries. In restructured power systems, ancillary services

are among significant issues which have important role in reliable and optimum operation in electricity market. Reactive power provision is one of the most important ancillary services in electricity market. The problem of voltage instability is gaining more and more importance from last few past years, because of the growth of power systems and scarcity of the reactive power management. The services of voltage control connected to reactive power supply are one of the fundamental factors which are used to guarantee stability and security of the power system.

Reactive power reserve present at a source is an important and basic need for maintaining desired level of voltage stability margin. The voltage instability is totally associated with the lack of reactive power support for system caused by the limitation in generation or transmission of the reactive power. Power network may have the transfer capability of reactive power but if reactive reserve is not present in the system the reactive power limit violation occurs. So the reactive power is a key ancillary service to maintain all operation in power system.

This paper proposes a methodology for voltage stability enhancement as well as the maximization of reactive reserves at various sources in proportion to their participation factors automatically calculated based on incremental load flow model. A brief overview on Teaching-Learning Based Optimization technique and its implementation in reactive power reserve optimization is also explained.

II. PROBLEM IDENTIFICATION

1. Reactive Power Reserve

The problem of voltage stability enhancement has been determined as an optimal search problem whose objective is to:-

- i. Maximize the reactive reserves based on the participation of reactive sources when loading condition increases
- ii. Maintaining the desired stability margin with respect to current operating loading point

The reactive power sources consist of a number of synchronous generators and shunt capacitors and reactors on the transmission network. When a disturbance occurs, the real power component of line loadings does not change significantly, on the other hand the reactive power flow can change dramatically. Reason behind that is the voltage drops resulting from the contingency decreases the reactive power generation from line charging and shunts capacitors, so that increasing reactive power losses and system becomes unstable. So that sufficient reactive reserves should be available to meet the reactive power changes because of a disturbance.

In simple words, the reactive power reserve is the ability of the generators to support bus voltages under increased loading condition or system contingencies. The reserves of reactive sources can be considered a measure of the degree of voltage stability. Amount of reactive power, which can be delivering to network, depends on present operating condition and the location of the source and field and armature heating of the alternators. The changing in loading scenario also has impact on reactive reserves. Availability of reactive power reserve of a generator is calculated using generator capability curves.

The active power and reactive power generation output at a synchronous generator may be represented as follows:

$$P_{gi} = \frac{E_q V_{gi}}{X_d} \sin \delta + \frac{V_{gi}^2}{2} \left(\frac{1}{X_d} - \frac{1}{X_q} \right) \sin 2\delta \quad (1)$$

$$Q_{gi} = \frac{E_q V_{gi}}{X_d} \cos \delta + V_{gi}^2 \left(\frac{\sin^2 \delta}{X_d} - \frac{\cos^2 \delta}{X_q} \right) \quad (2)$$

Where,

V_{gi} is the terminal voltage of the i th generator based on the per unit system

$E_q \approx i_{gi,fd}$ ($i_{gi,fd}$ is the field current)

In order to write an analytical model to relate the reactive power limit to the maximum field current, we use a cylindrical rotor model with $X_d = X_q$. Thus, from (2), the maximum reactive power with respect to the field current limit may be obtained as follows:

$$Q_{gi \max} = -\frac{V_{gi}^2}{X_d} + \sqrt{\frac{V_{gi}^2 I_{gi,fd \max}^2}{X_d^2} - P_{gi}^2} \quad (3)$$

Thus, the maximum reactive power $Q_{gi \max}$ of the generator is determined by the maximum field current $i_{gi,fd \max}$. The relationship also shows that the maximum reactive generation is a function of the terminal voltage. The maximum reactive power output should also satisfy the armature current limitation as follows:

$$Q_{gi \max} = \sqrt{V_{gi}^2 I_{gia \max}^2 - P_{gi}^2} \quad (4)$$

The reactive power reserve of the i th generator is then represented as follows:

$$Q_{gi \text{ max res}} = Q_{gi \text{ max}} - Q_{gi} \tag{5}$$

Where, $Q_{gi \text{ max}}$ the smaller of the two values is obtained from (3) and (4) and Q_{gi} is the reactive power output under normal operating conditions. A generator's reactive reserve is calculated by (5) if Q_{gi} is lower than $Q_{gi \text{ max}}$. However, if Q_{gi} reaches its limit, the reactive reserve is set to zero and Q_{gi} varies as a function of the terminal voltage.

III. Proximity Indicator based on Sensitivity analysis

It is assumed that load flow Jacobian at current solution point is known. Following relation can be written based on sensitivity analysis:

$$S_{\lambda \text{max}} \leq \sqrt{\sum_{j,k} (S_{j,k})^2} \tag{6}$$

Where, $S_{\lambda \text{max}}$ is greatest Eigen value of sensitivity matrix given as the inverse of load flow Jacobian ($S_{j,k}$) is (j, k) th element of sensitivity matrix [S], which is inverse of load flow Jacobian.

It is observed from matrix theory that minimum eigen value magnitude of load flow Jacobian is reciprocal of greatest eigen value of sensitivity matrix [S]. Hence following relation follows:

$$J_{\lambda \text{min}} \geq 1 / \sqrt{\sum_{j,k} (S_{j,k})^2} \tag{7}$$

Where, $J_{\lambda \text{min}}$ is minimum eigen value of Jacobian. Right hand side of the above expression is lower bound on the minimum eigen value and termed in further application of this paper as proximity indicator (τ).

Under low loading condition elements of sensitivity matrix are smaller and value of proximity indicator is large. As the load on the system increases the value of proximity indicator decreases since element of sensitivity matrix ($S_{i,k}$) increases in magnitude.

In the vicinity of collapse point the value of proximity indicator practically becomes zero. Hence magnitude of ' τ ' has been used for voltage stability assessment and control in this paper. For secure operation a threshold value of proximity indicator must be maintained. Variation of proximity indicator can be co-related with load on the system with the help of power flow run. Computation of proximity indicator requires Jacobian inversion, which is available directly at the end of current load flow solution. Developed algorithm is for base point setting of reactive power control variables.

IV. Mathematical Formulation

The reactive reserve optimization problem is formulated as a problem whose objective is to maximize the effective reactive reserve subject to various operating and stability constraints. Objective function is given as follows:

$$J = \text{Max} \sum_i p_{gi} * (Q_{gi \text{ max}} - Q_{gi}) \tag{8}$$

Where,

p_{gi} is weighting factor or generator participation factor of i^{th} generator bus which is obtained at next predicted load condition. The bus, which participates to a smaller extent, is given higher weight and the bus participating to a greater extent should be given lesser weight such that reserve at such bus is reduced and increased respectively. Such weighting factors can be obtained by incremental power flow equations with some algebraic manipulation.

$$p_{gi} = \Delta Q_{gi} / (\text{max} \Delta Q_{g \text{ pl}}) \tag{9}$$

Where,

ΔQ_{gi} is the change in reactive reserve of i th generator bus at base case loading

$\Delta Q_{g \text{ pl}}$ is the change in reactive power injection at the generator buses at next predicted loading interval

Equation (8) for the objective function can be optimized according to the following constraints:

- Power flow Equations

$$P = f(V, \delta) \tag{10}$$

$$Q = g(V, \delta) \tag{11}$$

Where,

P and Q represent Active power and reactive power respectively

V is the Voltage and δ is the Load Angle

- Inequality constraints on load bus voltages

$$V_i^{min} \leq V_i \leq V_i^{max} \quad (12)$$

Where,

'i' is the number of Load Buses

V_i is the i^{th} load bus voltage under base case loading condition

V_i^{min} , V_i^{max} are the lower and upper bound on i th load bus voltage.

- Voltage stability constraint

$$\tau \gg \tau_{th} \quad (13)$$

Where, τ_{th} is threshold value of 'τ' proximity indicator

- Reactive power generation constraint

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max} \quad (14)$$

Where,

Q_{gi} is the generated reactive power of i th generator bus

Q_{gi}^{min} , Q_{gi}^{max} are the lower and upper limits of reactive power in the generator

- Inequality constraint as control variables

$$X_i^{min} \leq X_i \leq X_i^{max} \quad (15)$$

Where,

X_i is the control variables selected for i th generator bus

$i = NC$ and NC is the number of control variables.

V. TEACHING-LEARNING BASED OPTIMIZATION TECHNIQUE (TLBO)

1. An Overview

Population based algorithms which are mainly nature inspired and which simulates different natural phenomena to solve a wide range of problems are popular in research fields. Many Researchers had proposed a number of algorithms in the past considering different natural phenomena. The Teaching-learning-based optimization technique is a recently proposed room. TLBO is a teaching-learning process-inspired algorithm proposed by Rao et al. [2] based on the influence of a teacher on the output of learners in a class. The algorithm describes the teaching-learning ability of the teacher and learners in a classroom. The teacher and learners are the two vital components of the algorithm.

This algorithm is divided in two basic modes of the learning:

- Through teacher (known as the teacher phase)
- Interacting with the other learners (known as the learner phase)

TLBO is a population based optimization method. In this optimization algorithm, a group of learners, n , is considered as a population and different subjects offered to the learners are considered as different design variables, M , of the optimization problem. A learner's result is analogous to the 'fitness' value of the optimization problem. The best solution in the entire population is considered as the teacher. The terms used as design variables are represented as the parameters involved in the objective function of the given optimization problem and the best solution is the best value of the objective function. The process of working of TLBO is divided into two parts. The first part consists of 'Teacher Phase' and the second part consists of 'Learner Phase'.

In Teacher phase 'Teacher' plays an important role as the teacher is generally considered as a highly learned person who shares his or her knowledge with the learners. The quality of a teacher affects the outcome of learners. It is obvious that a good teacher trains learners such that they can have better results in terms of their marks or grades, So in this first case of TLBO all the terms are related to the relation of teacher and the learner. Whereas in Learner phase, the 'Learners' are the main participants, who participates in learning process of two types. The first one is through teacher and the second one is from the group discussions and interactions between the other learners in a class.

The process of this algorithm is very simple and user friendly which can be understand to everyone who knows the learning relation between a teacher and learners. This can also be better understandable with the help of flowchart and the implementation process of this formulated problems discussed below.

2. Flow Chart of TLBO

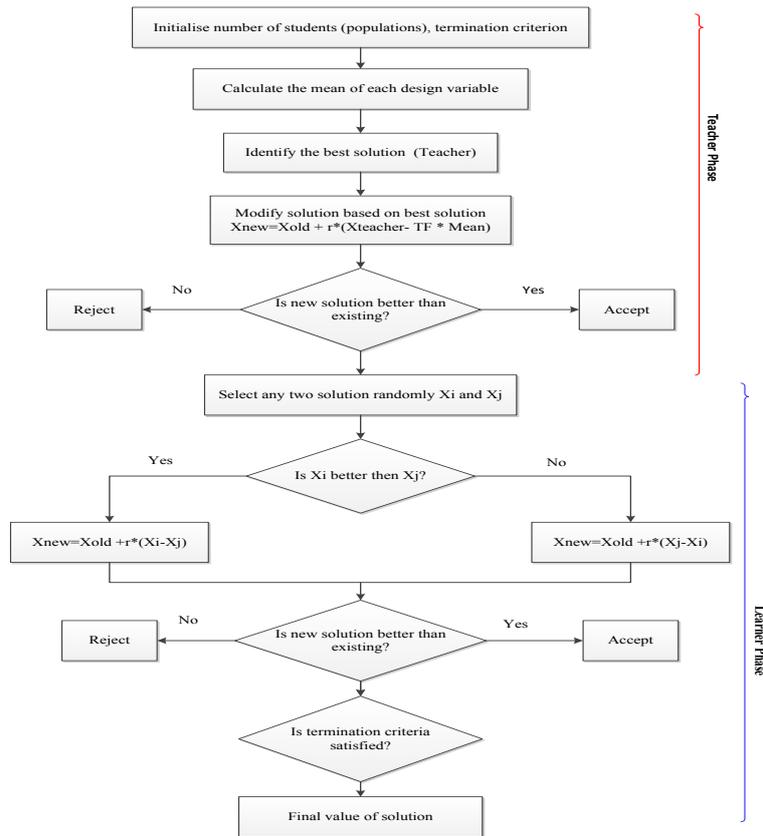


Fig.1. Flow chart of TLBO

IV. IMPLEMENTATION OF TLBO ALGORITHM TO SOLVE FORMULATED PROBLEM

Step by Step method to solve a formulated problem using TLBO can be given as:

Step1: Data input- reactive power control variables and system parameters (resistance, reactance and susceptance etc.)

Step2: Base case load flow solution is obtained by using power flow analysis.

Step3: Next interval predicted (100% loading) selected for further implementation.

Step4: Load flow for the next predicted net interval load is obtained.

Step5: Initialization- generate population of size ‘M’ for control variables $[X_1, X_2, \dots, X_M]$ from uniform distribution for $(X_i^{min} \leq X_i \leq X_i^{max})$ and $i \in NC$ where NC is the number of control variables.

Step6: Run load flow for each sampled vector $X_i = 1, 2, \dots, M$.

Step7: If a vector satisfies all inequality constraints in base case condition as well as next predicted interval call it ‘F’ (feasible) otherwise call it ‘NF’ (not feasible).

Step8: With the help of feasible set of control variable start teacher phase.

Step9: Select base vector or new teacher ‘Tnew’ and class new mean (M new) which is feasible and gives the best value of objective function using relation (8).

Step10: The old mean is calculated by simply calculating the mean of each control vector column wise. This provides the mean for the particular subject which is (M_i) .

Step11: Calculate the difference between these two mean by using equation (16) and using this difference generates a new population using relation (17).

$$Difference_mean_i = r_i * (M_{new} - TF * M_i) \tag{16}$$

$$X_{new_i} = X_{old_i} + Difference_mean_i \tag{17}$$

Step13: Learner phase started with a population of learners from teacher phase. Select two learners i and j randomly and generate a new population by using relation (18) and (19).

If,

$$f(X_i) > f(X_j) \\ X_{new_i} = X_{old_i} + r_i * (X_i - X_j) \tag{18}$$

Else

$$X_{new_i} = X_{old_i} + r_i * (X_j - X_i) \tag{19}$$

Step14: Then compare the old and new population which gives better function value is selected as initial population for next generation.

Step15: This process is continues until no improvement in objective function is noticed in next generations or the maximum number of generations has been executed.

V. Results And Discussions

The developed TLBO algorithm has been implemented on 6-bus IEEE standard test systems.

1. 6-Bus System

This system consists of two generator buses and four load buses. This system contains four reactive power control variables namely two generator bus voltages, one shunt compensation at buses 4th and 6th and one OLTC at line number 3th and 4th. The limits of PV-bus voltages, shunt compensations and OLTCs have been assumed as 0.95 pu to 1.15 pu , 0.00 pu to 0.055 pu and 0.90 to 1.10 respectively. Reactive power limits (lower and upper) of generating bus 1, lying between 0.0000 to 1.0000 pu and generating bus 2 are lying between – 0.0400 pu to 0.0500 pu. Total base case real and reactive power load on the system are 0.67pu and 0.16 pu respectively. Value of proximity indicator at base case condition is 0.5593 and the reactive reserves of two generators are 0.5346 pu and 0.2823 pu.

The desired range of load bus voltage is 0.90 pu and 1.05 pu. Threshold value of proximity indicator has been assumed as $\tau_{th} = 0.5500$. Here the study of reactive reserve is done at stressed condition of loading assume 100% loading condition so the real and reactive power load on system are 1.35 pu and 0.32 pu respectively and the value of proximity indicator is 0.4584.

Table 1 shows PV- bus voltage and all other load bus voltages under current loading case condition. Initially, 100 populations of each control variable have been generated randomly using MATLAB random formula according distribution characteristic of control variable and 10 best values are selected which satisfied all inequality constraints and objective function J. Figure 1 shows the initial population of particles (reactive power control variables) which satisfy all specified inequality constraints for 6-bus test system.

Table 2 contains optimized set of control variables and all load bus voltages for 6-bus system after teaching- learning- based optimization algorithm with teaching factor TF =1 Figure 2 shows the plot of objective function (J) with respect to number of iterations for 6-bus system. Best initial solution (particle) selected as V_1 is 1.1497 pu V_2 is 1.1433pu, Q_{s6} is 0.0550 pu and TAP A_{34} is 0.9440 pu.

Reactive reserves at bus No. 1 and 2 with optimized solution are 0.5975 pu and 0.3336 pu and the participation factor are 4.9599 and 3.2109 respectively. Magnitude of proximity indicator with optimized solution is 0.6566. Objective function J is 4.0347 pu. Table 3 contains different phases of TLBO algorithm. Table 4 contains maximum value of objective function and Table 5 contains the Effect of TLBO in reactive reserve maximum value in different stages & number of iteration required for convergence of 6-bus test system.

2. Figures and Tables

Table-1

Results of Load flow program for 6-bus test system under stressed condition.

Total load: $P_d = 1.35$ pu, $Q_d = 0.32$ pu

Proximity indicator (τ_{min}) is 0.4584.

S.N.	Control variable	Control variable magnitude in(pu)	Load bus voltage	Load bus voltage magnitude in (pu)
1	V_1	1.000	V_3	0.8570*
2	V_2	1.000	V_4	0.8760*
3	Q_{s6}	0.000	V_5	0.8460*
4	A_{34}	1.000	V_6	0.8680*

(* describe the load bus voltage level below the specified limit)

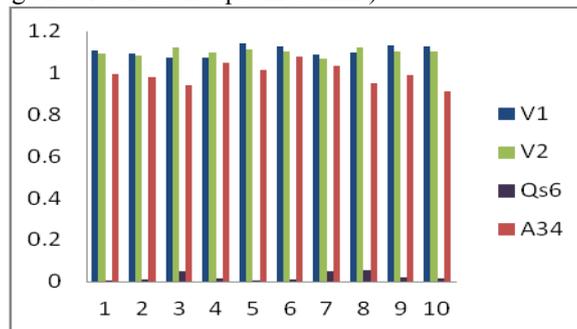


Fig.2.The initial population of control variables satisfying all the constraints

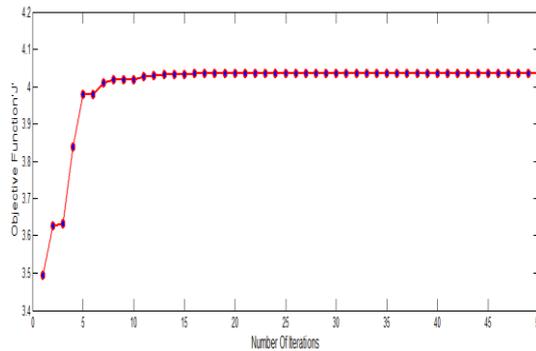


Fig.3. Plot of objective function J verses number of iterations

Table-2

The optimized set of control variables and all load bus voltages for 6-bus system under stressed condition.
 Total load: $P_d=1.35$ pu, $Q_d=0.32$ pu
 Proximity indicator (τ_{min}) = 0.6566

S. N.	Control variable	Control variable magnitude in(pu)	Load bus voltage	Load bus voltage magnitude in (pu)
1	V_1	1.1497	V_3	1.0338
2	V_2	1.1433	V_4	1.0500
3	Q_{S6}	0.0550	V_5	1.0181
4	A_{34}	0.9440	V_6	1.0421

Table-3

Represents the max value of objective function for first generation in each phase of TLBO algorithm.

Initialization (pu)	Teacher phase (pu)	Learner phase (pu)
2.9989	3.0189	3.3349

After 30th generation the maximum value of objective function is obtained which is 4.0347 pu. The result varies with different execution in MATLAB programming of TLBO algorithm as the numbers of iterations for convergence are different with different time of execution.

Table-4

Represents the values of the Objective function after 30th generation.

Initial value of J at stressed condition (pu)	Optimized value of J at stressed condition (pu)
2.5111	4.0347

Table-5

Effect of TLBO in reactive reserve maximum value in different stages & number of iteration required for convergence of 6-bus test system.

Stage number	Max objective fun.(J) (pu)	Maximum number of iteration for convergence
1	4.0345	54
2	4.0345	65
3	3.8407	114
4	4.0240	22
5	4.0345	103
6	4.0345	61
7	4.0322	15
8	4.0345	69
9	4.0345	39
10	4.0053	16
11	4.0311	16
12	4.0345	70
13	4.0341	31
14	4.0345	101
15	4.0345	88
16	4.0345	104
17	4.0345	38
18	3.8407	122
19	4.0345	167
20	4.0345	99

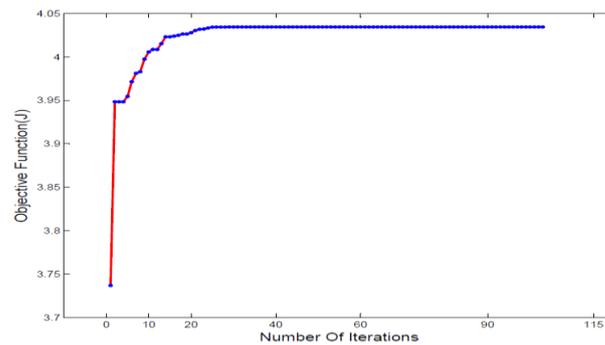


Fig.4 Plot of objective function with respect to number of iterations

VI. Conclusions

This paper represented an algorithm for maximization of reactive power reserves in order to maintain voltage profile for the next predicted loading condition. This has been achieved via TLBO algorithm. Advantage of TLBO algorithm is that its mechanization is simple without much mathematical complexity. The global optimal solution is obtained and local optimal solution is avoided and the main feature of this algorithm is, it does not depend upon different parameters just like used in other optimization techniques. The most important part about this methodology is that not only reactive reserve is optimized but also provides required static voltage stability margin with the help of inequality constraint such as proximity indicator and the value of proximity indicator and bus voltages also optimized through this technique so as the voltage stability margin enhances.

REFERENCES

Journal Papers:

- [1] L.D.Arya, Puspendra Singh, L.S.Titare "Anticipatory reactive power reserve maximization using differential evolution", *Electrical Power and Energy Systems* 35 (2012) 66-73.
- [2] R.V.Rao, V.J.Savsani, D.P.Vakharia, "Teaching-Learning-Based Optimization method for continuous non-linear large scale problems". *Information Sciences* 183 (2012) 1-15.
- [3] Wu QH, Cao YJ, Wen JY. Optimal reactive power dispatch using an adaptive genetic algorithm. *Int J Electr Power Energy System* 1998;20(8):563-9.
- [4] Yoshida H, Fukuyama Y, Kawata K, Takayama S, Nakanishi Y. A particle swarm optimization for reactive power and voltage control considering voltagesecurity assessment. *IEEE Trans Power Syst* 2001;15(4):1232-9.
- [5] Zhang Wen, Liu Yutian. Multi-objective reactive power and voltage control based on fuzzy optimization strategy and fuzzy adaptive particle swarm. *Int J Electr Power Energy Syst* 2008;30(9):525-32.
- [6] Varadarajan M, Swarup KS. Differential evolutionary algorithm for optimal reactive power dispatch. *Int J Electr Power Energy Syst* 2008;30(8):435-41.
- [7] Zhang X, Chen W, Dai C, Cai W. Dynamic multi-group self-adaptive differential evolution algorithm for reactive power optimization. *Int J Electr Power Energy Syst* 2010;32:351-7.
- [8] Vaahedi E, Masour Y, Fuchs C, Granville S, Latore MDL, Hamadoni Zadeh H. Dynamic security constrained optimal power flow/var planning. *IEEE Trans Power Syst* 2001;16(1):38-43.
- [9] Menezes T, da Silva LC, da Costa VF. Dynamic var sources scheduling for improving voltage stability margin. *IEEE Trans Power Syst* 2003;18(2):969-71.
- [10] Dong F, Chowdhury B H, Crow M L, Acar L. Improving voltage stability by reactive power reserve management. *IEEE Trans Power Syst* 2005;20(1): 338-44.
- [11] Yang N, Yu CW, Wen F, Chung CY. An investigation of reactive power planning based on chance constrained programming. *Int J Electr Power Energy Syst* 2007;29(9):650-6.
- [12] Pablo A. Ruiz and Peter W. Sauer, "Reactive Power Reserve Issues", in Proc.38th *North American Power Symp.* (NAPS 2006), Sep. 2006, pp. 439-445.
- [13] Arya LD, Choube SC, Kothari DP. Emission constrained secure economic dispatch. *Int J Electr Power Energy Syst* 1997;19(5):279-85.
- [14] R. Venkata Rao and Vivek Patel, "An elitist teaching-learning-based optimization algorithm for solving complex constrained optimization problems", *International Journal of Industrial Engineering Computations* 3 (2012) 535-560.
- [15] Arya LD, Pande VS, Kothari DP. A technique for load shedding based on voltage stability considerations. *Int J Electr Power Energy Syst* 2005;27:506-17.
- [16] A. Subramanian, Dr. G .Ravi, "Voltage Collapse Enhancement and Loss Reduction by Reactive Power Reserve" *International journal of computer applications*, Volume 12-No.12, January 2011.
- [17] L.D. Arya, L.S. Titare, D.P. Kothari "Improved particle swarm optimization applied to reactive power reserve maximization" *Electrical power and energy systems* (2012).
- [18] Ajarapu V, Christy C. The continuation power flow: a tool for steady state voltage stability analysis. *IEEE Trans PS* 1992;7(1):416-22.
- [19] O. Alizadeh Mousavi, M. Bozorg, A. Ahmadi-Khatir, R. Cherkaoui, "Reactive Power Reserve Management: Preventive Countermeasure for Improving Voltage Stability Margin" IEEE 2012.

Books:

- [20] Kundur P. *Power System Stability and Control*. Mc Graw-Hill Inc.; 1994.
- [21] Deb K. *Multi Objective Optimization Using Evolutionary Algorithms*. 2003.