Tweakof Voltage Profile Considering Uncertain Load Models in Power Systems using TLBO

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Abstract *- Actual power system exhibits various uncertainties. This paper focuses on theload uncertainty impact on potential variables at multiple frames. Various load models based on normal, exponential, beta, gamma and lognormal distribution have been used. Subjected to above uncertain inputs adverse case is identified by severity indexwhile considering line flow limits. The violation in stability limits due to load uncertainties have been limited by designing the constrained objective function to improve voltage profile and in turn reduce active and reactive power losses by minimizing severity index. A single objective problem is designed to minimize severity of bus index, subsequently minimum voltage deviation and minimum power losses were achieved while satisfying the operating constraints. The SVC is used as a control variable. The selection of candidate busesfor placement of SVCs is obtained by calculating the L-Index of load buses. Lastly, Teaching Learning based Optimization (TLBO) is used to obtain optimal value of control variable. The results are validated with the help of other optimization technique namely, Black Hole Algorithm (BHA). IEEE-30 bus system is used to implement the aforementioned problem.*

Keywords *- Voltage Stability; load uncertainties; L-index; SVC; TLBO; BHA*

Nomenclature

A. *Abbreviations*

BHA Black Hole Algorithm
SVC Static VAR Compensator
PU Per Unit
PDF Probability Density Function
$LVSI$ Line voltage stability index
$TLBO$ Teaching Learning Based Optimization

B. *Notations*

eig Minimum Eigen value
J Load flow Jacobean Matrix

C. *Parameters*

N Normal Distribution
exp Exponential Distribution
db Deviation from Base Case
B Beta distribution
G Gamma distribution
ln lognormal distribution
Ψ Uncertain load adjustment factor either {N /exp / db / B / G / ln}
ξ Output uncertainties on the unknown quantities which is a combined effect of (N, exp, db, B, G, ln)
μ Mean Value
σ Standard Deviation
b Load regulating parameter
λ Parameter used for deviation from base case load

D. *Constants*

P_{Di}^{0} Base case real power load at ithPQ bus in MW
Q_{Di}^{0} Base case reactive power load at ithPQ bus in MVA
G_k Conductance of line k in PU
Y_{ij} Magnitude of the admittance of the line connected between i& j in PU
θ_{ij} Angle associated to Y_{ij}in degree
$V_{i\ \min}$ Minimum value of PU voltage magnitude at ith bus
$V_{i\ \max}$ Maximum value of PU voltage magnitude at ith bus

E. *Variables*

$|V|$ Voltage magnitude in PU
δ Voltage angle in degree
$P_{Di}(\psi)$ Uncertain Real Power load in MW at ith PQ bus
$Q_{Di}(\psi)$Uncertain Reactive Power load in MVAR at ith PQ bus
V_k^{ξ} Voltage magnitude in PU at kth PQ bus after incorporating ψ uncertainties in input parameters
V_k^{0} Voltage magnitude in PU at kth PQ bus in base case

δ_i^{ξ} Voltage angle at i[th]bus after inclusion of the effect of uncertainties in input parameters

P_{Gi}^{0} Active Power generation in MW at i[th] bus in base case

Q_{Gi}^{0} Reactive Power generation in MVAR at i[th] bus in base case

P_{Gi}^{ξ} Active Power generation in MW at i[th] bus due to the effect of uncertainties in input

Q_{Gi}^{ξ} Reactive Power generation in MVAR at i[th] bus due to the effect of uncertainties in input

$Q_{Gi\ \min}$ Minimum value of reactive power generated in MVAR at i[th] generator bus

$Q_{Gi\ \max}$ Maximum value of reactive power generated in MVAR at i[th] generator bus

$Q_{Gsh\ i\ \min}$ Minimum value of reactive power provided by shunt compensation in MVAR at i[th] bus

$Q_{Gsh\ i\ \max}$ Maximum value of reactive power provided by shunt compensation in MVAR at i[th] bus

ΔQ_{Gi}^{res} Technical reactive reserves in MVAR

P_{Loss} Real power losses in MW

Q_{Loss} Reactive power losses in MVAR

V_i^{ξ} i[th]Bus voltage magnitude in PU due to uncertain inputs

I. INTRODUCTION

Nowadays power system operators and planners are facing the problem of voltage instability due to increasingly non-uniform demand of electricity by the consumers. Since power system industry undergoes restructuring day by day it becomes tough to maintain the system voltage within acceptable limits and hence, reliability of the system. In modern power systems especially, inaccuracies and uncertainties lead to aberrations in planning and operation. The uncertainty includes ambiguity in generation, transmission, distribution network, distributed generation, loads, energy reserve or economic factors. Hence there is a need to redefine the representation of power system components and the approach should be switched from deterministic to probabilistic one. The deterministic approach does not account for the inherent random nature of the resources at site, system behaviour and customer requirements etc. In such situation, uncertainty in input parameters affects the transfer capability of the system. In recent decades, various load models have been proposed for voltage stability analysis [1, 2]. After exponential recovery load model [3] and adaptive load model [4] proposed according to the results from the measurement of actual power system load, dynamic load models have been introduced for voltage stability analysis. Byongjun and Ajjarapu [5] adopted generic load model for a piecewise global small-disturbance voltage stability analysis. Exponential recovery load model and adaptive load model have been adopted in [6] for voltage stability analysis where excitation and governor systems are in quasi steady state.Different ranges of parameters for the same load model have been reported in [5, 6]. The influence of dynamic load parameters on small-disturbance stability [7] has been revealed via quasi-optimisation procedure with the cost function, which reflects shift of selected Eigenvalues along the real axis when all load parameters varies within their constraints. To tackle uncertainties, probabilistic method has been introduced for power system study. An application of the probabilistic load flow (PLF) techniques to the expansion planning of power systems is presented in [8]. A method that reformulates the optimal power flow dispatch problem including power demand uncertainty is presented in [9].The uncertainty and sensitivity analysis for the system that involve both the subjective and stochastic uncertainty are discussed in [10]. In [11] a probabilistic small signal stability assessment (PSSSA) methodology based on the application of Monte Carlo approach for iterative evaluation, via modal analysis of small signal stability is presented. Available control measures must be utilized to ensure safe, secure and reliable operation of the system.

In the proposed work the assessment and improvement of voltage stability iscarried out with due consideration of variation in load parameters. Six different load models are used namely Normal, Exponential, Beta, Gamma, Lognormal distribution and deviation from base loading at different load buses. The minimum Eigen value of the Jacobian matrix in load flow is obtained for all the incorporated uncertainties. The critical Eigen value determines the stableprobability of a power system. Stability margin is deduced from critical loading level, i.e. the loading at which system is 'probabilistically' stable. Teaching Learning Based Optimization (TLBO)[12] is employed to find optimum value of control variable which satisfies the objective function, i.e. minimization of severity in L-index, subjected to uncertain inputs. The results obtained are compared with Black Hole Algorithm (BHA) [13].The main objective of the proposed work is to provide probability density function (PDF) to input data and find the PDF of output data, secondly, finding healthy and critical mode of operation based on dynamic systems' Eigen value. Subsequently, with respect to critical case compute the most effective control action to boost reactive power reserve in the system and hence improve voltage stability. Lastly, determine the optimal value of control variable to minimize severity index and hence enhance voltage stability and reduce overall losses.

Section I gives brief insight to the previously carried out work. The uncertain load models are present in section II. Section III gives overview of TLBO. Section IV provides the problem formulation followed by methodology in section V. Section VIpresents the results of proposed method and its comparison withanother technique and conclusions are discussed in the last section.

II. UNCERTAIN LOAD MODELLING

Numerous ambiguities are present in power system operation. One of them is dynamic variation in load parameter, which affects voltage stability margin assessment [14]. For the same load model, different ranges are presented in [7]. Dynamic load models were introduced to study about voltage stability. For analysing load variation in a day, 24 hours are divided into 24 subsections. Uncertain load can be represented by probabilistic distributions functions and/or deviation by some scaling parameters.

A. Normal distribution representation of uncertain load

The load bus no. 21 is chosen for modelling the load as normally distributed. The active and reactive load are modelled as normally distributed load with μ_1 and σ_1 being20 and 3 respectively for real load and 12 and 3 respectively for reactive load.The general formula for the pdf of the normal distribution for uncertain loadis [1, 16],

$$f(X_D) = \frac{e^{\frac{(X_D - \mu)}{2\sigma_1^2}}}{\sigma_1\sqrt{2\Pi}} \tag{1}$$

where, $\infty \leq X_D \leq \infty$; $\sigma_1 > 0$

μ_1 is the mean value of the uncertain load (also called the location parameter) and σ_1 is the standard deviation of the uncertain load (also called the scale parameter).

B. *Exponential distribution representation of uncertain load*

The formula for the pdf of the exponential distribution for uncertain load is [1],

$$f(X_D) = \frac{e^{\frac{(X_D - \mu)}{b}}}{b} \tag{2}$$

where, $X_D \geq \mu$ and $b > 0$.
Exponential distribution of uncertain load (both real and reactive) have been modelled at bus no. 12.Here, exponential distributed real power load modelling is done as follows,

$$P_{Di}(\Psi_{exp}) = P_{Di}^{0} + f(P_D) \tag{3}$$

where, x = linearly spaced numbers $\left(0 - P_{X12}^{0}\right)$and b = 1.8 Similarly, reactive load modelling is done.

C. Beta Distribution representation of uncertain load:

Most of the distributions are defined in terms of location and scale parameter but beta distribution is defined in terms of lower and upper bounds. However, location and scale parameter can be expressed in terms of lower and upper bounds. The formula for the pdf of the beta distribution for uncertain load is,

$$f(X_D) = \frac{(X_D - d)^{a-1}(c - X_D)^{b-1}}{B(a,b)(c-d)^{a+b-1}} \tag{4}$$

where, $d \leq X_D \leq c$; $a>0$; $b>0$

a, b = Shape parameter
c= upper bound
d= lower bound

Beta distributed real power load is at bus no. 24 with a=0.8 and b=0.75.Here, the beta distributed load modelling is done as follows,

$$P_{Di}(\Psi_B) = P_{Di}^{0} + f(P_D) \tag{5}$$

Same modelling is performed for reactive load.

D. Deviation from base case loading:

Bus no. 25 is selected for deviation from base case load modelling [1]. For real & reactive power loading the load varies from rated to 150% of rated load,which can be represented as follows,

(i) Real load modelling

$$P_{Di}(\Psi_{db}) = P_{Di}^{0}(1+\lambda) \tag{6}$$

(ii) Reactive load modelling

$$Q_{Di}(\Psi_{db}) = Q_{Di}^{0}(1+\lambda) \tag{7}$$

where, λ = scaling parameter (linearly spaced numbers between -1 to 1.5).

E. Gamma Distributionrepresentation of uncertain load:

The formula for the pdf of the gamma distribution for uncertain load is [1],

$$f(X_D) = \frac{(X_D - \mu)^{a-1}}{b^a\Gamma(a)} e^{-\left(\frac{X_D - \mu}{b}\right)} \tag{8}$$

where, $P_D \geq \mu$; $a > 0$ and $b > 0$.

Here, the gamma distributed real and reactive power load modelling is done as follows,

$$P_{Di}(\Psi_G) = f(P_D)$$

$$Q_{Di}(\Psi_G) = f(Q_D) \tag{9}$$

F. Lognormal distributionrepresentation of uncertain load:

Many probability distributions are not a single distribution, but are in fact a family of distributions. This is because the distribution has one or more shape parameter. It allows a distribution to take on a variety of shapes, depending on the value of the shape parameter. These distributions are particularly useful in modeling applications since they are flexible enough to model a variety of uncertainty load data sets. The following is the equation of the lognormal distribution for uncertain load [1],

$$f(X_D) = \frac{e^{-\frac{\left(\ln\left(X_{D-\mu}/m\right)\right)^2}{2a^2}}}{\sigma(X_D - \mu)\sqrt{2\Pi}} \tag{10}$$

where, $P_D \geq \mu$; $\sigma > 0$ and $a > 0$
'm' is the scale parameter. Lognormally distributed real power load is at bus no. 14 with μ=0.3451 and σ=0.5. Same modelling is performed for reactive load.

III. OVERVIEW OF BHA AND TLBO

A. Black Hole Algorithm 'BHA'

Black Hole technique was developed by A. Hatamlou [13], inspired by the black hole phenomenon. The BH algorithm is a population based method. In BHA, the evolution of population is done by moving all the candidates towards the best candidate in each iteration, namely, the black hole. In addition, there is the probability of crossing the event horizon during moving stars towards the black hole. Every star (candidate solution) that crosses the event horizon of the black hole will be sucked by the black hole. The absorption of stars by the black hole is formulated as follows:

$$x_i(t+1) = x_i(t) + rand(x_{BH} - x_i(t))$$
$$i = 1,2,\ldots N$$
(11)

Where $x_i(t)$ and $x_i(t+1)$ are the locations of the i^{th} star at iterations t and $t+1$, respectively. x_{BH} is the location of the black hole in the search space, $rand$ is a random number in the interval [0,1]. N is the number of stars (candidate solutions). Every time a candidate (star) dies, it is sucked in by the black hole, another candidate solution (star) is born and distributed randomly in the search space and starts a new search. This is done to keep the number of candidate solutions constant. The next iteration takes place after all the stars have been moved. The radius of the event horizon in the black hole algorithm is calculated using the following equation:

$$R = \frac{f_{BH}}{\sum_{i=1}^{N} f_i}$$
(12)

Where f_{BH} is the fitness value of the black hole and fi is the fitness value of the i^{th} star. When the distance between a candidate solution and the black hole (best candidate) is less than R, that candidate is collapsed and a new candidate is created and distributed randomly in the search space.

B. Teaching Learning Based optimization 'TLBO'

TLBO is a teaching-learning process inspired algorithm based on the effect of influence of a teacher on the output of learners in a class [12].Group of learners is considered as population. In the entire population, the best solution is considered as the teacher.Different design variables are considered as different subjects offered to the learners.learners' results are analogous to the ''fitness'' value of the optimization problem. The working of TLBO is divided into two parts: ''Teacher phase'' and ''Learner phase.''

Teachers phase

In the first part of the algorithm learners learn through the teacher. During this phase, a teacher tries to increase the mean result of the classroom from any value M_1 to his or her level (i.e., T_A). A teacher can move the mean of the classroom M_1 to any other value M_2 which is better than M_1 depending on his or her capability. Difference between the existing mean and new mean is given by:

$$Difference\_Mean_i = r_i\left(M_{new} - T_F M_j\right) \tag{13}$$

Where r_i is the random number between (0,1) and T_F is the teaching factor can be either 1or 2. Based on this Difference mean the existing solution is updated according to following expression:

$$X_{new,i} = X_{old,i} + Difference\_Mean_i$$
(14)

Learner phase:

It is the second part of the algorithm where learners increase their knowledge by interaction among themselves. A learner learns new things if the other learner has more knowledge than him or her. Mathematically, at any iteration considering the two different learners X_i and X_j

Population after crossover

$$X_{new,i} = X_{old,i} + r_i\left(X_j - X_i\right) if\ f(X_i) > f(X_j)$$

$$X_{new,i} = X_{old,i} + r_i\left(X_i - X_j\right) if\ (X_i) < f(X_j)$$

(15)

IV. PROBLEM FORMULATION

A single objective problem has been formulated with consideration of load uncertainties.

a. *Objective Function:*

Enhanced voltage stability can be achieved by minimizing the voltage stability indicator L-index value at every bus of the system and consequently global power system L-Index

$$f_1 = \min[L_{\max}] \quad (16)$$

While minimizing the L-index,minimum voltage deviation [14] due to input uncertainties is also obtained.

$$\min \sum_{\forall k}^{N_{PQ}} \left|V_k^{\xi} - 1.0\right| \quad (17)$$

Minimumnetwork losses, either for the whole of the network or for certain section and lines, are non-separable functions of dependent and independent variables [20].

$$\min \sum_{\forall k}^{N_t} G_k \left[\left(V_i^{\xi}\right)^2 - \left(V_j^{\xi}\right)^2 - 2V_i^{\xi} V_j^{\xi} Cos\left(\delta_i^{\xi} - \delta_j^{\xi}\right)\right]$$

(18)

b. *Equality constraints*

$$P_{Gi}^{\xi} - P_{Di}^{\Psi} + P_{DGi}^{'} = \sum_{\forall i} \left|V_i^{\xi}\right| \left|V_j^{\xi}\right| \left|Y_{ij}\right| Cos\left(\theta_{ij} + \delta_i^{\xi} - \delta_j^{\xi}\right)$$

(19)

$$Q_{Gi}^{\xi} - Q_{Di}^{\Psi} - Q_{DGi}^{'} = -\sum_{\forall i} \left|V_i^{\xi}\right| \left|V_j^{\xi}\right| \left|Y_{ij}\right| Sin\left(\theta_{ij} + \delta_i^{\xi} - \delta_j^{\xi}\right)$$

(20)(Static load flow equations with consideration of uncertain inputs are modelled as equality constraints)

c. *Inequality Constraints:*

Voltage limit is from 0.95 PU to 1.05 PU.

$$V_{i\ \min} \le V_i^{\xi} \le V_{i\ \max} \quad (21)$$

Reactive power generation for all the generators or voltage controlled buses.

$$Q_{Gi\ \min} \le Q_{Gi}^{\xi} \le Q_{Gi\ \max} \quad (22)$$

The uncertainty incorporated in the system is limited by minimum to maximum uncertain load adjustment factor.

$$\Psi_{\min} \le \Psi \le \Psi_{\max} \quad (23)$$

Another inequality constraint is the reactive power provided by the SVCwhich is taken to be 0 – 27.5 MVAR, eq. (24), which is 20% of total reactive demand corresponding to critical case. The optimal value of SVC is decided using the optimization techniques.

$$Q_{Gsh\ i\ \min} \le Q_{Gsh\ i} \le Q_{Gsh\ i\ \max} \quad (24)$$

d. *Security constraints*

Load bus voltage limit is given by,

$$V_{Li\ \min} \le V_{Li}^{\xi} \le V_{Li\ \max} \quad (25)$$

Transmission line loading limitis given by,

$$S_{Li}^{\xi} \le S_{Li\ \max} \quad (26)$$

While altering the loads it is to be noted that minimum Eigen value of load flow Jacobian should be greater than zero which means system is not operating near collapse point, this can be limited by,

$$eig[J] > 0 \quad (27)$$

After satisfying all the constraints effective reactive reserve can be calculated by,

$$\Delta Q_{gi}^{res} = Q_{Gi\max} - Q_{Gi}^{\xi} \quad (28)$$

V. METHODOLOGY

The proposed approach to solve optimal reactive power compensation problem using TLBO technique is described here under.

Step 1: Start the load flow with uncertain input values for dynamic load.

Step 2: Compute minimum Eigen value of the load flow Jacobian for each input alteration.

Step 3: Identify case having least Eigen value (closer to 0).

Step 4: Calculate L-Index value for all the load buses [18], for most critical case using the formula (27).

$$L = \max_{j\in\alpha_L}\{L_j\} = \max_{j\in\alpha_L}\left|1 - \frac{\sum_{i\in\alpha_G} F_{ji} V_i}{V_j}\right|$$

(29)

Step 5: Rank the buses in descending order of L-Index and select three buses with larger values as critical buses for placement of SVC. The SVChas been placed at bus number 16, 17 and 19 as they are the weakest nodes in the system, thus reactive support is provided at them to boost the overall voltage profile of the system.

Step 6: Generate population for SVC, (0-27.5) of size 'M' and distribute randomly,

$$S^{(0)} = [X_1^{(0)}, X_2^{(0)}, \ldots\ldots X_M^{(0)}] \quad (30)$$

$$X_i^{(0)} = [x_{i1}^{(0)}, x_{i2}^{(0)}, \ldots\ldots x_{iD}^{(0)}]^T \quad (31)$$

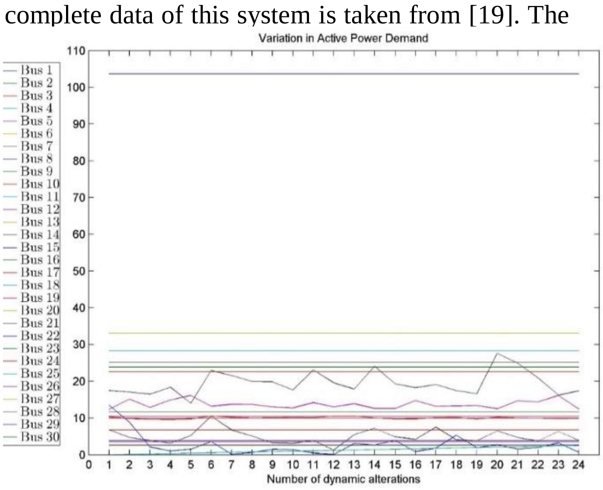
where, $x_{ij}^{(0)} = x_{j,\min} + (x_{j,\max} - x_{j,\min}) rand_j$

Step 7: Compute the objective functionfor all the generations of the population.

Step 8: Select all the feasible vectors and proceed through steps mentioned in section III.

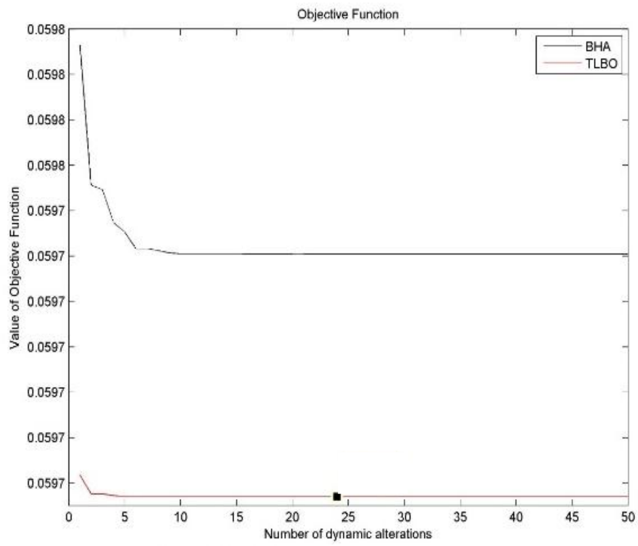
VI. Results and Disscussions

The proposed methodology has been implemented for optimal sizing and placement of reactive compensation device, i.e. SVC, while accounting the dynamic alterations in loads, on the IEEE –30 bus system. The results have been compared with another optimization technique to verify the effectiveness and applicability of proposed methodology. Dynamics alterations are made corresponding to the base case values and the most critical case, having least Eigen value, is identified and reactive compensation value is decided correspondingly. The range for compensation is approximately 20% [21]of the reactive load requirement corresponding to critical case. The desired range for load bus voltage is taken as 0.95 – 1.05 P.U. The base MVA of the system is 100. The complete data of this system is taken from [19]. The



identify weak buses in the system for critical case. The three buses having higher value of L – Index are the critical buses. Buses 16, 17 and 19 are the critical nodes corresponding to critical case. These buses are selected for application of reactive compensation through SVC. Bus 19 has the closest value to 1.0, thus it is a critical bus as far as voltage stability is concerned.

Fig. 1 variation of real power load in MW



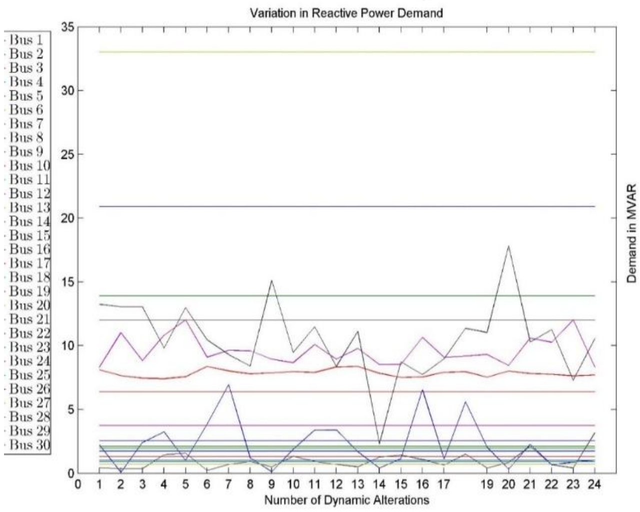


Fig. 2 variation of Reactive power load in MVAR

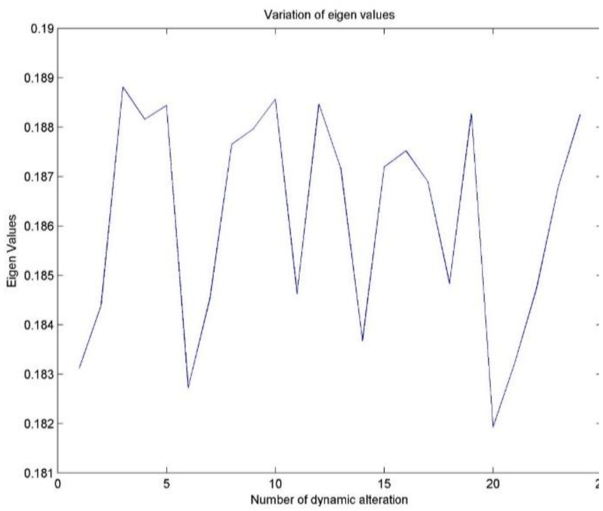


Fig. 3 variation in minimum Eigen value of load flow Jacobean

Here our objective is to minimise L-index, while focusing on reducing voltage deviation at load buses, voltage profile and losses have been reduced from those in the base case. This is clearly depicted in table 2 andfigure 5.Initially, 500 random particles are generated of 0 – 27.5 MVAR reactive compensation through SVC for the three selected buses. Maximum number of iterations are 50.The particles that satisfy all the inequality constraints are feasible solutions and further used in optimization process. The objective function is evaluated focusing on L-index at 19th bus and voltage profile at 17th bus as its voltage profile is the worst in base case.The optimum value of compensation, value of objective function and time elapsed in computation for each optimization technique is shown in table 1. The convergence of the objective function is depicted in figure 4.

Fig. 4 Convergence of objective function

The comparison in voltage magnitude, L- index, are presented in table 2. Bar graph representation of loss variation for critical case and after applying compensation consequent to each optimization technique is given in figure 6. The enhancement of stability in voltage can be very well deduced from the increase in reserve margins depicted in figure 5, as from generator end the voltage stability is directly related to reactive reserves available at the generators [21].

Table 1: Optimal Compensation at Selected Buses Using Different Optimization Techniques

Sr. No.	Selected buses for compensation	Amount of compensation using different Optimization Technique	
		BHA	***TLBO***
1	16	27.14	27.36
2	17	26.38	27.08
3	19	2.24	1.72
Total Compensation 'MVAR'		55.76	56.16
Value of objective function		0.05974	0.05968
Time elapsed 'sec.'		860.12	2178.19

Table 2:Voltage Profile for Critical Case and after Optimization

Bus no.	Before optimization		After optimization			
	Critical case		***TLBO***		***BHA***	
	V_i^{ξ}	***L-Index***	V_i^{ξ}	***L-Index***	V_i^{ξ}	***L-Index***
1	1.000	0.000	1.000	0.0000	1.000	0.0000
2	0.990	0.000	0.990	0.0000	0.990	0.0000
3	0.959	0.0433	0.963	0.0439	0.963	0.0440
4	0.956	0.0422	0.961	0.0427	0.961	0.0428
5	0.972	0.0302	0.974	0.0304	0.974	0.0305
6	0.952	0.0372	0.957	0.0378	0.957	0.0379
7	0.949	0.0500	0.953	0.0504	0.953	0.0504
8	0.950	0.0382	0.955	0.0388	0.955	0.0388
9	0.976	0.0333	0.987	0.0323	0.987	0.0324
10	0.942	0.0296	0.956	0.0315	0.956	0.0316
11	0.976	0.0333	0.987	0.0323	0.987	0.0324
12	0.978	0.0481	1.000	0.0422	1.000	0.0423
13	1.000	0.0000	1.000	0.0000	1.000	0.0000
14	0.972	0.0574	0.990	0.0480	0.990	0.0480
15	0.973	0.0465	0.987	0.0361	0.987	0.0360
16	**0.936**	**0.0618**	**0.967**	**0.0719**	**0.967**	**0.0722**
17	**0.932**	**0.0478**	**0.969**	**0.0553**	**0.969**	**0.0557**
18	0.947	0.0620	0.963	0.0538	0.962	0.0538
19	**0.936**	**0.0656**	**0.953**	**0.0597**	**0.953**	**0.0597**
20	0.936	0.0581	0.953	0.0540	0.953	0.0540
21	0.944	0.0101	0.947	0.0118	0.947	0.0118
22	0.950	0.0000	0.950	0.0000	0.950	0.0000
23	1.000	0.0000	1.000	0.0000	1.000	0.0000
24	0.962	0.0147	0.962	0.0164	0.962	0.0164
25	0.979	0.0128	0.979	0.0150	0.979	0.0151
26	0.963	0.0319	0.963	0.0345	0.963	0.0345
27	1.000	0.0000	1.000	0.0000	1.000	0.0000
28	0.940	0.0332	0.945	0.0338	0.945	0.0338
29	0.978	0.0333	0.977	0.0333	0.977	0.0333
30	0.965	0.0564	0.964	0.0563	0.964	0.0564
Eigen Value	0.1819		0. 1852		**0.1853**	
Active Loss (MW)	27.21		**27.18**		27.21	
Reactive Loss (MVAR)	35.69		**33.69**		33.74	

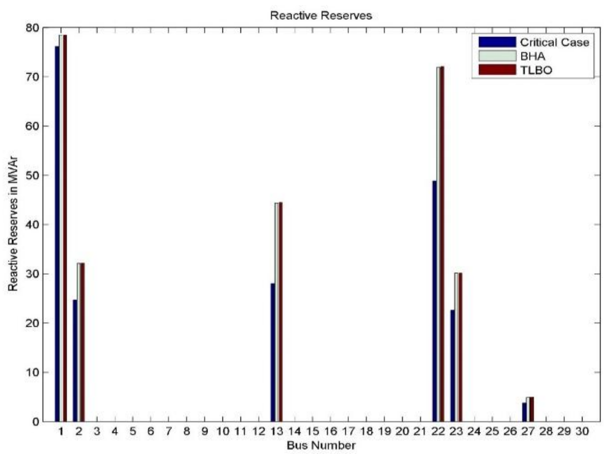


Fig. 5 Reserve Variation Corresponding to Critical Case and After Optimization

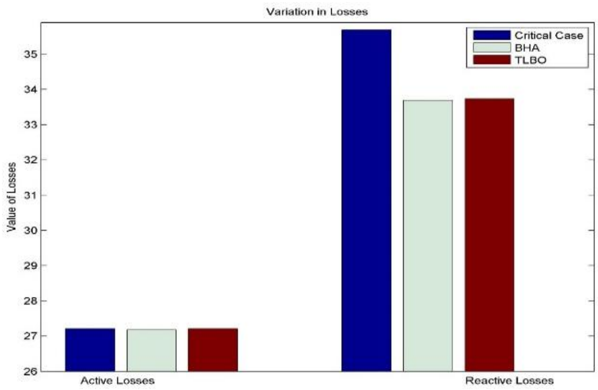


Fig. 6 Losses Corresponding to Critical Case and After Optimization

VII. CONCLUSION

In this paper, the method for optimal setting of reactive power control variables with the objective function of minimum L-index and simultaneously minimum voltage deviation and loss minimization under various load uncertainties are proposed. A single objective optimization problem considering various operating constraints have been formulated. The proposed algorithm has been applied to IEEE 30- bus system. From the results, it can be confirmed that voltage magnitude is enhanced at all the weak buses and simultaneously the losses are also minimized. Overall results, agreeing with objective function, compensation value, time elapsed in computation, voltage profile enhancement and loss minimization are obtained from TLBO and BHA. But the better results are obtained corresponding to the TLBO. The results obtained by TLBO have been compared to the results obtained by BHA to validate its accuracy and effectiveness.

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