SOLVING MULTI OBJECTIVE ORPD PROBLEM USING AIS BASED CLONAL SELECTION ALGORITHM WITH FACTS DEVICES

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Abstract: *In this paper, a solution for the multi objective optimal reactive power dispatch (ORPD) problem using an artificial immune system based clonal selection algorithm is presented. The proposed AIS based clonal selection algorithm uses principle of cloning the antibodies and followed by hyper maturation to minimize the voltage stability index (L-index), voltage deviations at all load buses and the transmission real power losses by incorporating the multi type FACTS devices namely Unified power flow controller (UPFC) and Generalized Unified power flow controller (GUPFC). The proposed algorithm also utilizes the concept of non dominated sorting and crowding distance comparison procedures to solve the multi objective optimization problem. After getting pareto optimal front, the best compromise solution is obtained using fuzzy decision maker. The algorithm was implemented and tested on the standard IEEE 30 bus test system before and after placement of FACTS devices. The proposed method results are presented for multi-objective ORPD problem with two objectives and three objectives case studies using FACTS devices.*

Key words: Optimal Reactive Power Dispatch, Clonal selection algorithm, UPFC, GUPFC, multi-objective optimization.

1. Introduction.

The optimal reactive power dispatch (ORPD) problem is a significant issue in modern power system that will control tap ratios of transformers, reactive power compensation devices and generator terminal voltages to minimize specific objective while satisfying equality, inequality constraints and maintaining reliability. To solve the ORPD problem, a number of conventional optimization techniques are available. These methods consist of the Linear programming [1], Non-linear Programming (NLP) [2], Quadratic Programming (QP) [3] and Interior point methods (IP) [4]. Even though these techniques are successfully applied to solve optimization problems; still some difficulties are associated with them. These techniques generally suffer from algorithmic complexity, may or may not give the solution, and sensitive to initial search point.

Now a day's some of the swarm intelligence and evolutionary search (ES) methods like particle swarm optimization (PSO) [5], Honey bee mating optimization (HBMO) [6], Gravitational search algorithm (GSA) [7], Evolutionary algorithms [8],[9] are able to overcome the difficulties which are faced by the conventional optimization techniques. Even though these methods will give the best results compared to other methods they may suffer from some less guaranteed convergence.

In recent years the FACTS devices technology is increasing with ongoing expansion of the electric utility. The multi type FACTS devices such as UPFC [10-12] and GUPFC [13], [14] are able to improve the system loadability and the system security. These devices can control voltage magnitude, phase angle at required bus and also the line impedance which will significantly effects the power flow through the transmission lines. In ref [15, 16] various optimization techniques to solve active and reactive power dispatch problems, and also the various constraints, objectives were presented.

This paper presents an artificial immune system based algorithm (AIS) [16, 17] which is inspired from theoretical immunology. It can able to detect the antibodies (Ab's) or foreign cells which are harmful to the body and it will clone the antibodies with high affinity and followed by higher maturation. Removes the antibodies with low affinity and accelerates the convergence and tries to provide the solution consistently.

In general there is more number of objectives to be considered at a time. These are linked with each one another. If we want to minimize or maximize only one objective the other objective may get affected and may not give a reasonable solution. So in order to solve the multi objective problem Kalyan Deb introduced a fast and elitist non dominated sorting Genetic algorithm [18, 19]. Here the non dominated sorting algorithm works faster than other methods such as multi objective evolutionary algorithms. This method will give the solution in a single run when compared to weighted sum method. So in this paper non dominated sorting algorithm has been adapted in to the artificial immune system based algorithm [20] to solve the optimal reactive power dispatch problem.

The paper was organized in to nine sections. The UPFC and GUPFC modeling were described in section 2 and section 3. The proposed methodology and its algorithm were explained in section 4. The section 5 deals with the multi objective optimization and procedure for finding the best compromise solution. The problem formulation for the ORPD problem was given in section 6. In section 7 the implementation algorithm for solving ORPD problem including FACTS was described. The results and discussions are given in section 8. At the end conclusions are given in section 9.

2. UPFC Modeling.

The Unified power flow controller consists basically of a two power electronic based switching converters as shown in Fig.1. These converters are operated from a common dc link consists a dc storage capacitor. The UPFC can be represented in two voltage sources which are the fundamental output voltage waveforms of the two converters. Converter 2 performs the main function of the UPFC by injecting an ac voltage with controllable phase angle and magnitude in series with the transmission line through a series transformer. The function of converter 1 is to supply or absorb the real power demanded by converter 2 at the common dc link. Converter 1 is also generate or absorb controllable reactive power and acts as an independent shunt reactive compensation for the line. The proposed UPFC model was taken from ref [10].The leakage impedance of the two transformers was modeled as reactance in series with the voltage sources.

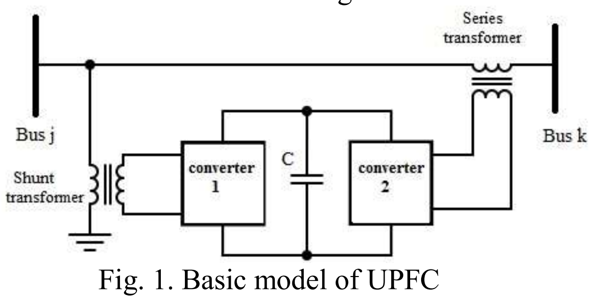

Fig. 1. Basic model of UPFC

$$V_{pq} = rV^{i\gamma} \quad (1)$$

where $0 \leq r \leq r_{max}$ & $\leq \gamma \leq 360^o$

Bus 'j' voltage is taken as the reference voltage of the system V_j= $V_j\angle 0^o$ and $V_j' = V_j + V_{pq}$. Voltage sources V_{sh} and V_{pq} are controllable in their both phase angle and magnitudes. 'r' is the p.u voltage in series with the line and γ is the phase angle of the series voltage source. These will operated within a specified operating limits shown in Eq (1). The fig.2 shows the two voltage source model of the UPFC.

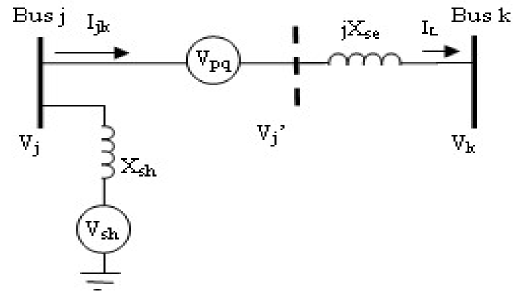

Fig. 2. Two voltage source model of UPFC

By considering the losses within the UPFC and incorporated in to the system will make the problem more practical study. Here the UPFC model considers the 2% losses in the system which should be supplied by the shunt converter. The net effect of the UPFC [11] on the network is represented by a power injection model in to load flow. The injected powers at Bus j and Bus k can be represented as shown below.

$$P_{j,UPFC} = 0.02rb_{se}V_j^2\sin\gamma - 1.02rb_{se}V_jV_k\sin(\theta_j - \theta_k + \gamma) \quad (2)$$

$$P_{k,UPFC} = rb_{se}V_jV_k\sin(\theta_j - \theta_k + \gamma) \quad (3)$$

$$Q_{j,UPFC} = -rb_{se}V_j^2\cos\gamma \quad (4)$$

$$Q_{k,UPFC} = rb_{se}V_jV_k\cos(\theta_j - \theta_k + \gamma) \quad (5)$$

Where$b_{se} = 1/X_{se}$

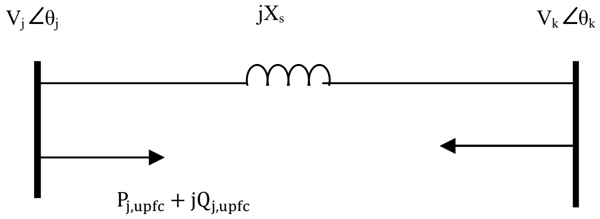

Fig. 3. Power injection model of the UPFC

It is very easy to incorporate the UPFC power injection model in to the Newton raphson load flow algorithm. Since the UPFC is connected between bus j and k the elements of Jacobian matrix are modified by adding an appropriate derivative of the power injections at the nodes where the UPFC is placed.

3. GUPFC Modeling.

The Generalized unified power flow controller usually consists of two or more converters which extend the property same as unified power flow controller but it uses more than one series converter to control power flow through more than two transmission lines. The basic GUPFC consists of a two series converter which are connected in series with the transmission lines and one shunt converter.

Fig.4 shows the operational principle of GUPFC with three converters.

During steady state operation of GUPFC it will control the voltage at the shunt bus and power flow through the transmission line by using shunt injected voltage source and two series injected voltage source converters are used to control magnitude and phase angle at required buses. So the is consists of a three voltage sources here can be represented in Equation 6, 7 and 8.

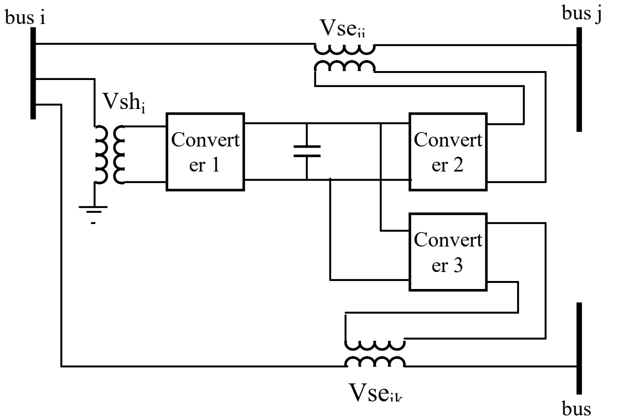

Fig. 4 Simple GUPFC having three converters

$$Vsh_i = V\angle\theta_i \tag{6}$$
$$Vse_{ij} = rVe^{i\gamma} \tag{7}$$
$$Vse_{ik} = rVe^{i\gamma} \tag{8}$$

Where 'r' is the percentage of bus voltage injected in series with the transmission line and 'γ' is the phase angle at which it is injected. It is very easy to incorporate the GUPFC as a power injection model in the Newton raphson algorithm by changing the appropriate Jacobian matrices. The power injection model was taken from [13]. The power injection model of the GUPFC is shown in Fig. 5. After considering the 2% loss within the GUPFC the power injection model the corresponding equations are given in 9 to 14.

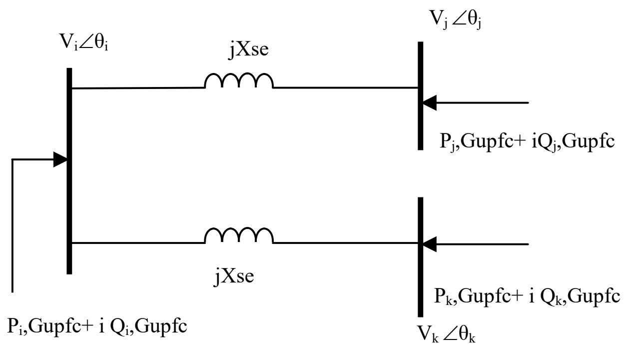

Fig. 5 Power injection model of the GUPFC

$$P_{i,Gupfc} = 0.04rV_i^2B_{se}\sin\gamma - 1.02rV_iV_jB_{se}\sin(\delta_{ij}+\gamma) - 1.02rV_iV_kB_{se}\sin(\delta_{ik}+\gamma) \tag{9}$$
$$Q_{i,Gupfc} = -2rV_i^2B_{se}\cos\gamma + Q_{sh} \tag{10}$$
$$P_{j,Gupfc} = rV_iV_jB_{se}\sin(\delta_{ij}+\gamma) \tag{11}$$
$$Q_{j,Gupfc} = rV_iV_jB_{se}\cos(\delta_{ij}+\gamma)) \tag{12}$$
$$P_{k,Gupfc} = rV_iV_kB_{se}\sin(\delta_{ik}+\gamma) \tag{13}$$
$$Q_{k,Gupfc} = rV_iV_kB_{se}\cos(\delta_{ik}+\gamma) \tag{14}$$

Where B_{se} =1 / Xse

4. Overview of artificial immune system based clonal selection algorithm.

The Artificial immune system (AIS) [18] is derived from natural immune system. The natural immune system is a very complex pattern recognition system which protects the body from foreign cells. It can able to classify the cells is it belong to its own kind or other. The cells came from outside of the body which causes some disease to body are called Anti bodies (Ab's). To fight against the Ab's immune system generates some Antigens (Ag's). The computerized algorithm AIS can observe the immune functions, principles and their models of the Ab's. There are three immunological principles primarily developed in the AIS algorithm those are (a) Immune network theory, (b) Negative selection mechanism, (c) Clonal selection principles [19]. In this paper Clonal selection principles were used as immunological principles.

Some of the terms used in this algorithm are

Fitness: It is the value of objective function which is to be optimized.

Affinity: It is the absolute distance between the best and current individual.

Clone and maturation: Clones are the identical copies of the best individual and maturation is the process to become variants of their parents. Clones with highest fitness will go maturation to a lesser extent as compared to the clones with low fitness.

Step by step procedure for clonal selection algorithm:

Step1: Initialize the population randomly with each population containing all the control variables.

Step2: Calculate the Affinity (fitness) value of each Antibody in the population. Clone the individual in the population (NC) by using Eq.16 for each Antibody which will become a temporary population of clones.

Step3: The population of clones undergoes maturation process through a genetic operation called mutation by using Eq.8 (maturate inversely proportional to the affinity). The affinity of each clone is calculated again.

Step4: A new population from the mutated clones is selected as the original population.

The process will repeat from step 1-4 until the solution converged to an optimum value.

$$NC = \sum_{j=1}^{Nsel} Nc_j \tag{15}$$

NC is the total number of clones and it is the sum of each individual clones of the antibody (Nc). The number of clones for each antibody ‘j’ is selected by using below equation

$$\mathrm{Nc_j} = \mathrm{round}\left(\frac{\beta N_{sel}}{j}\right) \quad (16)$$

Where N_{sel} is total number of selected Antibodies;
β - is the multiplication factor of clone size.

$$\mathrm{Nc_j} = \mathrm{Nc_j} + \alpha * N(0,1) * \mathrm{Maxfit} \quad (17)$$

Where α – is the maturation rate

5. Problem formulation.

ORPD is the non-linear problem which is to minimize certain objective functions by satisfying some equality and inequality constraints. The ORPD problem is generally represented as below.

Min $f(x, u)$, subjected to $g(x, u) = 0$; $h(x, u) \leq 0$

Where f(x, u) is objective function which is to be minimized or maximized, g(x, u) equality constraints and h(x, u) is the system operating constraints.

Here x represents the set of control variables consisting of Generator real power outputs except slack, Generator bus voltages, Tap changing transformer settings and Shunt Reactive power compensation and UPFC and GUPFC parameters.

$\mathbf{x}=[V_{g1},\ldots V_{gn},T_{c1},\ldots T_{cn},Q_{sc1},\ldots Q_{scn},U_1,\ldots U_n]$

Where gn is the number of generators, cn is number of tap changing transformers, scn is the number of shunt VAR compensators. U_n is the n^{th} FACT device. U is the vector of state variables which consists slack bus real power and load bus voltages, Generator reactive power outputs, transmission line loadings.

$u=[P_{g1}, V_{L1,\ldots}, V_{Lnp},Q_{g1},..Q_{gn}, S_{l1},\ldots S_{lbn}]$

np is the total number of load buses, gn is the number of generators, bn is the total number of lines.

Objective functions:

a) Minimization of voltage stability index (L-index):

This objective is to maintain the voltage stability and move the system away from the voltage collapse point. It is in between 0 (under no load) and 1(Voltage collapse). This can defined mathematically as voltage stability indicator L-index and can be expressed as

$$L_j = \left|1 - \sum_{k=1}^{ng} F_{jk}\frac{V_k}{V_j}\right|,\ k = ng + 1 \ldots.\mathrm{Nbus} \quad (18)$$

$F_{jk}$is an element of matrix F and can be calculated by using

$$[F] = -[Y_{LL}]^{-1}[Y_{Lg}]$$

Where $[Y_{Lg}]$ and $[Y_{LL}]$ are the sub matrices of bus admittance matrix (Y_{Bus}).Nbus is total number of buses.

b) Minimization of voltage deviations (VD):

It will meet the consumers demand with a good quality of the supply. The decrease in the sum of the all the load bus voltage violations it will make the load bus voltages to a rated voltage.

$$\mathrm{Vd}(x,u) = \sum_{j=1}^{Nld}\left|V_j - V_j^{sp}\right| \quad (19)$$

Where Nld - is the number of voltage deviations.

c) Minimization of real power loss (PL):

It is to minimize the real power transmission loss in the system which can be expressed as below.

$$P_L = \sum_{i=1}^{nbr} g_i\left[V_j^2 + V_k^2 - 2V_jV_k\cos(\delta_j - \delta_k)\right] \quad (20)$$

where g_i is the ith transmission line conductance connected between bus j and k; $V_j, V_k, \delta_j, \delta_k$ are bus voltage magnitudes and phase angles of the j^{th} and k^{th} bus, nbr is the total number of transmission lines.

Constraints:

Equality constraints: These constraints are standard load flow equations which can be formulated as follows.

$$P_{gj} - P_{dj} - V_j\sum_{k=1}^{ng} V_j(G_{jk}\cos\delta_{jk} + B_{jk}\sin\delta_{jk}) = 0 \qquad j \in \mathrm{Nbus} \quad (21)$$

$$Q_{gj} - Q_{dj} - V_j\sum_{k=1}^{ng} V_j(G_{jk}\cos\delta_{jk} - B_{jk}\sin\delta_{jk}) = 0 \qquad j \in \mathrm{Nbus} \quad (22)$$

Where P_{gj}, Q_{gj} and P_{dj}, Q_{dj} are the real and reactive power generations and real and reactive power demands at jth and kth buses. G_{jk}, B_{jk} are the conductance and susceptance of the transmission line connected between j and k buses.

In equality constraints: These constraints represent the system operating limits as below.

a) *Generator constraints:*

Generator real and reactive power outputs, Generator voltages are restricted to minimum and maximum limits as mentioned below

$$Q_{gj}^{min} \leq Q_{gj} \leq Q_{gj}^{max}, \qquad j = 1 \ldots.\mathrm{ng}$$
$$V_{gj}^{min} \leq V_{gj} \leq V_{gj}^{max}, \qquad j = 1 \ldots.\mathrm{ng}$$

b) *Tap changing transformers constraints:*

Tap changing transformers are restricted to some minimum and maximum limits as follows

$$Tc_j^{min} \leq Tc_j \leq Tc_j^{max}, \qquad j = 1 \ldots.\mathrm{NTc}$$

where NTc is the total tap changing transformers.

c) *Shunt VAR constraints:*

Shunt reactive power injections at different buses are limited to some minimum and maximum limits

$$Q_{scj}^{min} \leq Q_{scj} \leq Q_{scj}^{max},\ j = 1 \ldots.\mathrm{Nsc}$$

where Nsc is the total shunt VAR compensators.

d) *Security constraints:*

These consists constraints regarding Voltage magnitudes at load buses and transmission line loading as mentioned below

$$V_{Lj}^{min} \leq V_{Lj} \leq V_{Lj}^{max}, \qquad j = 1 \ldots.\mathrm{Nld}$$
$$S_{Lj} \leq S_{Lj}^{max}, \quad j = 1 \ldots.\mathrm{Nl}$$

where Nl is the total number of transmission lines.

e) *FACTS devices constraints:*

The control variables limits of UPFC and GUPFC are given below

$V_{pq} = rV_je^{i\gamma}$ for UPFC

$Vse_{ij} = rVe^{i\gamma}$ and $Vse_{ik} = rVe^{i\gamma}$ for GUPFC; where $0 \leq r \leq r^{max}$; $0 \leq \gamma \leq 2\Pi$

Reactive power generation from shunt devices is assumed to be maximum of 0.05 and r^{max} was taken a maximum of 0.1 p.u.

Constraints handling technique:

All the security constraint violations are handled by sum of penalties and is added to the objective function as below.

$$J_{pen} = J_{Lf} + J_{Bv} + J_{Qg} \quad (23)$$

Penalty function for line flow violations is

$$J_{Lf} = K_l \sum_{j=1}^{nl} (|S_{lj}| - S_{lj}^{lim})^2 \quad (24)$$

Penalty function for bus voltage violations

$$J_{Bv} = K_v \sum_{j=1}^{Npq} (V_{lj} - V_{max})^2 \text{ if } V_{lj} > V_{max} \text{ (or)}$$

$$J_{Bv} = K_v \sum_{j=1}^{Npq} (V_{min} - V_{lj})^2 \text{ if } V_{lj} < V_{min} \quad (25)$$

Penalty function for reactive power generation violation is

$$J_{Qg} = K_g \sum_{j=1}^{Ng} (Q_{gj} - Q_{max})^2 \text{ if } Q_{gj} > Q_{max} \text{ (or)}$$

$$J_{Qg} = K_g \sum_{j=1}^{Ng} (Q_{min} - Q_{gj})^2 \text{ if } Q_{gj} < Q_{min} \quad (26)$$

where K_l, K_v, K_g are the corresponding scaling factors.

6. Multi objective optimization.

The more number of real world problems are deals with simultaneous optimization of several objective functions rather than single objective optimization. If we want to minimize / maximize one objective function the other the other objectives may get affected. The control variable which corresponds to one objective function is not feasible for the other objective function. In that way they are so many possible solutions exist between the objective functions. In general the multi objective optimization problem can be stated as follows

Maximize/ minimize: $f_n(X), \quad n = 1,2, \dots N$ (27)

Subjected to: $g_j(X) \geq 0 \quad j = 1,2, \dots J$ (28)

$h_i(X) = 0 \quad i = 1,2, \dots I$ (29)

$X_k^{min} \leq X_k \leq X_k^{max} \quad k = 1,2, \dots\dots K$ (30)

Here X is the set of control variables that satisfy the equality, inequality constraints and minimize or maximize the set of objective functions.

$$X = [x_1, x_2, \dots\dots x_n]^T$$

In multi objective optimization instead of getting one solution there is a possibility of getting number of solutions. These set of solutions are generally called as pareto optimal set. Customary optimization techniques recommend that converted in to a multi objective problem to single objective optimization problem. These conventional techniques will take a longer time for getting all the solutions which are feasible for individual objective functions. This will give single solution corresponding to each run.

To get all possible solutions in pareto set, it requires multiple runs. In recent days the non dominated sorting genetic algorithm (NSGA) [20] was one of the first such evolutionary algorithm (EA)'s to get a solution while maintain diversity of the solution. This non dominated sorting technique will provide pareto optimal set of solutions in a single run.

In this algorithm all the populations are arranged in different fronts depending up on number of objectives. For example if there are two objectives with ten populations, each set of population containing two objective function values. These populations are split into different fronts based on their objective function values. From the fig.6, the population in front 1 is having much better solutions compared to the population in front 2. It indicates that the population in front 2 dominated by the population in front 1. After non dominated sorting all the population in each front is assigned by a rank for example population in front 1 is assign by rank 1 and the population in front 2 is assign by rank 2 etc.

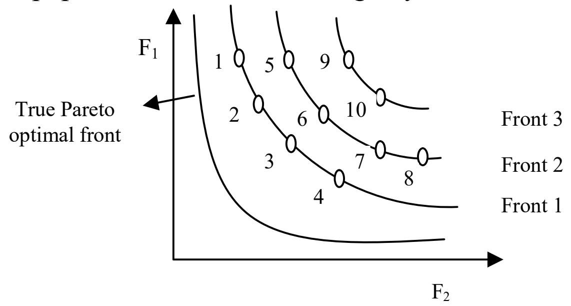

Fig. 6. Example for non dominated sorting having 10 populations in to different fronts

The crowding distance will be calculated for every individual in each front. The crowding distance is the distance between the individual neighboring solutions of same front. The crowding distance will be calculated by using the equation (31)

$$J(d_\ell) = J(d_\ell) + \frac{(J(\ell+1).m - J(\ell-1).m)}{f_m^{max} - f_m^{min}} \quad (31)$$

where $J(\ell).m$ is the value of m^{th} objective function of the ℓ^{th} individual in J. The populations which are present in the boundary are initialized with crowding distance to infinity.

Once the all the population are sorted using non domination sort and followed by crowding distance calculation these will undergo a selection process using crowding distance comparison operator.

Best compromise solution: After getting the non dominated set of solutions to find the best compromise solution [14] fuzzy decision maker was implemented. In this fuzzy decision maker each objective function represented as a member ship function. For the i^{th} objective function, f_i of individual j can be represented by a membership function μ_i^j defined as

$$\mu_i^j = \begin{cases} 1 & f_i \leq f_i^{min} \\ \frac{f_i^{max} - f_i}{f_i^{max} - f_i^{min}} & f_i^{min} \leq f_i \leq f_i^{max} \\ 0 & f_i \geq f_i^{max} \end{cases} \quad (32)$$

where f_i^{max} and f_i^{min} are the maximum and minimum values of the i^{th} objective function amongst all non-dominated solutions.

For every non-dominated solution j, the normalized member-ship function calculated as

$$\mu^j = \frac{\sum_{i=1}^{N} \mu_i^j}{\sum_{j=1}^{p} \sum_{i=1}^{N} \mu_i^j} \quad (33)$$

where P is the total non dominated solutions and the value of which the membership function is higher that corresponding solution is the best compromise solution.

7. Implementation of AIS based clonal selection algorithm to solve ORPD problem with FACTS devices:

This section describes application of clonal selection algorithm for solving multi-objective ORPD problem using UPFC and GUPFC. The power injection model of the proposed two FACTS devices is incorporated by modifying the appropriate Jacobian elements in the Jacobian matrix. The following steps will explain the implementation of proposed algorithm with FACTS.

Step 1: Generate the population of anti bodies with initial number of population which are distributed randomly in the search space. Store them in archive 'X';

$X=[x_1\ x2\ \ldots x_{npop}]$

where $x_i=[V_{g1},\ldots V_{gn},T_{c1},\ldots T_{cn},Q_{sc1},\ldots Q_{scn},U_1,\ldots U_n]$

Step 2: For each antibody must satisfy the equality and in equality constraints such as sum of the real power generation must be equal to real power demand.

$$\sum_{i=1}^{ng} Pg_i = P_d \quad (34)$$

Step 3: Modify the Jocobian matrix using power injection model of the FACTS devices considered. Run the Newton raphson load flow algorithm for each anti body and calculate the slack bus power, line flows and the transmission losses.

Step 4: Evaluate the fitness of each anti body which is nothing but the objective function value of each antibody.

a. Voltage stability index using equation (18)
b. Sum voltage deviations at load buses using equation (19)
c. Power loss using equation (20)

Step 5: Do the non dominated sorting and crowding distance calculation for the initial number of anti bodies.

Step 6: Set iteration count iter=0;

Step 7: Increment the iteration count by 1.

Step 8: Select the best anti bodies after the non dominated sorting and crowding distance comparison operation and store them in an archive X_{best}. For the selected best population do the cloning and maturation process which is shown below

a) Cloning of population set

Nc=[Nc1 Nc2 ……Ncn]

where Nc_i is the number of clones of the ith antibody from the archive x_{best} and the number of clones will be calculated from equation (16)

b) Each clone will undergo some hyper maturation process through equation (17)

Step 9: Each antibody will be again tested for constraint violation.

Step 10: Recalculate the fitness of all clones using equations 18 to 20

Step 11: Check for the stopping criteria if number of iterations reached to maximum then go to nest step otherwise go to step 7

Step 12: Obtain the pareto optimal set from the final population.

Step 13: Find the best compromise solution by using fuzzy decision maker which is discussed in section 6.

8. Results and discussions:

The proposed methodology is applied on a standard IEEE-30 bus test system which consists of six generators, four tap changing transformers and two shunt capacitors. The total real power load demand of the systems is 283.4MW.The proposed method implemented using MATLAB programming. The parameters of the clonal selection algorithm and the minimum and maximum limits of the control variables are shown in Table.1 and Table.2 respectively. Nine shunt capacitors which are placed at buses 10, 12, 15, 17, 21, 22, 23, 24, and 29.

Table.1: Algorithm parameters

Algorithm Parameter	Values
Population Size :	40
Best population :	30
Clone size factor :	1
No' f iterations :	200

Table.2: Control variables min and max limits

Control Variables	Minimum	Maximum
Vg (p.u)	0.95	1.1
Tc	0.9	1.1
Qsh (p.u)	0	0.05
r%	0	0.1
'γ' in rad	0	2∏

Before applying the proposed optimization technique with FACTS devices a contingency ranking analysis is carried on standard IEEE 30 bus test system using the MIPOWER software. The contingency ranking analysis results are presented in Table 3. To find the best location for FACTS devices the contingency ranking analysis was utilized. The device was placed such that which transmission line contingency makes the system more severe in voltage stability at load buses.

There were a total of 41 transmission lines present in the test system. For each line contingency ranking has been given based on the Performance Index of Voltage (PIV). If the PIV is more, the voltage collapse is also more. Therefore from the Table 3, it can be identified that contingency case line number 16 connected between the buses 25 and 26 having a high voltage performance index, hence it was given as rank 1. Therefore the line connected between the buses 25 and 26 is chosen as best location for the placement of the FACTS device to improve the voltage stability of the system.

Table 3 Contingency Ranking analysis results

Contingency Line No	From Bus	To Bus	PIV	Rank
1	2	4	13.7900	33
2	3	4	12.3900	35
3	2	5	17.2400	6
4	1	3	11.0200	38
5	6	8	15.7400	20
6	12	14	14.8200	31
7	12	15	12.7700	34
8	12	16	14.7600	32
9	14	15	16.1100	15
10	16	17	16.0400	17
11	15	18	15.3700	26
12	18	19	16.0800	16
13	19	20	15.9600	19
14	10	20	15.1600	28
15	24	25	16.3800	11
16	25	26	417.500	1
17	27	29	17.4700	4
18	27	30	17.4000	5
19	29	30	16.3400	13
20	8	28	15.7100	22
21	6	28	15.6000	24
22	4	12	9.24700	41
23	6	10	15.1800	27
24	6	9	15.7100	21
25	10	9	11.5300	37
26	11	9	10.9800	39
27	12	13	10.9700	40
28	28	27	37.4400	2
29	1	2	12.3100	36
30	2	6	14.9100	30
31	4	6	15.6200	23
32	5	7	16.5200	10
33	6	7	18.0600	3
34	12	14	15.0000	29
35	23	24	16.7100	7
36	22	24	16.6200	8
37	15	23	16.0300	18
38	21	22	16.6100	9
39	10	22	16.1500	14
40	10	21	15.4100	25
41	10	17	16.3600	12

In multi objective optimization two or more objectives will be taken simultaneously for optimization. The simulation studies are classified as two cases. The first case is corresponding to two objective optimization where as second case is corresponding to three objectives optimization.

Case 1: a) Power loss & Voltage deviation objectives
b) L-index & Voltage deviations objectives

Case 2: Power loss, L-index & Voltage deviation as objectives

These case studies are conducted again with and without the FACTS.

Case 1-a) Power loss & Voltage deviation objectives: This case study is an example of two objectives optimization in which, the power loss and voltage deviation are taken as objectives. The Pareto optimal front is shown in Figure 7. The control variables corresponding to minimum power loss, minimum voltage deviation and compromise solution are shown in Table 4.

The extreme points of the pareto front are solutions corresponding to single objective optimization. It can be observed that for power loss minimization its value is 4.52MW, for voltage deviation minimization it is 0.1054 without placing FACTS devices in the system. The best compromised solution for power loss and voltage deviation is 4.76MW, 0.4933. When UPFC was placed in the system the power loss was much reduced to 4.27MW and the voltage deviation was minimized to 0.0958. The compromised solution was given by power loss and voltage deviation as 4.48MW and 0.4294. When the GUPFC was placed the power loss was much reduced to a value of 4.23MW and 0.1159 voltage deviation. The compromised solution by using GUPFC was obtained as 4.46MW and 0.4587.

Case 1-b) L-index & Voltage deviation objectives: In this case both the L-index and voltage deviations are taken as objectives. The Pareto optimal front is shown in Figure 8. The control variables corresponding to L-index, minimum voltage deviation and compromise solution are shown in Table 5. The extreme points of the pareto front are solutions corresponding to single objective optimization. It can be observed that for L-index minimization its value is 0.105, for voltage deviation minimization it is 0.103 without placing any FACTS devices in the system. The best compromised solution for L-index and voltage deviation is 0.1304, 0.2249. When UPFC was placed in the system the L-index was minimized to 0.1053 and the voltage deviation was minimized to 0.0932. The compromised solution was given by L-index and voltage deviation as 0.1265 and 0.3375 respectively. When the GUPFC was placed the L-index was much reduced to a value of 0.0855 and voltage deviation as 0.0955. The best compromised solution obtained by using GUPFC is 0.1041 and 0.2732.

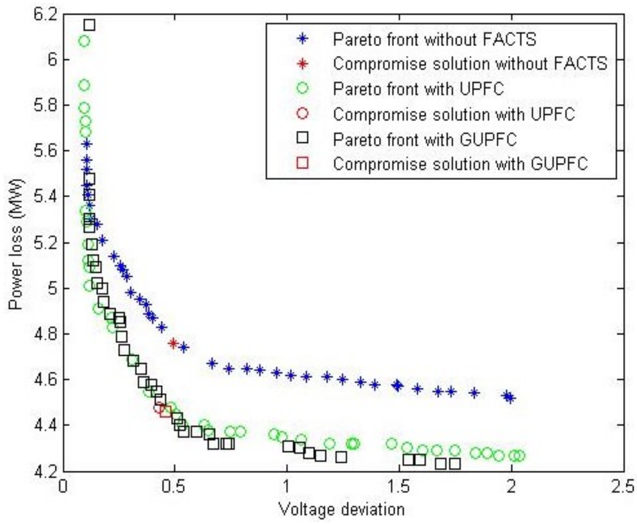

Fig. 7. Pareto optimal front for Voltage deviation and power loss objectives

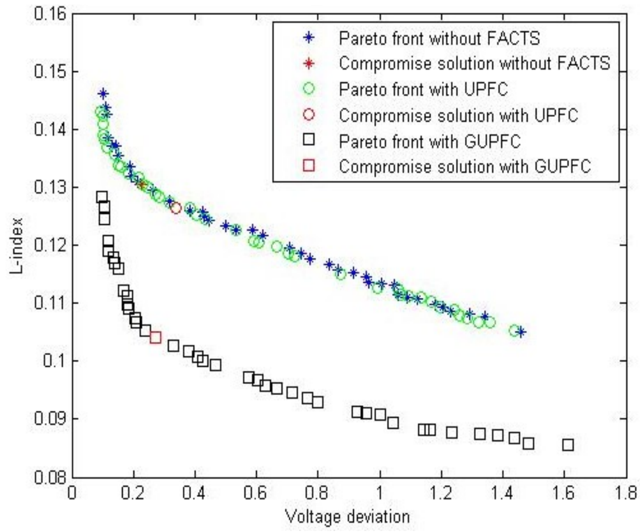

Fig.8 Pareto optimal front for Voltage deviation and L-index as objective

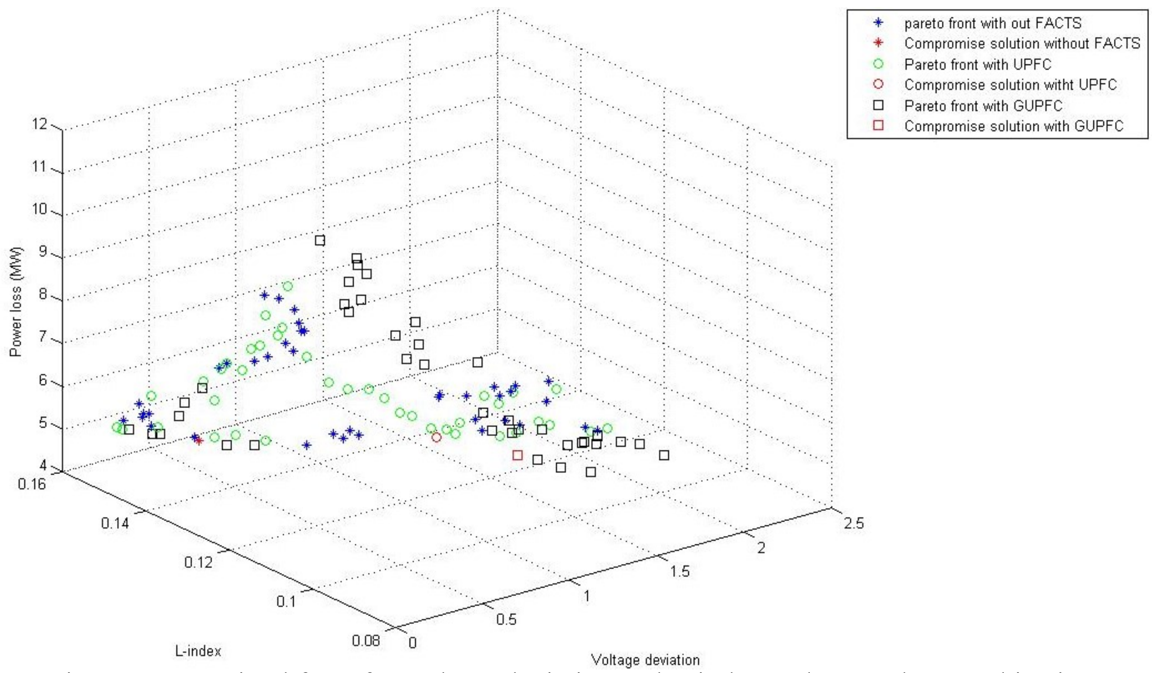

Fig.9 Pareto optimal front for Voltage deviation and L-index and power loss as objective

Case 2: Power loss, L-index and voltage deviation as objective: This case is an example of tri-objective optimization, in which the power loss, L-index and voltage deviations are taken as objectives at a time. The Pareto optimal front is shown in Figure 9. The control variables corresponding to minimization of L-index, voltage deviation, power loss and compromise solution are shown in Table 6. The extreme points of the pareto front are solutions corresponding to single objective optimization. It can be observed that for Power loss minimization it was 4.53MW, L-index minimization its value is 0.1179, for voltage deviation minimization it was 0.1057 without placing any FACTS devices in the system. The best compromised solution for power loss, L-index and voltage deviation is 5.42MW, 0.1384 and 0.2698. When UPFC was placed in the system the power loss was minimized to 4.49MW, L-index was minimized to 0.1045 and the voltage deviation was minimized to 0.1034. The best compromised solution was given by power loss as 5.61MW, L-index as 0.1159 and voltage deviation as 1.0935. When the GUPFC was placed the power loss was reduced to a value of 4.53MW, L-index of about 0.0875 and voltage deviation as 0.0947. The best compromised solution by using GUPFC was obtained as power loss of 6.15MW, L-index 0.0955 and voltage deviation 1.0695.

Table.4: Optimal control variables with power loss and voltage deviation as objectives

	Without FACTS			With UPFC			With GUPFC		
Control variables	Power loss minimization	VD minimization	Compromize solution	Power loss minimization	VD minimization	Compromize solution	Power loss minimization	VD minimization	Compromize solution
VG 1 (p.u)	1.1	1.0176	1.1	1.1	1.0037	1.0946	1.1	1.0397	1.1
VG 2 (p.u)	1.0945	1.0125	1.0871	1.0952	0.9941	1.0879	1.0957	1.001	1.0902
VG 3 (p.u)	1.077	1.0019	1.064	1.0805	1.0111	1.0637	1.0742	1.002	1.0646
VG 4 (p.u)	1.0683	1.0064	1.0118	1.0834	0.9821	0.9803	1.0211	1.0509	1.0217
VG 5 (p.u)	1.0766	1.0203	1.0709	1.077	1.0181	1.0625	1.0779	1.0157	1.0699
VG 6 (p.u)	1.1	1.0036	1.0169	1.1	1.0249	1.0151	1.1	0.978	1.0187
T 1	1.054	1.0256	1.058	1.0029	0.9872	1.0414	1.0656	1.0658	1.0927
T 2	0.9481	0.9372	1.0371	1.0295	0.9857	1.0884	0.9574	1.0334	1.1
T 3	0.9751	0.9697	1.0418	0.9782	1.0244	1.0624	0.9909	0.9163	1.034
T 4	0.9702	0.9801	1.0272	0.9758	0.9745	1.0278	0.977	0.9619	1.0242
Qsh 10	0.0484	0.0169	0	0.0318	0.0241	0.0393	0.05	0.0385	0.0189
Qsh 12	0.0341	0.0374	0.0183	0.0392	0.05	0.05	0.05	0.0025	0.0012
Qsh 15	0.05	0.0482	0.0438	0.0419	0.0323	0.05	0.0023	0.0208	0
Qsh 17	0.05	0.0011	0.0326	0.0427	0.0173	0	0.0251	0.0013	0
Qsh 21	0.05	0	0.0398	0.0422	0.0433	0.0185	0.0483	0.0362	0.0422
Qsh 22	0.0333	0.0271	0.0343	0.0467	0.0053	0.05	0.0349	0.0379	0.016
Qsh 23	0.0361	0.0382	0.0124	0.011	0.0225	0.0278	0.0057	0.0348	0.022
Qsh 24	0.0267	0.05	0.0451	0.04	0.0277	0.0316	0.05	0.05	0.0142
Qsh 29	0.0228	0.0457	0.0127	0.0301	0.0326	0.0405	0.0167	0.0179	0.0126
r	-	-	-	0.0352	0.075	0.0426	0.0302	0.021	0.0388
Gama (deg)	-	-	-	91.882	91.9028	91.8769	233.3006	233.0473	233.2182
Qsh	-	-	-	-	-	-	0.0463	0.0297	0.0287
PL(MW)	**4.52**	5.63	4.76	**4.27**	6.08	4.48	**4.23**	6.15	4.46
∑VD	1.9972	**0.1054**	0.4933	2.0388	**0.0958**	0.4294	1.7511	**0.1159**	0.4587
L-index	0.1224	0.1419	0.1457	0.1184	0.1398	0.14	0.1221	0.145	0.1432

Table.5: Optimal control variables with L-index and voltage deviation as objectives

	Without FACTS			With UPFC			With GUPFC		
Control variables	L-index Minimization	VD minimization	Compromise Solution	L-index Minimization	VD minimization	Compromise Solution	L-index Minimization	VD minimization	Compromise Solution
VG 1 (p.u)	1.1	1.0109	1.0774	1.1	0.9983	1.0905	1.1	1.0321	1.0573
VG 2 (p.u)	1.096	1.0012	1.0577	1.0936	0.989	1.0611	1.1	1.0085	1.0403
VG 3 (p.u)	1.0169	1.0013	1.004	1.0082	1.0107	1.0023	1.0344	1.0094	0.9816
VG 4 (p.u)	1.0024	1.0275	0.9501	1.0201	0.9762	0.95	0.9567	0.9525	0.9524
VG 5 (p.u)	1.0449	1.0175	1.024	1.0249	1.0251	1.0212	1.1	1.0186	1.0299
VG 6 (p.u)	1.0748	1.0232	0.9508	1.0788	1.0437	0.95	1.0754	0.9888	1.0189
T 1	0.9	1.0441	0.9025	0.9	1.0131	0.9	0.9	0.9678	0.9368
T 2	0.9	0.9759	0.9669	0.9012	0.9124	0.9075	0.9	0.9727	0.9928
T 3	0.9004	0.9901	0.9008	0.9	1.0384	0.9	0.9	0.9437	0.9235
T 4	1.1	0.9748	0.9977	1.0981	0.9883	1.0142	1.1	1.0329	1.1
Qsh 10	0.05	0.0226	0.0263	0.0358	0.0035	0.012	0.05	0.0085	0.049
Qsh 12	0.0446	0.0049	0.018	0.0388	0	0.05	0.0464	0.03	0.0354
Qsh 15	0.05	0.0476	0.0176	0.0478	0.0436	0.028	0.042	0.05	0.0013
Qsh 17	0.05	0.0024	0.0077	0.05	0.0013	0.0318	0.0492	0.001	0.05
Qsh 21	0.05	0.0249	0.05	0.05	0.0169	0.0443	0.05	0.0262	0.029
Qsh 22	0.05	0.0262	0.0427	0.05	0.0118	0.0453	0.05	0.05	0.0366
Qsh 23	0.05	0.043	0.0494	0.05	0.0417	0.0278	0.049	0.0483	0.0258
Qsh 24	0.05	0.0461	0.05	0.05	0.05	0.05	0.0011	0.0474	0.0174
Qsh 29	0.05	0.0325	0.05	0.05	0.05	0.05	0.0473	0.0494	0.05
r	-	-	-	0.0405	0.0366	0.0379	0.0444	0.0243	0.0759
Gama (deg)	-	-	-	83.27	83.3284	83.2626	283.2897	169.55	283.3669
Qsh	-	-	-	-	-	-	0.05	0.05	0.0375
L-index	**0.105**	0.146	0.1304	**0.1053**	0.1431	0.1265	**0.0855**	0.1283	0.1041
∑VD	1.4586	**0.103**	0.2249	1.4381	**0.0932**	0.3375	1.6102	**0.0955**	0.2732
PL (MW)	6.89	5.81	6.31	7.25	6.59	6.81	6.8	5.86	7.03

Table.6 Optimal control variables with L-index, voltage deviation and power loss as objectives

	Without FACTS				With UPFC				With GUPFC			
Control variables	Power loss Minimization	L-index Minimization	VD minimization	Compromise Solution	Power loss Minimization	L-index Minimization	VD minimization	Compromise Solution	Power loss Minimization	L-index Minimization	VD minimization	Compromise Solution
VG 1 (p.u)	1.1	1.1	1.0093	1.0204	1.1	1.0994	1.0169	1.0772	1.1	1.0983	1.0164	1.0762
VG 2 (p.u)	1.0942	1.0979	0.9954	1.0121	1.0947	1.1	0.9886	1.0669	1.092	1.1	0.9849	1.0664
VG 3 (p.u)	1.0767	1.0717	1.0119	1.0083	1.0786	1.0257	1.0082	1.0263	1.0746	1.0598	1.0046	1.028
VG 4 (p.u)	1.0926	1.0884	0.9837	0.9957	1.0562	0.9855	1.0248	0.9556	1.0786	1.011	0.9846	1.0099
VG 5 (p.u)	1.0757	1.0805	1.0176	1.0085	1.0778	1.0732	1.0187	1.0288	1.072	1.0847	1.0193	1.0709
VG 6 (p.u)	1.1	1.1	1.0183	1.0386	1.1	1.0741	1.0029	1.0786	1.1	1.0679	1.0411	1.0956
T 1	1.0155	1.0186	0.9977	0.9768	1.0509	0.9	0.9744	0.9	0.9895	0.9571	0.9905	0.9825
T 2	0.9723	0.977	1.0088	1.0196	0.9323	0.9	1.0922	0.9149	1.0131	0.9	1.0248	0.9387
T 3	0.9657	0.9733	0.98	0.9756	0.9826	0.9008	0.9672	0.9271	0.9649	0.9	1.0246	0.928
T 4	0.9726	0.9801	0.972	0.9709	0.9754	1.1	0.9843	1.0458	0.9814	1.0988	0.9911	1.0959
Qsh 10	0.0048	0.0074	0.05	0.0375	0.0477	0.0459	0.0439	0.0475	0.0417	0.0407	0.0328	0.0497
Qsh 12	0.0022	0.0253	0.009	0.0122	0.05	0.05	0.05	0.0454	0.0182	0.0479	0.0344	0.0099
Qsh 15	0.0403	0.0497	0.0488	0.05	0.05	0.0491	0.05	0.0266	0.0405	0.0083	0.0361	0.0432
Qsh 17	0.0486	0.05	0	0.0147	0.05	0.05	0.0105	0.0419	0.05	0.0277	0.0082	0.0025
Qsh 21	0.05	0.05	0.0427	0.0473	0.05	0.0478	0.0284	0.0241	0.048	0.0487	0.0453	0.0081
Qsh 22	0.0309	0.0382	0.0353	0.0342	0.0433	0.05	0.0298	0.027	0.0484	0.0493	0.0465	0.0279
Qsh 23	0.0232	0.0275	0.0264	0.0349	0.0198	0.05	0.05	0.0231	0.0167	0.0397	0.0447	0.0123
Qsh 24	0.0352	0.05	0.05	0.0469	0.04	0.0492	0.0447	0.0472	0.0222	0.0394	0.0364	0.0025
Qsh 29	0.0335	0.05	0.0254	0.039	0.0421	0.05	0.0467	0.0464	1.1	1.0983	1.0164	1.0762
r	-	-	-	-	0.0194	0.0366	0.0225	0.0539	0.0019	0.058	0.0246	0.0677
Gama (deg)	-	-	-	-	72.915	72.9558	20.5401	72.9906	88.2917	295.6662	81.8707	295.6891
Qsh	-	-	-	-	-	-	-	-	0.0289	0.0274	0.023	0.0356
PL(MW)	**4.53**	4.57	6.13	**5.42**	**4.49**	6.78	6.46	5.61	**4.53**	5.77	6.69	6.15
L-index	0.1205	**0.1179**	0.1458	**0.1384**	0.1191	**0.1045**	0.1428	0.1159	0.1166	**0.0875**	0.1345	0.0955
∑VD	2.0611	2.0661	**0.1057**	**0.2698**	2.0567	1.5093	**0.1034**	1.0935	2.0361	1.7208	**0.0947**	1.0695

9. Conclusion.

In this article, a new artificial immune system based Clonal selection algorithm is presented to solve multi objective ORPD problem with L-index, voltage deviation and power loss as objectives. The proposed method was implemented in presence of two different types of FACTS devices such as UPFC and GUPFC. In this study only single device was placed at a fixed location. The results proved that with the FACTS devices performance is better than base case. The usage of these VSC based FACTS devices are able to reduce the power loss and improving the system security. The Pareto optimal solution obtained for two objectives and three objectives optimization shows better with GUPFC than UPFC.

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