B. Srinivasa Rao[1,*], A. Bala Naga Lingaiah[2]

J. Electrical Systems 13-1 (2017): 27-42

JES Journal of Electrical Systems

Regular paper

Solving Multi Objective ORPD Problem Using AIS Based Clonal Selection Algorithm with UPFC

In this paper, a solution for the multi objective optimal reactive power dispatch problem by using an artificial immune system (AIS) based clonal selection algorithm was presented. The proposed AIS based clonal selection algorithm uses cloning of 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 device namely the UPFC. The proposed algorithm also uses concepts of non dominated sorting and crowding distance comparison procedures to solve the multi objective optimization problem. Finally, a fuzzy decision maker strategy is applied to find the best compromise solution. The algorithm was implemented and tested on two standard IEEE 30-bus and 57-bus test systems with UPFC. The proposed results are compared with and without placing the UPFC by considering two objectives for optimization.

Keywords: Optimal Reactive Power Dispatch, Clonal selection algorithm, UPFC, Multi-objective.

Article history: Received 21 November 2015, Accepted 14 September 2016

1. INTRODUCTION:

The optimal reactive power dispatch (ORPD) problem is an significant issue in modern power system that will control tap ratios of transformers, reactive power compensation devices and generator terminal voltages to minimize specific object 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], Genetic algorithm [8] are able to overcome the difficulties which are faced by the conventional optimization techniques. In [9] optimal reactive power dispatch using dynamic VAR source was discussed. 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 playing vital role with ongoing expansion of the electric utility. The multi type FACTS devices such as UPFC [10-12] can able to improve the system loadability and the system security. These can control voltage magnitude and phase angle at desired bus and the line impedance and also the power flow

[*] Corresponding author: B. Srinivasa Rao
V. R. Siddhartha Engineering College, Vijayawada, 520007, A.P, India,
[1] Email: balususrinu@vrsiddhartha.ac.in ; [2]Email: balu0215@hotmail.com

through the lines. In recent years various optimization techniques [13-15] were proposed to solve reactive power dispatch problems, by considering various constraints, with different objectives. In [16], a new hybrid GAPSO based algorithms was presented to solve multi objective optimal reactive power dispatch problem for minimising transmission loss and voltage stability with UPFC.

This paper presents an artificial immune system based algorithm (AIS) [17, 18] which is inspired from theoretical immunology. It can able to detect the antibodies (Ab's) or foreign pathogens 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 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 optimization problem Kalyan Deb introduced a fast and elitist non dominated sorting Genetic algorithm [19]. Here the non dominated sorting technique works faster than other methods such as multi objective evolutionary algorithms. This method will give the solution in a single run. So this non dominated sorting technique has been adapted in to the artificial immune system based algorithm [17] to solve the optimal reactive power dispatch problem.

The paper was organized in to seven sections. The UPFC modeling was described in section II. In section III the proposed methodology and its algorithm was explained. Section IV deal with the multi objective optimization and procedure for finding the best compromise solution. The problem formulation for ORPD and proposed AIS based clonal selection algorithm implementation stpes to solve this problem was given in section V and VI respectively. In section VII the results and discussions are given. At the end valid conclusions are drawn.

2. UPFC MODELING:

The Unified power flow controller consists basically of a two power electronic based switching converters shown in Fig.1. These converters are operated from a common dc link consists a dc storage capacitor. The UPFC can be represented with two voltage sources which are producing 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.

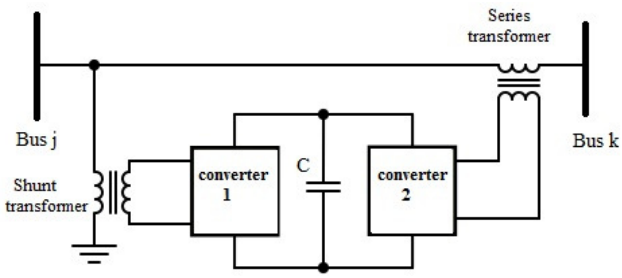

Fig.1 Basic model of UPFC

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 [10]. The Fig.2 shows the two voltage source model of the UPFC. The leakage impedance of the two transformers was modeled as reactance in series with the voltage source V_{pq}.

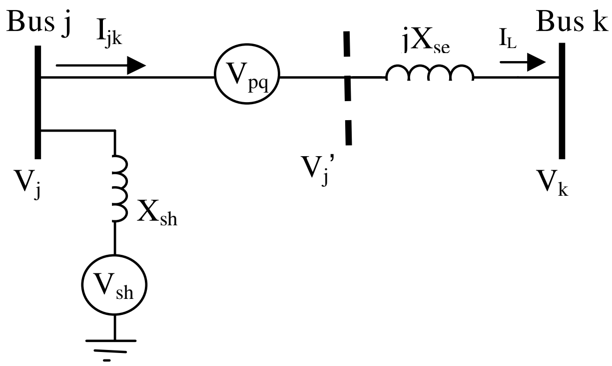

Fig.2 Two voltage source model of UPFC

At bus 'j' voltage is taken as 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 with respect to their magnitude as well as phase angle. Here 'r' is the p.u voltage in series with the line and γ is the phase angle of the series voltage source. These variables will be operated within specified operating limits as shown in Eq (1).

$$V_{pq} = rV^{i\gamma};\ 0 \leq r \leq r_{max} \text{ and } 0 \leq \gamma \leq 360^o \tag{1}$$

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 2% losses in the system which should be supplied by the shunt converter. The net effect of the UPFC [12] on the network is represented by a power injection model for load flow studies. The injected powers at bus j and bus k can be represented as shown below.

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

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

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

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

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

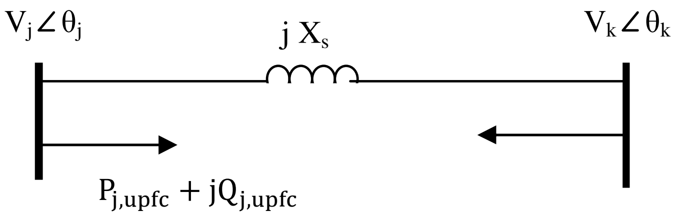

Fig.3 Power injection model of the UPFC

It is very easy to incorporate the UPFC as power injection model in the Newton raphson load flow algorithm. Since the UPFC is connected between buses 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. OVERVIEW OF THE CLONAL SELECTION ALGORITHM:

The Artificial immune system (AIS) [17] 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 or coming from outside. 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 such as a) Immune network theory, b) Negative selection mechanism and c) Clonal selection principles [18]. 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 variant of their parents. Clones with highest fitness will go maturation to a lesser extent as compared to the clones with low fitness. The size of cloning population can be estimated by using the Eq. 6.

$$\mathrm{NC} = \sum_{j=1}^{\mathrm{Nsel}} \mathrm{Nc_j} \qquad (6)$$

NC is the total number of clones and it is the sum of each individual clones of the antibody ($\mathrm{Nc_j}$). The number of clones for each antibody 'j' is selected by using the Eq.7

$$\mathrm{Nc_j} = \mathrm{round}\left(\frac{\beta \mathrm{N_{sel}}}{\mathrm{j}}\right) \qquad (7)$$

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

$$\mathrm{Nc_j} = \mathrm{Nc_j} + \alpha * \mathrm{N}(0,1) * \mathrm{Maxfit} \qquad (8)$$

where α – is the maturation rate.

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.7 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.

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

This process will repeat from Step 1-4 until the solution gets converged to an optimum value.

4. MULTI OBJECTIVE OPTIMIZATION:

Most of the 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 objectives may get affected. The control variables which satisfy one objective function are not feasible for the other objective function. In that way there are many possible solutions exist between the objective functions. In general the multi objective optimization problem can be stated as follows.

$$\text{Maximize/minimize: } f_n(X), \quad n = 1,2, \dots N \tag{9}$$

$$\text{Subjected to: } g_j(X) \geq 0 \quad j = 1,2, \dots J \tag{10}$$

$$h_i(X) = 0 \qquad i = 1,2, \dots . I \tag{11}$$

$$x_k^{min} \leq x_k \leq x_k^{max} \qquad k = 1,2, \dots .. K \tag{12}$$

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

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

In multi objective optimization instead of getting one solution there is a possibility of getting multiple solutions. These set of solutions are generally called as pareto optimal set. Conventional 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) [19] was one of the first such evolutionary algorithm (EA) 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.

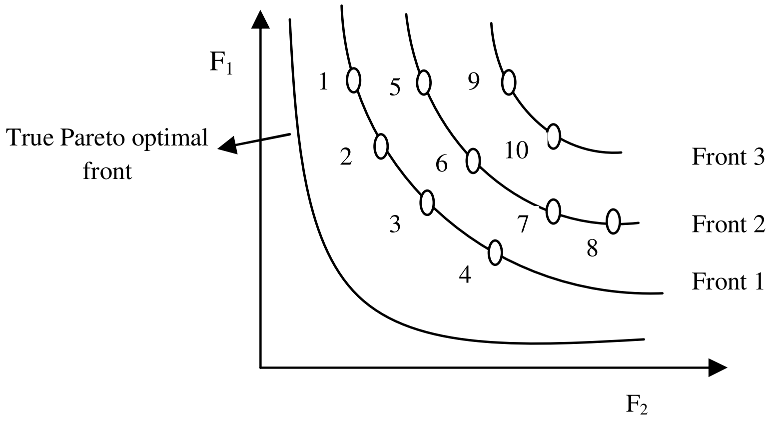

Fig. 4 Example for non dominated sorting having 10 populations in to different fronts

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.4, 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.

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 (13).

$$J(d_\ell) = J(d_\ell) + \frac{(J(\ell+1).m - J(\ell-1).m)}{f_m^{max} - f_m^{min}} \quad (13)$$

$J(\ell).m$ 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 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, the best compromise solution [12] can be obtained by using fuzzy decision maker approach. In this fuzzy decision maker each of the 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

$$\mu_i^j = \begin{cases} 1 & f_i \le f_i^{min} \\ \frac{f_i^{max} - f_i}{f_i^{max} - f_i^{min}} & f_i^{min} \le f_i \le f_i^{max} \\ 0 & f_i \ge f_i^{max} \end{cases} \quad (14)$$

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

$$\mu^j = \frac{\sum_{i=1}^{N} \mu_i^j}{\sum_{j=1}^{p} \sum_{i=1}^{N} \mu_i^j} \quad (15)$$

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.

5. OPTIMAL REACTIVE POWER DISPATCH PROBLEM:

Optimal reactive power dispatch (ORPD) is the non-linear problem which is to minimize certain objective functions by satisfying various equality and inequality constraints. The ORPD problem is generally represented as below

Min $f(x, u)$

Subjected to $g(\mathbf{x}, \mathbf{u}) = 0;\ h(\mathbf{x}, \mathbf{u}) \le 0$

where g(**x, u**) generally the load flow equation. 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 parameters.

$$\mathbf{x} = [P_{g2},\ldots P_{gn},V_{g1},\ldots V_{gn}, T_{c1},\ldots T_{cn}, Q_{sc1},\ldots Q_{scn}, U_1,\ldots U_n] \qquad (16)$$

Where **gn** is the number of generators, **cn** is number of tap changing transformers, **scn** is the number of shunt VAR compensators. $\mathbf{U_n}$ is the n^{th} FACT device.

u is the vector of state variables which consists slack bus real power, load bus voltages, generator reactive power outputs and transmission line loadings.

$$\mathbf{u}=[P_{g1}, V_{L1,\ldots}, V_{Lnp}, Q_{g1},..Q_{gn}, S_{l1},\ldots S_{lbn}] \qquad (17)$$

np is the total number of load buses and **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

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

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. By minimizing sum of all the bus voltage violations, the load bus voltages can be maintained to a rated voltage.

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

Where *np* - is the number of load buses.

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.

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

g_i is the i^{th} 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} buses, bn - is the total number of transmission lines.

Constraints:

Equality constraints:

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

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

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

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. And *bn* - is the number of transmission lines.

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

$$P_{gj}^{min} \le P_{gj} \le P_{gj}^{max}, \qquad j = 1 \ldots. ng \qquad (23)$$

$$Q_{gj}^{min} \le Q_{gj} \le Q_{gj}^{max}, \qquad j = 1 \ldots. ng \qquad (24)$$

$$V_{gj}^{min} \le V_{gj} \le V_{gj}^{max}, \qquad j = 1 \ldots. ng \qquad (25)$$

b) Tap changing transformers constraints:

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

$$Tc_j^{min} \le Tc_j \le Tc_j^{max}, \qquad j = 1 \ldots. cn \qquad (26)$$

c) Shunt VAR constraints:

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

$$Q_{scj}^{min} \le Q_{scj} \le Q_{scj}^{max}, \; j = 1 \ldots. scn \qquad (27)$$

d) Security constraints:

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

$$V_{Lj}^{min} \le V_{Lj} \le V_{Lj}^{max}, \; j = 1 \ldots. np \qquad (28)$$

$$S_{Lj} \le S_{Lj}^{max}, \quad j = 1 \ldots. bn \qquad (29)$$

e) UPFC constraints:

The control variables limits of UPFC are given below

$$V_{pq} = rV_j e^{i\gamma}, \qquad (30)$$

where $0 \le r \le r^{max}$; $0 \le \gamma \le 2\Pi$

Constraints handling technique:

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

$$J_{pen} = J_{Lf} + J_{Bv} + J_{Qg} \qquad (31)$$

Penalty function for line flow violations is

$$J_{Lf} = K_l \sum_{j=1}^{nl} (|S_{lj}| - S_{lj}^{lim})^2 \qquad (32)$$

Penalty function for bus voltage violations

$$J_{Bv} = K_v \sum_{j=1}^{Npq} \left(V_{lj} - V_{max}\right)^2 \text{ if } V_{lj} > V_{max} \text{ or} \qquad (33)$$

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

Penalty function for reactive power generation violation is

$$J_{Qg} = K_g \sum_{j=1}^{Ng} \left(Q_{gj} - Q_{max}\right)^2 \text{ if } Q_{gj} > Q_{max} \text{ or} \qquad (34)$$

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

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

6. IMPLEMENTATION OF AIS BASED CLONAL SELECTION ALGORITHM TO SOLVE MULTI-OBJECTIVE ORPD PROBLEM WITH UPFC:

This section describes application of clonal selection algorithm for solving multi-objective ORPD problem with UPFC. The UPFC incorporated as power injection model for Newton Raphson (NR) load flow solution as described in section “UPFC modelling”. The following steps will explain the implementation of proposed algorithm for multi-objective ORPD with UPFC.

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’.

$$X=[x_1\ x_2\ \ldots..x_{npop}]$$

Where $x_i=[P_{g2},\ldots P_{gn}, V_{g1},\ldots V_{gn}, T_{c1},\ldots T_{cn}, Q_{sc1},\ldots Q_{scn}, U_1,\ldots U_n]$

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

$$\sum_{i=1}^{ng} Pg_i = P_d \qquad (35)$$

Step 3: Run the NR 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 of 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 set of anti bodies.

Step 6: Set iteration count *iter=0*;

Step 7: Increment the iteration count by 1*(iter=iter+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=[Nc_1 Nc_2 ……Ncnbest]

Where Nc_i is the number of clones of the i^{th} antibody from the archive X_{best} and the number of clones will be calculated from equation (7)

b. Each clone will undergo some hyper maturation process through equation (8)

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

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

Step 11: Check for the stopping criteria i.e. if number of iterations reached to maximum then go to next 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 IV.

7. RESULTS AND DISCUSSIONS:

The proposed methodology is applied to standard IEEE 30-bus and 57-bus test systems. The IEEE 30-bus system consists of six generators, four tap changing transformers and two shunt capacitors. The total real power load demand of the systems is 283.4MW. And the IEEE 57-bus test system consists of seven generators, seventeen tap changing transformers and three shunt capacitors at buses 18, 25 and 53. The real power demand of the system is 1250.8MW. The proposed method implemented using MATLAB programming. The parameters of the clonal selection algorithm and various control variables limits are shown in Table.1 and Table.2 respectively.

Table.1 Algorithm parameters

Parameters	Value
Population Size :	40
Best population :	30
Clone size factor :	1
Maximum number of iterations :	200

Table.2 Control variables limits

Control variables	Minimum	Maximum
Vg	0.95	1.1
Tc	0.9	1.1
Qsh	0	0.05
‘r’ (%)	0	10
γ (degrees)	0	360

Here the results are presented by considering two objectives at a time. The voltage stability index (L-index), sum of the voltage deviations at load buses and real power loss are considered as objectives. These studies are categorized into the following two cases.

Case a: Power loss and voltage deviations as objectives

Case b: Voltage stability index and voltage deviation as objectives

These two case studies are carried out on two different test systems with and without FACTS device. In IEEE 30-bus test system UPFC is placed in line connected between buses 12 and 15. For an IEEE 57-bus test system the UPFC was placed between buses 23 and 24.

Case a: Power loss and voltage deviations as objectives

i) *For IEEE 30-bus test system:* In case of power loss and voltage deviation as objectives the pareto optimal set before and after placing the UPFC was shown in Fig.5. The optimal solution and corresponding control variables are also shown in Table.3. The best value of power loss was obtained as 2.88MW before placing the UPFC after the placing the device the best value of power loss reduced to 2.67MW. The best value of voltage deviation was about 0.1087 before placing the device after placing the UPFC it was obtained as 0.098. The best compromise solution is 3.33MW power loss and 0.2306 voltage deviation before placing the UPFC. After placing the UPFC the best compromise solution obtained as 3.23MW power loss and 0.1651 voltage deviation.

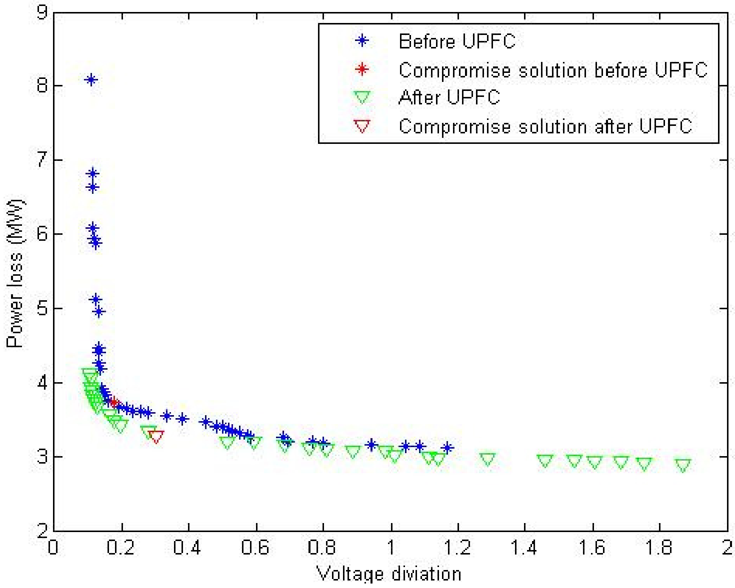

Fig.5 Pareto optimal front with Power loss and VD as objectives for IEEE 30-bus system

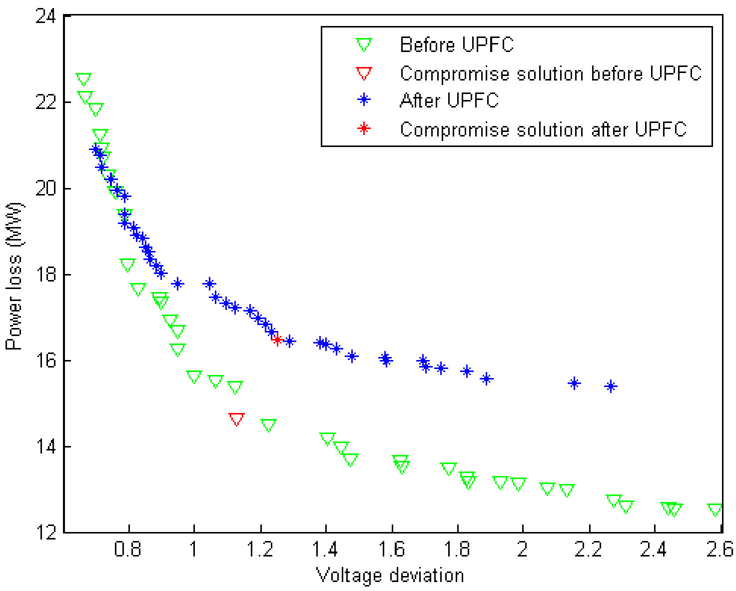

Fig.6. Pareto optimal front with Power loss and VD as objectives for IEEE 57-bus system

Table.3 Optimal solution with power loss and VD as objectives for IEEE 30-bus system

	Before UPFC			After UPFC		
Control variables	Best power loss	Best voltage deviation	Compromise solution	Best power loss	Best voltage deviation	Compromise solution
PG1 (MW)	52.88	74.45	53.67	57.91	110.77	64.07
PG2 (MW)	78.45	80	78.78	73.25	56.08	68.72
PG3 (MW)	34.99	25.16	34.69	34.93	31.05	35.
PG4 (MW)	29.99	20.09	30	29.97	18.22	28.84
PG5 (MW)	49.99	49.34	50	50	44.1	50
PG6 (MW)	39.99	38.87	39.59	40	30.16	40
Vg1 p.u	1.1	1.0182	1.0388	1.1	1.0001	1.0321
Vg2 p.u	1.0972	1.0172	1.034	1.0949	0.9759	1.025
Vg3 p.u	1.0883	1.0009	1.0144	1.0846	1.0008	1.0099
Vg4 p.u	1.0705	0.9934	0.9753	1.0796	1.0556	1.0408
Vg5 p.u	1.079	1.0178	1.011	1.0729	1.0194	1.0016
Vg6 p.u	1.0971	0.9988	1.0503	1.0771	1.0382	1.0005
Tc1	1.022	0.9994	0.9795	1.0515	1.0749	1.0141
Tc2	1.0107	1.0085	1.0353	0.9869	1.0029	1.0426
Tc3	0.9994	0.959	1.0144	0.9696	1.0475	0.9648
Tc4	0.9879	0.9686	0.9824	0.9661	0.9756	0.9525
Qsh10	0.0185	0.0475	0.0346	0.0007	0.0385	0.0014
Qsh12	0.0471	0.0252	0.0068	0	0.05	0.0456
Qsh15	0.0136	0.0419	0.0154	0.0355	0.046	0.0048
Qsh17	0.05	0.012	0.0107	0.038	0.0223	0.0462
Qsh21	0.05	0.0207	0.0435	0.038	0.044	0.0163
Qsh22	0.0004	0.0387	0.0495	0.0324	0.0366	0.0405
Qsh23	0.0227	0.0423	0.0064	0.0461	0.0049	0.0119
Qsh24	0.05	0.05	0.0413	0.0365	0.0447	0.0096
Qsh29	0.0275	0.0314	0.0219	0.0138	0.0429	0
r (%)	-	-	-	1.2	1.3	1.2
γ (degrees)	-	-	-	66.0841	66.1412	66.0075
PL (MW)	**2.88**	4.52	**3.33**	**2.67**	6.87	**3.23**
VD	1.8452	**0.1087**	**0.2306**	1.8754	**0.098**	**0.1651**

The voltage profiles of all the buses for IEEE 30-bus system with power loss and voltage deviation as objectives are shown in Fig.7 and Fig.8 before and after placing the UPFC respectively.

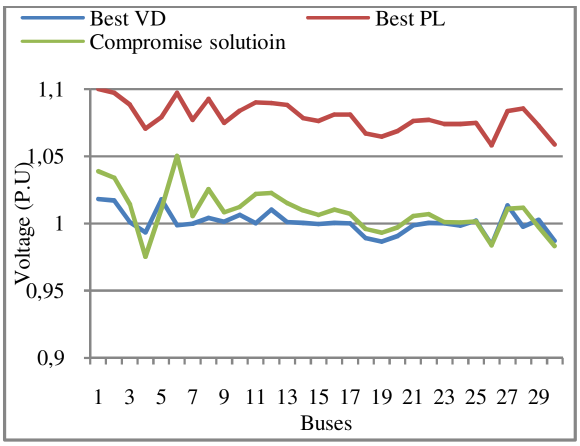

Fig.7 Voltage profiles without UPFC for Case a

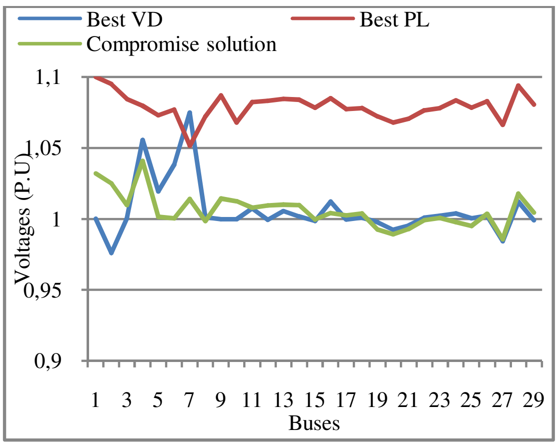

Fig.8 Voltage profiles with UPFC for Case a

ii) *For IEEE 57-bus test system:* The pareto optimal front for the 57-bus test system is shown in Fig. 6 and the corresponding optimal solution given in Table 4. For this test system the best compromise solution of the power loss was 16.4679MW and VD is about 1.2522 without UPFC. After placing the device the compromise solution was obtained as power loss 14.6613MW and VD was about 1.1263.

Table.4 Optimal solution with power loss and VD as objectives for IEEE 57-bus system

	Before UPFC			After UPFC		
Objective functions	Best power loss	Best VD	Compromise solution	Best power loss	Best VD	Compromise solution
PL (MW)	**15.3771**	20.9098	**16.4679**	**12.5281**	22.5466	**14.6613**
VD	2.2637	**0.7006**	**1.2522**	2.5831	**0.6624**	**1.1263**

Case b: Voltage stability index and voltage deviation as objectives

i) For IEEE 30-bus test system: In case of voltage stability index and voltage deviation as objectives the pareto optimal set before and after placing the UPFC is shown in Fig.9. The optimal solution and corresponding control variables are given in Table.5. The best value of L-index was obtained as 0.1053 before placing the UPFC after the placing the device the best value of L-index obtained as 0.0985. The best voltage deviation was about 0.1112 before placing the device after placing it was much reduced to 0.1013. The best compromise solution which satisfies both objectives was obtained as 0.125 L-index and 0.3732 voltage deviation before placing the UPFC. After placing the UPFC the best compromise solution obtained as 0.1151 L-index and 0.3022 voltage deviation.

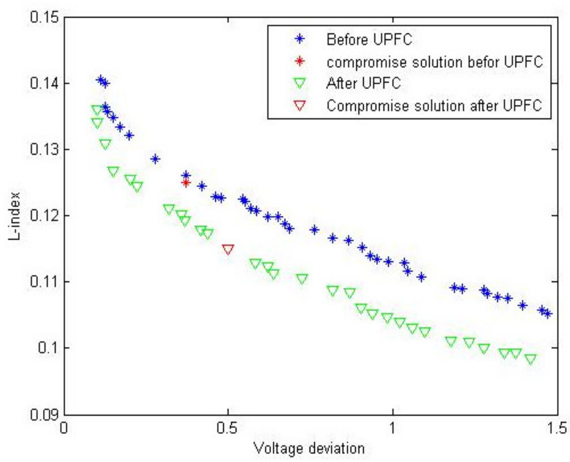

Fig.9 Pareto optimal front with L- index and VD as objectives for IEEE 30-bus system

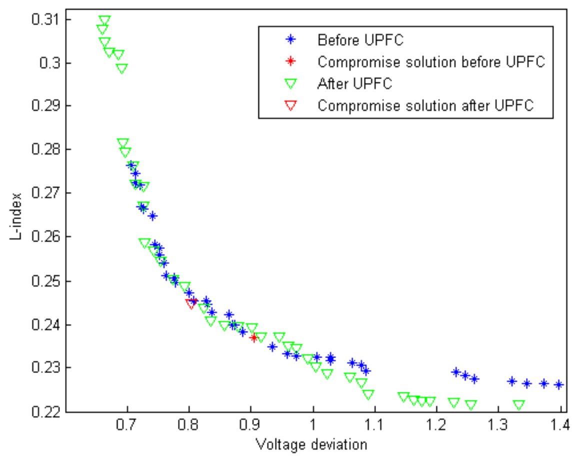

Fig.10 Pareto optimal front with L-index and VD as objectives for IEEE 57-bus system

Table.5 Optimal solution with L-index and VD as objectives IEEE 30-bus system

	Before UPFC			After UPFC		
Control variables	Best L-index	Best voltage deviation	Compromise solution	Best L-index	Best voltage deviation	Compromise solution
PG1 (MW)	127.92	151.06	138.27	133.97	133.08	144.23
PG2 (MW)	59.5	44.28	57.26	63.07	59.64	67.51
PG3 (MW)	34.52	30.76	34.6	15.75	10.38	10.12
PG4 (MW)	18.06	18.99	10	12.61	12.34	12.58
PG5 (MW)	33.96	16.28	38.4	48.46	45.32	43.46
PG6 (MW)	17.21	30.56	13.5	18.67	29.57	15.32
Vg1 p.u	1.0998	1.0358	1.0789	1.0993	1.0392	1.0959
Vg2 p.u	1.0982	1.024	1.0714	1.0971	1.0314	1.0787
Vg3 p.u	1.0253	1.0066	0.9889	1.0264	1.0093	0.9902
Vg4 p.u	0.9912	0.9591	0.9623	0.9771	0.9647	0.951
Vg5 p.u	1.0651	1.0184	1.0292	1.1	1.0187	1.0281
Vg6 p.u	1.0755	0.9698	0.95	1.0315	0.9646	0.9539
Tc1	0.9012	0.9701	0.9089	0.9	0.9877	0.9052
Tc2	0.9	1.0336	0.9101	0.9	0.9228	0.9062
Tc3	0.9	0.9	0.9014	0.9	0.9048	0.9046
Tc4	1.098	0.9769	1.0066	1.098	0.9792	1.0148
Qsh10	0.0276	0.029	0.0358	0.05	0.0011	0.05
Qsh12	0.05	0.0038	0.0161	0.0439	0.0251	0.0326
Qsh15	0.0462	0.0427	0.0491	0.0124	0.0244	0.0125
Qsh17	0.05	0.0427	0.05	0.05	0.0019	0.0187
Qsh21	0.05	0.0474	0.0443	0.05	0.0309	0.05
Qsh22	0.05	0.05	0.0488	0.05	0.009	0.0488
Qsh23	0.05	0.046	0.05	0.0427	0.0034	0.0211
Qsh24	0.05	0.05	0.05	0.05	0.0362	0.0471
Qsh29	0.05	0.0356	0.05	0.05	0.048	0.05
r (%)	-	-	-	10	4.83	10
γ (degrees)	-	-	-	26.4453	26.4976	26.4884
L-index	**0.1053**	0.1405	**0.125**	**0.0985**	0.1361	**0.1151**
VD	1.4691	**0.1112**	**0.3732**	1.4201	**0.1013**	**0.3022**

The voltage profiles of all the buses for IEEE 30-bus system with L-index and voltage deviation as objectives are shown in Fig.11 and Fig.12 before and after placing the UPFC respectively.

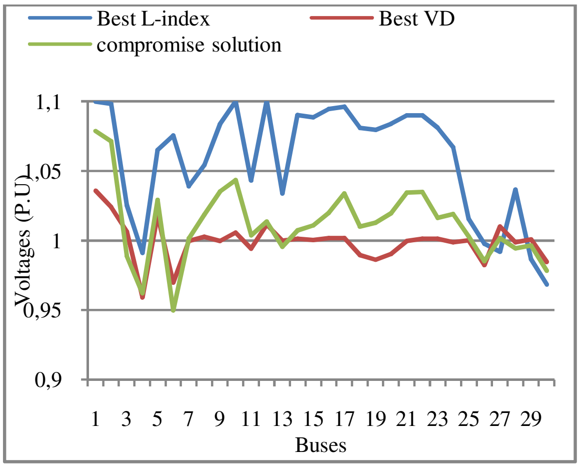

Fig.11 Voltage profiles without UPFC for Case b

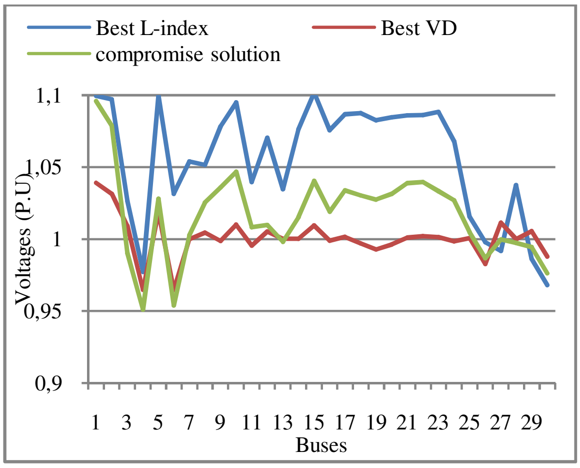

Fig 12 Voltage profiles with UPFC for Case b

ii) For IEEE 57-bus test system: The pareto optimal front of 57-bus system for case-b is shown in Fig. 10 and the corresponding optimal solution given in Table 6. For this system the best compromise solution of the L-index was 0.2360 and VD is about 0.9049 without UPFC. After placing the device the best compromise solution is further improved.

Table.6 Optimal solution with L-index and VD as objectives for IEEE 57-bus system

	Before UPFC			After UPFC		
Objective functions	Best L-index	Best voltage deviation	Compromise solution	Best L-index	Best voltage deviation	Compromise solution
L-index	**0.2261**	0.2764	**0.2369**	**0.2216**	0.3077	**0.2450**
VD	1.3976	**0.7052**	**0.9049**	1.3330	**0.6591**	**0.8039**

8. CONCLUSION:

In this paper, a new artificial immune system based Clonal selection algorithm is presented to solve multi objective optimal reactive power dispatch problem with two objectives. The proposed methodology is tested in presence of UPFC also. In this study only single device was placed at a fixed location. The proposed algorithm provides a good performance in terms of solution with two objectives optimization even in the presence of UPFC in the system. The presented results analysis for both the test systems shows that the proposed algorithm is well suited for solving multi objective optimal reactive power dispatch problem with and without FACTS device. The recent trend in power system is application of voltage source converter (VSC) based FACTs device will improve the system security by minimizing power loss.

Acknowledgments
This work was supported by UGC minor research project: MRP-6115/15(SERO/UGC)

References

[1] Kirschen, Daniel S., and Hans P. Van Meeteren. "MW/voltage control in a linear programming based optimal power flow." IEEE Transactions on Power Systems 3.2 (1988): 481-489.

[2] Lee, K. Y., Y. M. Park, and J. L. Ortiz. "A united approach to optimal real and reactive power dispatch." IEEE Transactions on power Apparatus and systems 5 (1985): 1147-1153.

[3] Quintana, V. H., and M. Santos-Nieto. "Reactive-power dispatch by successive quadratic programming." *IEEE Transactions on Energy Conversion* 4.3 (1989): 425-435.

[4] Granville, Sergio. "Optimal reactive dispatch through interior point methods." IEEE Transactions on Power Systems 9.1 (1994): 136-146.

[5] Del Valle, Y., Venayagamoorthy, G. K., Mohagheghi, S., Hernandez, J. C., & Harley, R. G. (2008). Particle swarm optimization: basic concepts, variants and applications in power systems. IEEE Transactions on evolutionary computation, 12(2), 171-195.

[6] Ali Ghasemi, Khalil Valipour, Akbar Tohidi, "Multi objective optimal reactive power dispatch using a new multi objective strategy", Electrical Power and Energy Systems 57 (2014) 318–334 .

[7] Arup Ratan Bhowmik, Ajoy Kumar Chakraborty, "Solution of optimal power flow using non dominated sorting multi objective opposition based gravitational search algorithm", Electrical Power and Energy Systems 64 (2015) 1237–1250

[8] W. Yan, S. Lu, D.C. Yu, A hybrid genetic algorithm-interior point method for optimal reactive power flow, IEEE Trans. Power Syst. 21 (2006) 1163–1209.

[9] Rabiee, Abbas, and Mostafa Parniani. "Optimal reactive power dispatch using the concept of dynamic VAR source value." 2009 IEEE Power & Energy Society General Meeting. IEEE, 2009.

[10] Vural, A. Mete, and Mehmet Tümay. "Mathematical modeling and analysis of a unified power flow controller: A comparison of two approaches in power flow studies and effects of UPFC location." International Journal of Electrical Power & Energy Systems 29.8 (2007): 617-629.

[11] Sharma, N. K., and P. P. Jagtap. "Modelling and application of unified power flow controller (UPFC)." Emerging Trends in Engineering and Technology (ICETET), 2010 3rd International Conference on. IEEE, 2010.

[12] Rao, B. Srinivasa, and K. Vaisakh. "Multi-objective adaptive clonal selection algorithm for solving optimal power flow considering multi-type FACTS devices and load uncertainty." *Applied Soft Computing* 23 (2014): 286-297.

[13] Zechun Hu, Xifan Wang , Gareth Taylor, "Stochastic optimal reactive power dispatch: Formulation and solution method", Electrical Power and Energy Systems 32 (2010) 615–621.

[14] Rajan, Abhishek, and T. Malakar. "Optimal reactive power dispatch using hybrid Nelder–Mead simplex based firefly algorithm." International Journal of Electrical Power & Energy Systems 66 (2015): 9-24.

[15] Ghasemi, M., Ghavidel, S., Ghanbarian, M. M., & Habibi, A. (2014). A new hybrid algorithm for optimal reactive power dispatch problem with discrete and continuous control variables. Applied soft computing, 22, 126-140.

[16] Shrawane, Shilpa S., Manoj Diagavane, and Narendra Bawane. "Optimal reactive power dispatch by furnishing UPFC using multi-objective hybrid GAPSO approach for transmission loss minimisation and voltage stability." Nascent Technologies in the Engineering Field (ICNTE), 2015 International Conference on. IEEE, 2015.

[17] Chun-Hua, L., Xin-Jan, Z., Wan-Qi, H., & Guang-Yi, C. (2009, August). A novel multi-objective optimization algorithm based on artificial immune system. In 2009 Fifth International Conference on Natural Computation (Vol. 4, pp. 569-574). IEEE.

[18] Wang, X. L., & Mahfouf, M. (2006, November). "ACSAMO: an adaptive multiobjective optimization algorithm using the clonal selection principle", In Proc. 2nd European Symposium on Nature-inspired Smart Information Systems, Puerto de la Cruz, Tenerife, Spain (pp. 959-971).

[19] Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. A. M. T. (2002). "A fast and elitist multiobjective genetic algorithm: NSGA-II" IEEE transactions on evolutionary computation, 6(2), 182-197.