



FORAGING ALGORITHM FOR OPTIMAL REACTIVE POWER DISPATCH WITH VOLTAGE STABILITY AND RELIABILITY ANALYSIS

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ABSTRACT

A novel bio-heuristic algorithm called Refined Bacterial Foraging Algorithm (RBFA) is proposed in the paper to solve the optimal power dispatch of deregulated electric power systems. The Optimal reactive power dispatch (OPD) problem has growing effect in modern electric power systems and the problem in need of to address the secure operation and optimal operation, with optimal location of FACTS devices, control of power flow based on stability indices and reliability analysis. So, this problem is well known as a multi-disciplinary and multi objective problem where in need of exact formulation and solution of the problem. The basic BFA is based on a metaphor of social interaction of E-coli bacteria the self adaptability of individuals in the group searching activities has attracted a great deal of interests in real word problems but it gives poor performance in global points when its applied to high dimensional and multi objective problems. To avoid the local optima and in order to track the good tracking ability of global solutions, the improved version of BFA algorithm is proposed and the proposed algorithm is called Refined Bacterial Foraging Algorithm (RBFA).The RBFA is improved version of the basic BFA with search direction phenomenon, variation of step sizes in chemotaxis behavior and variation of position updating process. The optimal dispatch problem consist of reactive power dispatch, optimal location of FACTS devices with transformer taps, real power loss and voltage stability margin are simultaneously optimized with effective controls and limits. The evaluation analysis of proposed work carried out with Standard IEEE systems. The simulation result shows the performance of RBFA is superior or comparable to that of the other algorithms and is greatly in terms of speed of convergence, optimization quality, robustness and fast convergence ability.

Keywords: *Bacterial Foraging Algorithm, Refined Bacterial Foraging Algorithm, Multi-Objective Optimization, FACTS Devices, Reactive Power Dispatch, Q-V Analysis, Stability Indices.*

1. INTRODUCTION

The optimal dispatch of a power system is required to proceed the optimal planning of devices or facilities for the power system. The important roles of optimal power system operation are real and reactive power dispatch and maintain the voltage stability limit, but it's directly connected with service quality and reliability of power system. However, the modern power system requires not only quality of supply and it's strongly connected with needs of economy and security of the system. In order to address these requirements the optimal reactive power dispatch problem (OPD) proposed here and its improved version of optimal power flow (OPF) problem.

The main objective of OPD is to consider and address the all the objectives of modern power systems. The main first objective of OPD is economy of the system, the economy of the system related to real power loss as a second objective and reactive power dispatch is third objective. The fourth objective is voltage stability enhancement and is related with voltage profile optimization, reliability analysis and control of voltage deviation level when before, during and post contingency condition. The final objective is optimal location of FACTS devices and its important objective in modern power systems when dynamic loading condition. The Main aim of OPD problem is to optimize the all the objectives in simultaneously. So, the Multi objective optimization technique



introduced is to address the OPD problem and single objective solution is not at all possible to solve the these type of issues, especially in multi-disciplinary problems [5] [6].

The simultaneously optimization not only consist of optimization and also satisfy the controls and limits related to optimization problem. The control strategies aim is to avoid some of the symptoms, voltage instability which lead to voltage collapse like heavy loading, transmission outages, or shortage of reactive power and the limits or constraints of OPD problem are real power generation, reactive power generation, bus voltages and settings of transformer taps with FACTS devices.

The increases of active power loss is affects the economy of the power systems and systems need to rescheduling for proper operation. The connection of above the reactive power loss leads to deviates the system voltage profile; finally it diminishes the reliability and stability of the system. So, the OPD problem is one of the most important and challenging problems in de-regulated environment and because, It is address to the optimal points of multi-objective functions of OPD problem as to determine the cost of operating, minimize the real power loss by Reactive power dispatch and it's by optimal location of the Flexible AC Transmission Systems (FACTS) with minimum cost while keeping an adequate voltage profile. Hence, the system in need of proper co-ordination between FACTS devices and transformer taps and stability indices will leads the compensation requirements, voltage stability and co-ordination controls [10][15].

The OPF has long history, initially the Carpentier introduced a generalized optimization model of power system for solving OPF problem and this model comprises only an economic dispatch solution with nonlinear programming application. After the year, the Dommel and Tinney was introduced methodology to solve the optimal power flow method but this method spokes only fuel cost minimization as a single objective problem. The later the optimal operation of power system problem mainly focused on two major areas real power dispatch and other is reactive power dispatch problem. The literature clearly states all the solution techniques based on single objective problems [7] [21].

Initially, the conventional technique are usually used for solve the optimal problems but these techniques produce local optimum when the search space is irregular and overcome these demerits, many techniques are introduced such as, such as

gradient based search technique[21], the Newton's method[21], interior point method[15] [18].But, the above mentioned techniques are failed, when finding the global solutions because solutions of these techniques are struck in local optima level and are needed well defined objective functions and constraints with derivative level. The development of evolutionary and other social intelligence techniques are plays major role in optimization problems, such as the computational intelligent techniques are Genetic Algorithm (GA) and Evolutionary Algorithm (EA) but GA has two major drawback's one is ability to track the local optima and second one is premature convergence and the EA is not only premature convergence but also languish. The Social intelligence techniques also Ant Colony Optimization (ACO), Particle Swarm Optimization and Foraging Algorithm (BFA) are well suitable for multi-objective and complex problems [5] [6] [15] [16].

In the past decades, the real power dispatch and reactive power dispatch or OPF problems has a single objective function such as either fuel cost optimization or reactive power compensation. But, the optimal power flow problem or OPD problem was modified and satisfy constraints of modern power systems in de-regulated environment and also consists of multi-objective optimization. The simultaneous optimization is needed here for get exact solution of this problem comprise of above mentioned modules. Therefore, the new algorithm is developed and presented to solve OPD problem in multi-objective perspective and this problem consists of non linear objective functions and set of nonlinear functional equality constraints and inequality constraints. The main purpose of an OPD problem is mainly for voltage profile optimization via reactive power dispatch with effective control of FACTS devices and reliability analysis. The problem is formulated as a nonlinear constrained MOB problem where the real power loss and voltage stability objectives are optimized simultaneously [9]-[16].

The control of reactive power flow, the maintaining the voltage stability and identification of weak buses and critical lines are the important problem in deregulated power system environment. So, in this paper introduced various stability indices to address all the issues. This paper presents a new method RBFA is proposed for solving multi-objective OPD problem with FACTS devices for economic operation of a power system. The FACTS technology is most interesting for transmission planners because it opens up new opportunities for controlling power and enhancing

the usable capacity of present, as well as new and upgraded of complex power system network. The proposed method can provide a good solution even the problem has many local optimum solutions at the beginning and computational implementation results involving IEEE standard test systems are given to demonstrate the validity of this method, and results are comparable with other technique. The proposed algorithm also identifies weak buses and selects those buses as candidate buses for installing new reactive power sources to enhance system security via stability indices and Q-V reliability analysis.

2. PROBLEM FORMULATION

In this work, the consideration FACTS device along with OPD problem is treated as optimization problem and it is formulated as a multi-objective optimization problem and this problem mainly focused on voltage profile optimization, weak bus identification by proposed model, voltage stability and reliability analysis via stability indices and Q-V reliability analysis. The most of the researchers are not considering real power dispatch and total fuel cost while operating the reactive power dispatch optimization, but here the proposed approach is considering all the sub problems of OPD problem. Because the modern power system in need of optimize without omitting any parameters which is related to optimal operation of power system.

2.1 Objective Functions

Real Power Loss (PL):

This objective is to minimize the real power loss in transmission lines that can be expressed as e :

$$P_L = \sum_{k=1}^{N_l} G_k [V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)] \tag{1}$$

Where N_l Is the number of transmission lines; G_k is the conductance of the k^{th} line; $V_i < \delta_i$ and $V_j < \delta_j$ are the voltages at the end buses i and j of the k^{th} line respectively. Here, the cost optimization also consider, while solving real power loss solution.

Active Power Losses:

$$P = P_g - P_l \geq 0 \tag{2}$$

Where P is the total transmission active losses of the power system in MW; P_g is the total active power generated in MW and P_l is the total load of the system in MW.

Average Voltage Deviation:

$$V_d = \sum_{i=1}^N [V_{act} - V_{des}] / N \tag{3}$$

Where V_d is the per unit(pu) average voltage difference; V_{act} is the actual voltage at bus bar i (pu) and V_{des} is the desired voltage at bus bar i (pu).

Maximum Voltage Deviation:

$$V_m = \text{Max } |V_{act} - V_{des}| \geq 0 \tag{4}$$

In summary, the optimization problem to be solved is the following

$$\text{Minimize } F = [P_L \ P \ V_d \ V_m] \tag{5}$$

Subject to **equality and in-equality constraints** are given below.

2.2 Problem Constraints:

Equality Constraints:

These constraints represent typical load flow equation as follows.

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] = 0 \tag{6}$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \sin(\delta_i - \delta_j) + B_{ij} \cos(\delta_i - \delta_j)] = 0 \tag{7}$$

Where $i=1 \dots NB$, NB is the number of buses; P_{Gi} and Q_{Gi} are the generator real and reactive power respectively. P_{Di} and Q_{Di} are the load real and reactive power respectively G_{ij} and B_{ij} are the transfer conductance and susceptance between bus i and bus j respectively.

Inequality Constraints:

These constraints represent the system operating constraints as follows.

Generation Constraints:

Generator power P_{Gi} , voltages V_G and reactive power output Q_G are restricted by their lower and upper limits as follows:

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max}, i=1, \dots, NG \tag{8}$$

$$V_{Gi}^{\min} \leq V_{Gi} \leq V_{Gi}^{\max}, i=1, \dots, NG \tag{9}$$

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max}, i=1, \dots, NG \tag{10}$$

Where NG is number of generators.

Transformer Constraints:

Transformer tap T settings are bounded as follows:

$$T_i^{\min} \leq T_i \leq T_i^{\max}, i=1, \dots, NT \tag{11}$$

Where NT is number of Transformers.

Switchable VAR sources Constraints:

Switchable VAR compensation Q_C is restricted by their limits as follows:

$$Q_{Ci}^{\min} \leq Q_{Ci} \leq Q_{Ci}^{\max}, i=1 \dots NC \tag{12}$$

Where NC is number of Switchable VAR sources.



Load Bus Voltages:

These include the constraints of voltages at load buses V_L as follows:

$$V_{Li}^{\min} \leq V_{Li} \leq V_{Li}^{\max}, i=1, \dots, NL \quad (13)$$

3. RELIABILITY ANALYSIS FOR OF CRITICAL LINES AND BUSES

3.1 Voltage Stability Analysis and Fast Line Flow Index

To show the effectiveness of proposed approach formulated and it's used to solve the voltage profile optimization and check the load ability of system subjected to power flow equations under various operating conditions. The proposed method gives better Voltage profile when installing the FACTS devices [15] under various operating conditions and the quality of solution based on better Voltage magnitude irrespective of operating conditions. So the proposed method enhances better voltage profile optimization via reliability analysis.

The Fast Line Flow Index (FLFI) method is to ensure the power flow control and stability index between the receiving and sending end power in the intercommoned power system network. In this method the set of power flow equations is to co-ordinate the real and reactive power flow control over a transmission line in both the directions of flow. The set of equations were used to analysis and identification of critical lines and weak buses.

The maximum voltage deviations are pointed out in the particular systems in the view of voltage stability analysis [10].the analysis of line flow approach is given for two bus system

$$L_{ji} = 4XQ_j / [(V_i \sin(\theta - \delta))^2] \quad (14)$$

L_{ji} - Fast Line Flow Index

θ - Angle in the impedance angle from impedance triangle

δ - Influence of the vector diagram, angle between sending end and receiving end voltage.

X-line reactance

Q_j - reactive power flow at the receiving end

V_i - sending end voltage

3.2 Voltage Stability Approach (VSA)

The Voltage Stability Approach (VSA) is comprises a Voltage Stability Index (VSI) against voltage collapse and line stability based on concept of maximum power transferred through a transmission line flow. The optimal location and control variables of FACTS devices are based on

voltage stability index of each transmission line. The loading of real or reactive powers are leads to identify the critical transmission paths and via weak buses.

A voltage stability index is deals the maximum voltage deviation via power flow in transmission, which is leads to maintain the voltage profile against loading condition. Therefore Voltage Stability Approach is gives the corrected voltage drop of a line segment is defined as the projection of the receiving end bus voltage of that segment on the voltage phasor of the generator which is the starting point of that transmission path. This index is given by

$$VSA = hV_{act} - \Delta V \quad (15)$$

Where V_{act} is actual generator voltage, h is parameter for correct the desired constant value and ΔV is sum of corrected voltage drops by the side of a transmission path. The real Power and Reactive Power flow in Transmission line is defined as a sequence of connected buses with declining voltage magnitudes again starting from a generator bus.

The FLFI and VSA are analysis to carry out the real and reactive power loading and with address of critical lines and weak buses. The voltage deviation and voltage stability enhancement is happen for placing of FACTS devices. The optimal location FACTS devices, Voltage control via reactive power support, the reliability analysis is carried out via Stability indices. Further Q-V analysis is deals of Voltage stability analysis and Reactive power compensation design in FACTS devices.

3.3 Q-V Analysis: Reactive Power Control and Voltage Stability Index

Q-V analysis encompass of voltage stability analysis, reactive power control variables and VAR compensation design is given below the matrix

$$\begin{bmatrix} J_{P\delta} & J_{PV} \\ J_{Q\delta} & J_{QV} \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta v \end{bmatrix} = \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix}$$

Where

ΔP and ΔQ are incremental real, reactive power.

$\Delta\delta$ and Δv are incremental bus voltages and bus angles

$J_{P\delta}$ J_{PV} J_{QV} and $J_{Q\delta}$ are sub matrixes of jacobian in power flow equation.

The Q-V analysis is method to identify FACTS devices for compensation in particular point after identification of weak buses and critical lines, by the way to improve the voltage stability and finally provides information to enhance voltage stability



by taking necessity actions. This analysis gives a detail view of stability enhancement by modifications and rescheduling of control variables like real and reactive power controls.

Power flow equations after the increments in bus voltage magnitude and angle, real and reactive power are can be written as follows.

$$\begin{bmatrix} J1 & J2 \\ J3 & J4 \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta v \end{bmatrix} = \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \quad (16)$$

OR

$$\begin{bmatrix} J_{P\delta} & J_{PV} \\ J_{Q\delta} & J_{QV} \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta v \end{bmatrix} = \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix}$$

The stability point of view, according to point of operation keeping real power constant is. The incremental relationship of Q-V analysis is given below.

$$[\Delta V] = [J_R]^{-1} [\Delta Q] \quad (17)$$

where J_R is known as reduced Jacobian and is given as follows.

$$J_R = J_{QV} - J_{Q\delta} J_{PV}^{-1} J_{P\delta} \quad (18)$$

The voltage stability analysis is further with help of sub matrix jacobian is given in the following equation

$$L_k = \frac{\partial Q_k}{\partial V_k} = -\frac{q_{dk}}{V_k} - B_{kk} \cdot V_k \quad (19)$$

Where,

q_{dk} Reactive power demand at nth bus

L_k Voltage stability index at nth bus

B_{kk} Imaginary part of Admittance matrix

Using the reduced Jacobian matrix, the sensitivity of Voltage stability index with respect to VAR injection at kth bus can be written as

$$VSI = \frac{\partial Q_k}{\partial V_k} \Delta V \quad (20)$$

Where

$$\Delta V = [J_R]^{-1} [\Delta Q_{inj}] \quad (21)$$

Voltage stability index depends upon the following parameters voltage profile improvement, reactive power demand, voltage at Kth bus and connectivity of the bus, i.e. B_{kk} . Generally the product $B_{kk} V_k$ is important and dominant. If B_{kk} is large then relatively lesser voltage magnitude may be sufficient to give required voltage stability margin.

$$L_k \approx L_k^f + \sum_{k=1}^{NC} A_{kj} \Delta C_k \quad (22)$$

Where ΔC_k is kth bus change in reactive power control variables.

NC is total number of reactive power control variables which includes PV buses, Tap changers and switchable shunt reactors.

A_{kj} is the sensitivity coefficient of VSI with respect to the change in reactive power control variables. In order to improve the Voltage stability and maintain the voltage profile end results of Q-V analysis; it is required to inject reactive power at the critical and weak buses

3.4 Proposed Strategy for Placement of Facts Devices

The result stability indices are to address to the optimal location of FACTS devices in addition to this the RBFA algorithm requires particle representation. Thus because of any optimization problem is need of parameters optimization of the optimization problem and the OPD problem also consists of many parameters. Since the goal of optimization was to allocate the FACTS devices, with optimal value of all the parameters and effective controls. A particle is represented with the following strings of variables control.

$$Z = [P_{g1} \dots P_{gN} \quad Q_{g1} \dots Q_{gN} \quad V_{g1} \dots V_{gN}, V_{L1} \dots V_{LN} \quad Q_{c1} \dots Q_{cN}]$$

Where

V_{gi}, V_{Li} = the voltage magnitude of generator bus.

P_{gi} = the active power generations at bus i .

Q_{gi}, Q_{ci} = the reactive powers and reactive power compensation devices.

FACTS devices = Weak bus identification and status of installing FACTS devices

$$X_{ij} = X_{T, \text{line}} + X_{TCSC} \quad (23)$$

$$Q_i = Q_{SVC} \quad (24)$$

$X_{T, \text{line}}$ = reactance of transmission line

4. BACTERIAL FORAGING ALGORITHMS

The optimization in BFA comprises the following process: Chemotaxis, swarming, reproduction, elimination and dispersal. Chemotaxis is the activity that bacteria gathering to nutrient-rich areas spontaneously [1] [7]. A Cell-to-cell communication mechanism is established to simulate the biological behavior of bacteria



swarming. Reproduction comes from the concept of natural selection and only the bacteria best adapted to their environment tend to survive and transmit their genetic characters to succeeding generations while those less adapted tend to be eliminated. Elimination – dispersal event selects parts of the bacteria to diminish and disperse into random position in the environment, which ensure the diversity of the species. [1] [7]

4.1 Chemotaxis

This is process achieved through swimming and tumbling by flagella. Depending upon the rotation of flagella in each bacterium decides it's pattern, whether it should move in a predefined direction as swimming or altogether in different directions as tumbling in the entire lifetime. The entire lifetime bacteria are set to two mode operation; these modes enable the bacteria to move in the random directions. An E-coli bacterium can move in two different ways alternatively: tumble and run. A tumble is represented by a unit walk with random direction, a unit walk with the same direction as the previous step indicates a run. A chemotactic process is started by one step of tumble and followed by uncertain steps of run, depending on the variation of the environment.

In a tumble, the position of the i_{th} bacterium is updated as:

$$\theta^i(j+1, k, l) = \theta^i(j, k, l) + C(i) \cdot \Phi(j) \quad (25)$$

Where $\theta^i(j, k, l)$ is the position of the i_{th} bacterium at the j_{th} chemotactic step of the k_{th} reproduction loop in the l_{th} elimination-dispersal event, $C(i)$ is the size of the step taken in the random direction specified by the tumble, $\Phi(j)$ is the angle of the direction which is randomly generated in the range of $(0, 2\pi)$. The fitness value of the i_{th} bacterium at $\theta^i(j, k, l)$ is represented by $J^i(j, k, l)$. If $\theta^i(j+1, k, l)$ the cost is better it means lower than at $\theta^i(j, k, l)$. Now the next step of step size of $C(i)$ in this same direction will be taken and once again, if the step resulted in a position with the better cost the previous step means another step taken. This swim is continued as long as it continuous to reduce the cost and its depending upon maximum number of steps, N_s . The N_c is number of chemotaxis steps.

4.2 Swarming

During the process, the E-coli bacterium produces attraction convergence characteristics and has to desire when anyone bacteria reaches the best position or location, it should attract other bacteria. So, that they converge in that location and this will happen by generation of attraction signal and also

in the meantime, each bacterium releases repellent to warn other bacteria to keep a safe distance from. The E-coli bacterium has own in is, a specific sensing, cell to cell signalling, actuation and decision-making mechanism and because of these properties is lead to provide global search . BFA simulates this social behavior by representing the cell to cell signaling

$$J_{cc}(\theta^i(j, k, l), \theta(j, k, l)) = \sum_{i=1}^S J_{cc}^i(\theta, \theta^i(j, k, l))$$

$$= \sum_{i=1}^S \left[-d_{attract} \exp \left(-w_{attract} \sum_{m=1}^P (\theta_m - \theta_m^i)^2 \right) \right]$$

$$+ \sum_{i=1}^S \left[h_{repellant} \exp \left(-w_{repellant} \sum_{m=1}^P (\theta_m - \theta_m^i)^2 \right) \right] \quad (26)$$

Where

- $d_{attract}$ - depth of the attractant effect
- $\omega_{attract}$ - measure of the width of the attractant
- $h_{repellant} = d_{attract}$ - height of the repellent effect
- $\omega_{repellant}$ - measure of the width of the repellent
- P-number of parameters to be optimized
- S-number of bacteria

Where $\theta^i = [\theta_1, \theta_2, \dots, \theta_p]T$ is a point optimization domain and it's the location of the i_{th} bacterium on the P-dimensional optimization domain, θ_m^i is the m_{th} component of i_{th} bacterium position, $\theta = \{\theta^i | i=1, 2, \dots, S\}$ represents the position of each member in the population of the S bacteria, θ_m^i is the m_{th} component of θ^i , θ_m^i is the m_{th} component of position θ^i for the t_{th} bacterium, $d_{attract}$ is a quantification of how much attractant is released, $\omega_{attract}$ is a measure of the diffusion rate of the chemical signal, $h_{repellant}$ and $\omega_{repellant}$ are the magnitude and width of the repelling effect respectively, $J_{cc}^i(\theta, \theta^i(j, k, l))$ indicates the signals released by the i_{th} bacterium and $J_{cc}(\theta^i, \theta)$ is time-varying function. $J_{cc}(\theta^i, \theta)$ represents the combined attraction and repelling effects received by the i_{th} bacterium.

4.3 Reproduction

After N_c chemotactic steps, a reproduction step is taken. Assume that, N_{re} is the number of reproduction steps is taken. The final population of bacteria undergoes the reproduction process and here, the least healthy bacteria die and other healthiest bacteria split into two at the same location. All the bacteria are sorted according to their fitness S_r ($S_r = S/2$, for convenience S is assumed to be a positive even integer) and the step fitness during the life and fitness values for the i_{th}

bacterium in the chemotactic loop are accumulated and calculated by:

$$\sum_{j=1}^{N_c} J_i(j,k,l)$$

$$j_H^i = \sum_{j=1}^{N_c+1} J_i(j,k,l) \quad (27)$$

Where j_H^i represents the health of the i_{th} bacterium.

For simplification the number of the bacteria keeps constant in each chemotaxis process. The characters including location and step length of the mother bacterium all reproduced to the children bacteria. Through this selection process the remaining S_r healthier bacteria are eliminated and discarded.

4.4 Elimination-Dispersal

The process of chemotaxis and reproduction are not enough for finding global solutions and to improving process of global search ability, the elimination-dispersal event introduced after N_{re} steps of reproduction. This elimination-dispersal event helps the bacterium avoid being trapped into local optima and dispersal events may place bacteria near global solutions and also the behavior of bacteria seeks out in favorable environments. The bacteria are eliminated and dispersed to random positions in the optimization domain according to the probability, p_{ed} and the number of the event is denoted as N_{ed} .

4.5 Refined Bacterial Foraging Algorithm

The survival of species in any natural evolutionary process depends upon their fitness criteria, which relies upon their food searching and motile behavior. The law of evolution supports those species who have better food searching ability and either eliminates or reshapes those with poor search ability. The genes of those species who are stronger are propagated in the evolution chain since they possess ability to reproduce even better species in future generations. So a clear understanding and modeling of foraging behavior in any of the evolutionary species, leads to attempts better solution for any optimization. So, this is way here proposed the new algorithm.

The basic foraging algorithm consists of four steps are Chemotaxis, swarming, reproduction, elimination and dispersal. Chemotaxis is the activity that bacteria gathering to nutrient-rich areas spontaneously. A cell-to-cell communication mechanism is established to simulate the biological behavior of bacteria swarming. Reproduction comes from the concept of natural selection and only the bacteria best adapted to their environment tend to survive and transmit their genetic characters

to succeeding generations while those less adapted tend to be eliminated. Elimination –dispersal event selects parts of the bacteria to diminish and disperse into random position in the environment. The proposed method based on foraging behavior of bacteria and some modifications is made through from basic foraging algorithm. The modified algorithm named as Refined Bacterial Foraging Algorithm (RBFA) and RBFA is proposed in this paper. The performance of basic foraging algorithms is well suitable in single objective problems and static environments and step length of the basic BFA is a constant parameter which may guarantee good searching results for small optimization problems. However it is applied to multiple objectives, dynamic environments and high dimensional problems it's gives poor performance and convergence characteristics also not good and many times it trapped into local optima solutions. The process of search direction and step length is important in multiple objectives and dynamic environments. The proposed approach made some modification in step length; Chemotaxis behavior and adding velocity vector for improve speed of convergence and attaining global solution and also suitable diversity for global search and its improves speed of convergence.

4.6 Search Direction And Chemotaxis Process:

The Chemotaxis behavior is modelled by a tumble-run process that consists of a tumble step and several run steps. The tumble run process follows gradient searching principles, which means the bacteria's position is updated in the run steps by the gradient information provided by the tumble step. In each bacteria step size, unit length, dimension and random direction coordination are much important, a search direction $W_{id}(j)$ and a step length $L_{id}(j)$ are calculated separately for each bacteria i , on each dimension d for each time step or tumble-run process or iteration j , $W_{id}(j) = 1$ means the i -th bacteria goes towards the positive direction of the coordinate axis on the dimension d , its indicates the follow tumble process and consecutive run process. $W_{id}(j) = -1$ means the bacteria goes towards the negative direction, its follow again tumble process and $W_{id}(j) = 0$ means the bacteria stays at the current position; it means the bacteria reaches more nutrient position.

When any one of bacteria finds best position, it should attract other bacteria so that they converge in that location. The Figure.1 and Figure.2 shows the difference of random direction and after the search dimension estimation, there is enough change in tumble-run process. In this search

direction estimation leads to finding the distance of best bacteria from rest of others and the process convergence time minimized. While the distance known, it's easy to attain the swarming process for new Chemotaxis stage. The current position i_{th} the bacterium, in d dimensional search space and j_{th} tumble-run process is updated

$$X_{id}(j+1) = X_{id}(j) + L_{id}(j)W_{id}(j) \quad (28)$$

Once the direction and angle is decided by the tumble step, to reach the position it takes several steps (until the position of worst). The rotation angle Φ is related to the number of the dimensions, the number dimensions desired by objectives.

$$\phi = \frac{\pi}{\text{round}(\sqrt{d+1})} \quad (29)$$

Where, d - search dimension and π is the number of dimensions.

4.7 Position Updating Process

In this process the step size calculation are initiated with help of position updating process. The basic methodology is adopted in BFA, In order to meet these criteria. The E-coli cells provides attraction signal to each other, so that they swarm or swim together and towards to the best location and swarming pattern based on cell-to-cell communication. But in this process shows slow converge only and in order to improve this process, the velocity factor added with other bacteria so as to reach best bacteria position and this velocity vector added according to other bacteria position. The Figure.3 and Figure.4 shows strength of RBFA algorithm with help of velocity factor and attraction factor leads to converge the bacteria in global position. The position updating process mainly focus on best bacteria and each dimension is given by

$$X_{id}(j) = \alpha(X_{id \text{ best}} - X_{id}) \quad (30)$$

Where α is a factor to desire the strength of the bacterium's attraction factor for improving the strength of the bacterium's attraction towards to the best position and for faster convergence., X_{best} indicates the position of current best global solution updated after each function evaluation, and X_i is the position of the i_{th} bacterium at the j_{th} iteration after the tumble run process.

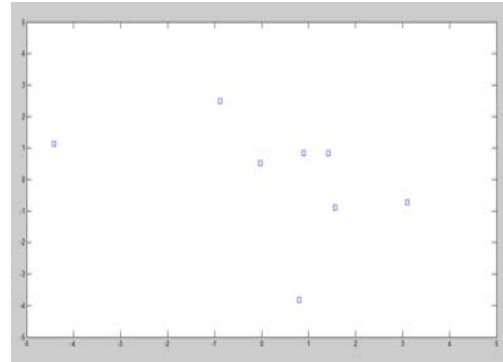


Fig.1. Initial Search With Random Directions

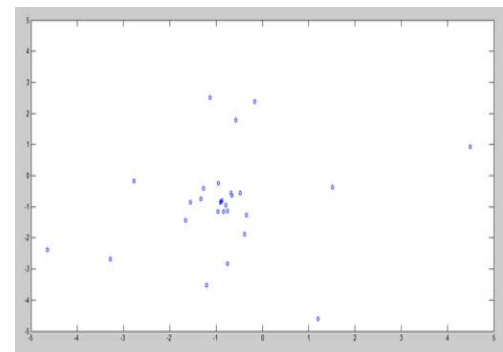


Fig.2. Modification Of Chemotaxis Behavior In Run Process With Help Of Search Direction And Search Dimension

If a anyone bacteria reaches better position in order to direct the other bacteria to best position, the attraction signal is not enough to reach the best position. Therefore, in order to attract other bacteria and also obtain the bacteria position by using equation

$$X_{id}(j+1) = \alpha(X_{id \text{ best}} - X_{id}) + V_j \quad (31)$$

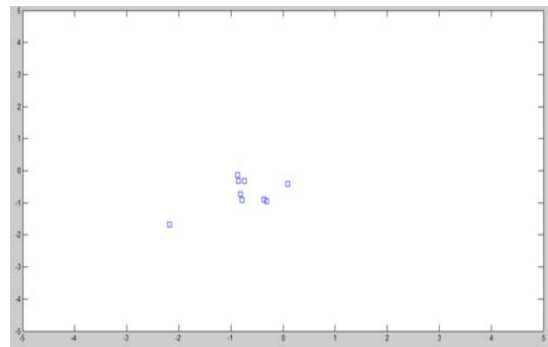


Fig.3. Reaching More Nutrient (Best) Position

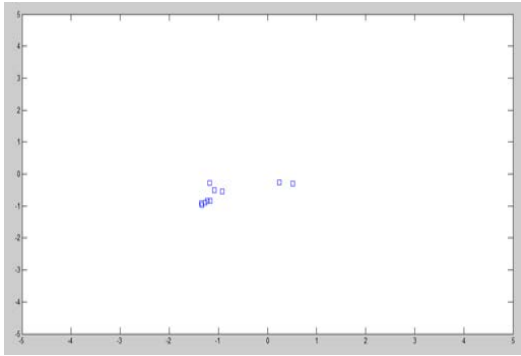


Fig.4. Communicating To Other Bacteria

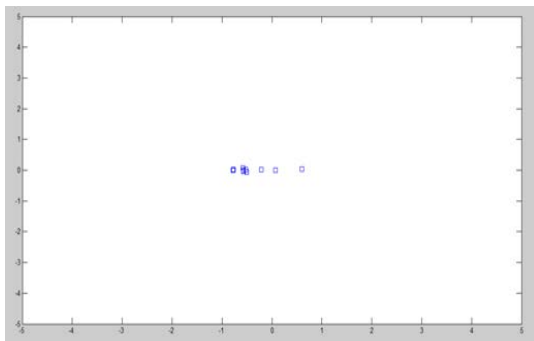


Fig.5. Reaching Global Point With Help Of Position Updating Process

So, in the process the velocity factor V_j is binding with position updating process and also is pilot to determine the best position according to the previous best positions. Update best bacteria position and add the velocity according to reach the best position, the velocity factor desired by depending upon according to position of best and other bacteria. The velocity factor V_j also gives direction to global best value or its used to identify global best value.

4.8 Step length

The basic BFA shows a step size is a constant parameter and it's suitable to finding the solution in single and small optimization problems. However, when applied to multiple objective problems and dynamic environmental problems it shows poor performance. The basic BFA with fixed step size is failure in reaching the optimal point for the following reasons. The first case, if step size is very high then the accuracy gets low although the bacterium reaches the locality of optimum point quickly and it moves around the maxima for the remaining chemotactic steps. The second case, if the step size is very small, it takes many chemotactic steps to reach the optimum point and its lead to slow convergence and rate of

convergence decreases. Meanwhile to reach the optimal point it takes convergence time and number of iterations increases. So, in order to reach the optimal point, speed of convergence and search ability the controlling of step length is essential. In this paper the proposed RBFA following consideration in determining step length process with help of search dimensions, If deviation is very high then the step size must be increased and if the deviation is small in which case the bacterium is close to the optimum point the step size is to be reduced and also improve the performance the swim walk considered instead of the constant step. The Figure.5 shows effect of best fitness of solution and reaching the global point with minimum of time.

For a each bacteria, the location of the i th bacterium at the j th chemotactic step, r th reproduction step and l th elimination / dispersal event is represented by $X_{id}(j,k,l) \in \mathbb{R}^p$. After a tumble, the location of the i th bacterium is represented by

$$X_{id}(j+1,r,l) = X_{id}(j,r,l) + L(i,j)\phi(j) \quad (32)$$

Where $L(i,j) = L_{id}(j)W_{id}(j)$

The $J(i,j,k,l)$ is cost function of corresponding $X_{id}(j,k,l)$. The fitness value of the i th bacterium at $X_{id}(j,k,l)$ is represented by $j_{id}(j,k,l)$. In this paper the minimum fitness value j_{min} is defined as the global optimum.

In a run, consecutive steps of size $L(i,j)$ is the same direction as the tumble is taken, in condition $X_{id}(j+1,k,l)$ the cost function $J(i,j+1,k,l)$ is better (lower) than $J(i,j,k,l)$. In this condition, the fitness value of the i th bacterium in the r th step of the run N_s indicates the maximum number of steps in a run and also r is smaller than N_s . This swimming operation is repeated as long as a lower cost is obtained until a maximum preset number of steps, N_s , is reached.

In BFA the step length L is a constant and it ensures accuracy and speed of the search. The size of the step length is dynamically adjusted in the reproduction and elimination-dispersal process, which ensures the bacteria moving towards the global optimum quickly at the beginning, and converging to the global optimum accurately in the end. So the i th bacteria in d th dimension search space the step length controlling vector is given by

$$L(id) = \min\{(L(id) - \mu), n\} \quad (33)$$

Where

μ - step length vector, n = constant controlling the decreasing rate of the step length. The value of 'n'



is desired by according to position updating process and Chemotaxis process.

4.8 Multi- Objective Optimization

Multi-objective Optimization (MOO) problems are defined as those problems "where two or more, sometimes competing and/or incommensurable, objective functions have to be minimized simultaneously". In general, for a problem with n objective functions, the multi-objective formulation can be as follows

$$\begin{aligned} &\text{Minimize/maximize } f_i(x) \text{ for } i=1, 2, 3\dots n \\ &\text{Subject to} \\ &G_j(x) \leq 0 \quad j=1, 2\dots J \quad (34) \\ &H_k(x) = 0 \quad k=1, 2\dots K \end{aligned}$$

(35)

Often the multi-objective is combined into a single objective so that optimization and mathematical methods can be used. There are n objectives and p variables so f(x) is an n dimensional vector and x is a p dimensional vector corresponding to p decisions or variables, solutions to a multi-objective optimization problem are often mathematically expressed in terms of non-dominated or superior points.

4.9 Load Flow Solution

Whenever the operating conditions changes the electric power system in need of power flow optimization. So, it is necessary to solve the load flow problem numerous times. The RBFA based OPF problem requires, first define the behavior of bacteria initially for initialization of control variables for secure operation and next find the optimal solution with help of Foraging and swimming of bacteria and the bacteria size is to beset according to the updating process. The algorithm able to find optimal solution subject to load flow convergence and objectives function of cost function both smooth and non-smooth functions. The load flow is solved using a RBFA-based load flow developed using incorporating a Jacobian acceleration stage. In order to keep computation time to a minimum during the optimization, the step length is very much important and search direction and dimension for the load flow is dynamically adjusted according to the proposed algorithm.

Many OPF solution techniques handle generation node reactive power limits through the use of penalty functions exclusively. This can lead to convergence problems due to distortion of the solution surface, or in some instances, it may be necessary to switch a node in order to obtain a load-flow solution. The reactive power limits on all PV nodes other than the slack node and switching to a

PQ node are important in control of voltage. The above all the requirements are satisfied by solving the OPD problem by using the Load Flow solution.

4.10. Computational Algorithm and PSEUDO Code of RBFA

The multi objective Optimal Power Dispatch based on multi-objective optimization problem is can be solved by using Refined BFA. Read system data, here the standard IEEE30 bus system data [20] is considered. It contains load data, line data and generator data [20] [18] with cost coefficients.

Randomly initialize the position of each bacterium in the domain, set the position and fitness value of the best bacterium. Initialize the parameters: S, p, N_c, N_s, N_{re}, N_c, P_{ed}, L (id), α, μ, V_j, and n.

Randomly initialize the position of each bacterium in the domain, set the position and fitness value of the best bacterium as X_{id}^b(j,k,l) and j_{min} (j, k, l) respectively.

```
FOR (each bacterium i=1: S)
  FOR (chemotactic loop j=1: Nc)
    FOR (dimensions=1: π)
      FOR (reproduction loop k=1: Nre)
        FOR (elimination-dispersal loop l=1: Ned)
          Evaluate the cost function J(i,j,k,l)
```

Let J_{last} = J(i,j,k,l) so that a lower cost could be found Calculate Jⁱ (j, k, l) and set it as J_{last};

Tumble:

Search direction identified with help of identification process according to RBFA For bacterium I, set Ji(j,r) as Jlast. A random vector Δ(i), with each element Δ_m(i), m=1,2..... p, a random number in the range [-1,1].

Move:

Move to a random direction $\frac{\Delta}{\sqrt{\Delta \times \Delta}}$ by a

unit walk, the new position is calculated by equation and start another chemotactic step.

Compute J(I,j+1,k,l) and use to compute J_{cc} (θ, P (j+1,k,l)) then use to find the new J(i,j+1,k,l).

Swim: let m = 0 (counter for swim length) While m < N_s (no climbing down too long)

Let m=m+1

If J(I,j+1,k,l) < J_{last} let J_{last} = J(I,j+1,k,l) then take another step in the same direction and compute the new J(I,j+1,k,l).

Swim:

```
Update Xid(j+1, k, l).
Recalculate Ji(j+1, k, l);
```

```

IF ( $J_{current} < J_{last}$ )
WHILE ( $J_{r+1}^i(j+1, k, l) < J_r^i(j+1, k, l)$ 
and  $r < N_s$ )
Set  $J_r^i(j+1, k, l)$  as  $J_{last}$ ;
Run:
Update  $X_{id}(j+1, k, l)$ 
Set new  $J_{r+1}^i(j+1, k, l)$  as
 $J_{current}$ ;
Swim:
Update  $X_{id}(j+1, k, l)$ 
Recalculate  $J_{r+1}^i(j+1, k, l)$ ;
END WHILE
END IF
END FOR (bacterium)
Calculate  $J_{min}(j+1, k, l)$ 
END FOR (chemotaxis)
Sum:
Evaluate the sum of the fitness value  $J_{health}^i$ 
for the  $i_{th}$  bacterium.
Sort:
Sort bacteria according to their health
 $J_{health}^i$  in ascending order.
Split:
The bacteria with the highest  $J_{health}^i$  values,
computed by die while the other  $S_r$  with the lowest
values split and take the same location of their
parents. Eliminate other then health bacteria are to
be eliminated.
Update:
Update the step length  $L(i, j)$ .
END FOR (reproduction)
Disperse:
Disperse certain bacteria to random places
in the optimization domain with probability  $P_{ed}$ .
Update:
Update the step length  $L(id)$ 
END FOR (elimination-dispersal)
END
If it's optimal solution is achieved means, the
program will stopped

```

5. RESULTS AND DISCUSSIONS

To evaluate the performance of the proposed method based multi-objective optimal power dispatch problem with considering different IEEE standard systems.

From the year 1994 to now, the evolutionary and social behavior algorithms were dominating the algorithm in the field of optimization and especially in the power system problems. These algorithms are most powerful and population based heuristic algorithms, and these algorithms have been successfully applied to solve the multi-objective based optimal power dispatch problems [5] [5]

[17]. So, the proposed technique results are compared with other social behavior algorithms. The other algorithms are like Ant Colony Algorithm (ACO) with reactive power planning problems was analyzed in [5], it gives better results when the problem is simple but increase the complexity of problem like adding FACTS devices, voltage and line flow stability and it shows slower convergence. The Particle Swarm Optimization (PSO) and modified PSO were proposed in various optimization problems [23]. Considering the PSO, the attaining results were good but when solving the multi-modal and multi-objective functions, the PSO and modified version of PSO easily trapped in local solution but solving identification of parameters are very complex, like learning rate and velocity, so it becomes complex process. The basic Bacterial Foraging Algorithm (BFA) were analyzed with the problem of multi-objective based Transmission expansion planning problem in [7]. The performance of BFA is better but step length is constant rate only. So, it's not suitable dynamic environments like power system problems. The Modified version of Bacterial Foraging Algorithm (MBFA) was considered in [6], for analysis of optimal power dispatch problem with considering FACTS devices. The performance of attraction and repellant factor is not so better and the end result shows the process is time consuming process. Finally, the proposed algorithm RBFA were tested with different multimodal functions and are listed in [2] and the performance of proposed technique compared with other technique like ACO, BFA and MBFA algorithms [2].

5.1 Case Studies and Discussions

This section deals effectiveness of proposed approach, tested with using IEEE 6-bus, IEEE 9, IEEE 30 bus, New England IEEE 39 bus system and considering FACTS devices, stability indices analysis and Q-V analysis for multi-objective based optimal power dispatch problem. The load flow analysis is carried out with Newton-Raphson method incorporating jacobian analysis and the proposed method tested with considering and without considering FACTS devices. The support of FLFI and VSA analysis the identification of real and reactive power loading are controlled by Q-V analysis after the address of critical lines and weak buses.

5.2 IEEE 30-bus system

First, the IEEE 30-bus system is considered for detail analysis and all aspects. The IEEE 30-bus system consists of 6 generator buses, 24 load buses and 41 transmission lines of which four transformer



with off-nominal tap ratio in lines 6-9,6-10,4-12,27-2 and 9 buses of compensations 10, 12, 15, 17, 20, 21, 23, 24 and 29. The load data, line data, generator data are obtained from [18] [20]. The lower voltage magnitude limits at all buses are 0.95 pu and the upper limits 1.1 pu for the generator buses 2,5,8,11 and 13,and 1.05 pu for the remaining buses including the swing bus 1.The lower limits and the upper limits of the transformer tap settings are 0.9 and 1.1 pu respectively. The proposed algorithms and all other algorithms are executed with help of simulation software MATLAB. The programs were coded with MATLAB 7.0 software package and executed via Pentium-IV Computer.

Table 1 Comparison Of Results.

Variable	BFA	MBFA	ACO	Proposed method
Total generation (MW)	292.84	295.03	292.86	292.91
Fuel cost (\$/h)	802.62	802.37	802.30	801.842
Losses (MW)	9.759	8.424	9.427	8.267
Simulation time (sec)	32.4	26.07	27.16	19.95
No. of Iterations	41	32	36	23

The objective of real power loss, reactive power compensation, voltage profile optimization and optimal location of FACTS devices with line flow, real and reactive power limits and tap setting values and results are tabulated in Table.1 and it shows the transmission losses greatly reduced and is comparable with similar social behavior algorithms. The total simulation time considerably reduced in MBFA and its compared to ACO and also basic BFO, but proposed method shows good organization in all the level because time consuming for convergence is very less even if consider multi-objective problem. The voltage stability limit is incorporated to improve the voltage stability in the various operating condition with impact of stability indices are good. The results of FLFI and VSA approaches is given in Table.2

Table 2. Results Of FLFI, VSA Approaches And Q-V Analysis.

SSC Bus	Vssc in p.u	Angle in degree	Qsh in p.u
30	1.0020	-18.0321	-0.0202
26	1.0014	-16.7872	-0.0137

Table 3. Results Voltage Magnitude For IEEE 30 Bus System

Bus Number	BFA	MBFA	ACO	Proposed method
1.	1.0600	1.0600	1.0600	1.0600
2.	1.0063	1.0322	1.0875	1.0430
3.	0.9954	1.0155	1.0175	1.0199
4.	0.9884	1.0329	1.0085	1.0107
5.	1.0683	1.0212	0.9671	1.0100
6.	0.9817	1.0399	0.9896	1.0099
7.	0.9683	1.0296	0.9719	1.0022
8.	0.9806	1.2487	0.9681	1.0100
9.	1.0192	1.0396	0.9897	1.0399
10.	1.0050	0.9715	0.9834	1.0225
11.	1.0648	1.0129	1.0103	1.0820
12.	1.0106	1.0234	0.9884	1.0500
13.	1.0234	1.0700	0.9946	1.0710
14.	0.9982	1.0461	0.9760	1.0326
15.	0.9976	1.0510	0.9735	1.0259
16.	1.0120	1.0400	0.9806	1.0311
17.	0.9972	0.9886	0.9799	1.0197
18.	1.0342	1.0984	0.9683	1.0123
19.	1.2340	0.9678	0.9683	1.0075
20.	0.9922	1.0981	0.9736	1.0105
21.	0.9752	1.0976	0.9693	1.0094
22.	0.9960	1.0977	0.9689	1.0137
23.	0.9794	0.9786	0.9598	1.0099
24.	0.9889	0.9473	0.9471	1.0018
25.	1.0712	0.9890	0.9247	1.0091
26.	0.9632	0.9742	0.9083	1.0262
27.	1.0175	1.0192	0.9187	1.0223
28.	1.0762	0.9761	0.9589	1.0088
29.	1.3142	1.0411	0.9061	1.0067
30.	0.9753	0.9794	0.8942	1.0000

The voltage profile of IEEE 30 bus system is given in Fig.6. and it shows lot of improvement in voltage profile after placing the FACTS devices. The results of FLFI, VSA approaches are identified the most critical buses are 30 bus and 26 bus but before



FLFI shows the most critical bus is 30 where place the shunt devices. The VSA approaches combined with FLFI and finally the results shows, the control of voltage deviation and stability improvement also important. Hence considered the most critical buses are bus 26 and bus 30. The installation of SSC and TCSC are listed in Table.2 and the values of compensation are listed in same table.

Table.4 Results Of Optimized Values Of Tap Settings For IEEE 30 Bus System.

RBFA	1.0294	1.0680	1.0083	0.9995
ACO	1.0950	1.0681	0.9100	0.9433
MBFA	1.0653	0.9965	1.0130	0.9666
BFA	0.9782	0.9554	0.9812	0.9666

The comparison purpose, the results of voltage profile for IEEE 30 bus system and comparison with similar algorithms are listed in Table.3. The voltage profile improvements in weak buses are marked in same table. The convergence characteristics are listed in table.1. of proposed technique, the critical line is 2-5 and weakest bus is bus number.5. Therefore the FACTS devices are installed in bus 5 and line 2 to 5, the corrected voltage and Q injection are tabulated in same table.

Table.5 Results IEEE 6 Bus System.

Bus No.	Optimized results of voltage values		Stability indices	Q-V Analysis
	FACTS Devices Installed			
	Before	After		
1	1.0000	1.0000	Corrected voltage at bus 5 is 0.1192 p.u Q -injection at bus 5 is 0.062 p.u	
2	1.0000	1.0200		
3	0.9334	0.9356		
4	0.9445	0.9456		
5	0.8723	0.9915		
6	0.9321	0.9421		

To demonstrate the effectiveness of the proposed RBFA technique, the 25 different optimization are been carried out and the best solution of Tap setting parameters are listed in Table.4.

5.3 IEEE6 Bus System

The extension of effective analysis of proposed technique analyzed with IEEE 6 bus system. The results of FLFI and VSA approaches and also optimized values are listed in Table.5. The results

of proposed technique, the critical line is 2-5 and weakest bus is bus number.5. Therefore the FACTS devices are installed in bus 5 and line 2 to 5, the corrected voltage and Q injection are tabulated in same table.

Table.6 Results IEEE 6 Bus System.

Bus No.	Optimized results of voltage values		Stability indices	Q-V Analysis
	FACTS Devices Installed			
	Before	After		
1	1.0000	1.0000	Corrected voltage at bus 5 is 0.1192 p.u Q -injection at bus 5 is 0.062 p.u	
2	1.0000	1.0200		
3	0.9334	0.9356		
4	0.9445	0.9456		
5	0.8723	0.9915		
6	0.9321	0.9421		

5.4 IEEE9 Bus System

The results of IEEE 9 bus system is listed in Table.6. In this case, the identification of weak bus is critical and because of real and reactive loading. The bus number 8 is most critical bus in IEEE9 bus system. Thus the results of FLFI and VSA approaches and the reactive power injection level is analyzed via Q-V analysis and Q-injection is listed in Table.6.

Table.7 Results IEEE 6 Bus System

Bus No.	Optimized results of voltage values		Stability indices	Q-V Analysis
	FACTS Devices Installed			
	Before	After		
1	1.0400	1.0400	Corrected voltage at bus 8 is 0.0765 p.u Q -injection at bus 8 is 0.2000 p.u	
2	1.0162	1.0210		
3	1.0134	1.0146		
4	0.9925	1.0042		
5	0.9523	0.9772		
6	0.9645	0.9821		
7	1.0040	1.0056		
8	0.8656	0.9421		
9	1.0057	1.0082		

5.5 IEEE39 Bus System

Finally, the New England IEEE39 bus system is considered for validity analysis of proposed RBFA algorithm. The data of IEEE39 bus system is obtained from [20]. The detail analysis of this case

is not analyzed here but proposed approaches are listed in Table.7. The result of FLFI and VSA approaches are the weak bus identification is bus number 15. The reactive power injection and installation of FACTS devices are carried out by Q-V analysis. The Values of index value and injection are listed in same Table.7.

5.6. Experimental Setup and Function Optimization

In this section mainly focused about function optimization and how the validity analysis carried out. The different algorithms are taken for validity analysis and listed in above section. In all the experiments, the basic BFA, MBFA and proposed algorithm are considered same bacteria size and maximum numbers of generations are varied according to the function and trapping level of local minima. The initial solution is generated randomly according to the function and is given in [22].

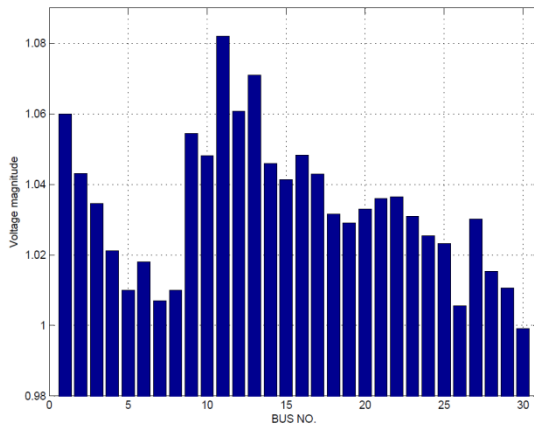


Fig.6 Voltage Profile Optimization Of IEEE 30 Bus

Table.7 Results IEEE 39 Bus System

Most critical bus and corrected voltage drop level		Q-V analysis
15	0.0721	Q -injection at bus 15 is 0.221 p.u with index value is 0.8714

5.7 Comparison of Results with Similar Bio-Inspired Algorithms

In order to strengthen the local search ability and to ability to track or attain the global optimal quickly, the bio-inspired algorithms are well suitable. The performance of proposed algorithm is compared with other bio- inspired algorithms like Ant Colony Algorithm (ACO), basic Bacterial Foraging Algorithm (BFA) and Modified version of Bacterial Foraging Algorithm (MBFA). All the above mentioned algorithms and proposed

algorithms are executed the same runs. The case studies and the results show the proposed algorithm is efficient in all categories. The application of proposed RBFA algorithm, the total real power losses is minimized during full load operating condition and during the optimization process the real power losses minimized with secured manner and all operating constraints are within the limits and this because of FLFI, VSA and Q-V analysis.

6. CONCLUSION

In this work, OPD is treated as a multiobjective problem and multidisciplinary problem by considering the multiple objectives of voltage profile, power loss, voltage deviation and optimal location of FACTS devices with reliability analysis of FLFI, VSA approaches and Q-V analysis. The validity analysis of proposed work has been carried out with help of IEEE 6, IEEE 9, IEEE 30 and New England IEEE 39 bus systems and the performance of proposed work is compared with various social foraging algorithms. The results of proposed work are well in speed of convergence, tracking of global solution and handling of control variables. The results are really encouraging and challengeable in multiobjective problems in deregulated power systems especially OPD problem.

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