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A SURVEY ON REACTIVE POWER OPTIMIZATION AND VOLTAGE STABILITY IN POWER SYSTEMS

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Abstract- Reactive power plays an important role in supporting the real power transfers by maintaining voltage stability and system reliability. It is a critical element for a transmission operator to ensure the reliability of an electric system while minimizing the cost associated with it. The traditional objectives of reactive power dispatch are focused on the technical side of reactive support such as minimization of transmission losses. Reactive power cost compensation to a generator is based on the incurred cost of its reactive power contribution less the cost of its obligation to support the active power delivery. In this paper, we tried to introduce reactive power optimization problem, miscellaneous objectives, voltage stability indices types and formulating of them, reviewing recent studies in this filed and comparison between them for checking performance of them. This paper also introduces complete references in this case with a short noting to them in text body. This paper will good reference for who they want begin to study in this field due to this paper supports all issues in reactive power optimization field.

Keywords: Reactive Power Optimization, Heuristic Algorithms Application, Reactive Power Compensation, Voltage Stability Indices, Real Power Loss Minimization.

I. INTRODUCTION

The reactive power optimization problem has a significant influence on secure and economic operation of power systems. The reactive power generation, although itself having no production cost, does however affect the overall generation cost by the way of the transmission loss. A procedure, which allocates the reactive power generation so as to minimize the transmission loss, will consequently result on the lowest production cost for which the operation constraints are satisfied [6].

The operation constraints may include reactive power optimization problem. The conventional gradient-based optimization algorithm has been widely used to solve this problem for decades. Obviously, this problem is in nature a global optimization problem, which may have several local minima and the conventional optimization methods easily lead to local optimum. On the other hand, in the conventional optimization algorithms, many mathematical assumptions, such as analytic and differential properties of objective functions and unique minima existing in problem domains, have to be given to simplify problem [6].

Otherwise, it is very difficult to calculate the gradient variables in the conventional methods. Further, in practical power system operation, the data acquired by the SCADA (Supervisory Control and Data Acquisition) system are contaminated by noise. Such data may cause difficulties in computation of gradients. Consequently, the optimization could not be carried out in many occasions. In the last decade, many new stochastic search methods have been developed for the global optimization problems such as Simulated Annealing (SA), Genetic Algorithms (GA) and Evolutionary Programming (EP) and etc. [6].

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 [3].

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 [3].

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 [3].

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 coordination between FACTS devices and transformer taps and stability indices will leads the compensation requirements, voltage stability and coordination controls [3].

The main objective of optimal reactive power dispatch (ORPD) of electric power system is to minimize an active power loss via the optimal adjustment of the power system control variables, while at the same time satisfying various equality/inequality constraints. The equality constraints are the power flow balance equations, while the inequality constraints are the limits on the control variables and the operating limits of the power system dependent variables.

The problem control variables include the generator bus voltages, the transformer tap settings, and the reactive power of shunt compensator, while the problem dependent variables include the load bus voltages, generator reactive powers, and the power line flows. Generally, the ORPD problem is a large-scale highly constrained nonlinear non-convex and multimodal optimization problem [11].

Linear programming (LP), non-linear programming and gradient based techniques have been proposed in the literature [19-22] for solving RPD problems. However, due to the approximations introduced by linearized models, the LP results may not represent the optimal solution for inherently non-linear objective functions such as the one used in the reactive power dispatch problem. It is very difficult to calculate gradient variables and a large volume of computations is involved in this approach [16].

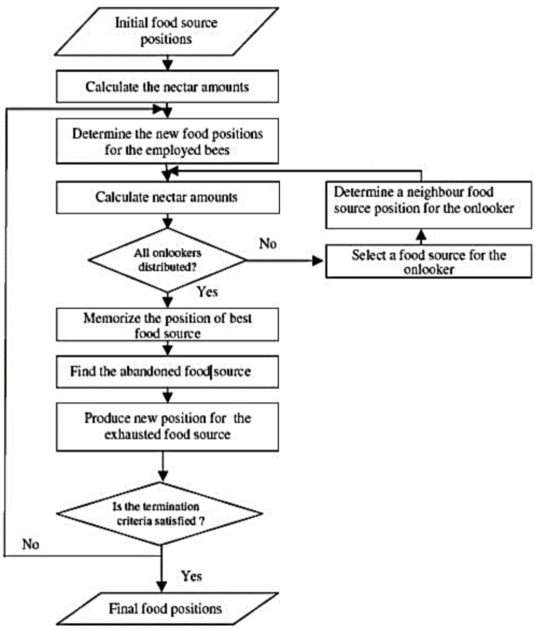

Figure 1. Flowchart of ABC algorithm for reactive power optimization [10]

Also, these conventional techniques are known to converge to a local optimal solution rather than the global one. Lately, expert system approach [23] has been proposed for the reactive power control computations. This approach is based on "If-then" based production rules. The construction of such rules requires extensive help from skilled knowledge engineers [16].

II. REVIEWING SOME STUDIES

A number of techniques ranging from classical techniques like gradient-based optimization algorithms to various mathematical programming techniques have been applied to solve this problem [24-31]. Each of these has individual merits in terms of computational time and convergence properties. However, mathematical programming techniques suffer from limited modeling capabilities i.e. they have severe limitations in handling nonlinear, discontinuous functions and constraints, and functions having multiple local minima, as is normally the case with the RPD problem.

The development of Soft Computing and Evolutionary algorithms over the last decade has enabled researchers to consider these issues in a better fashion. The advantages of Evolutionary algorithms in terms of modeling capability and search power have encouraged their application to the RPD problem in power systems [32-38]. K. Iba [32] was probably the first to apply GA to the reactive power dispatch problem. The method decomposes the system into a number of subsystems and employs interbreeding between the subsystems to generate new solutions.

All the controller states, including those with a continuous nature, are discretized and represented as integer values. K.Y. Lee et al. [33] employed a modified simple genetic algorithm for reactive power planning. The population selection and reproduction uses Benders cut in decomposed system and successive linear programming has been used to solve the operational optimization sub-problems.

However, a binary representation of control variables introduces an element of approximation at the representation stage itself. J.T. Ma and group [34-37] present an evolutionary programming approach for solving RPD. The technique uses a floating point representation for control variables. Mutation, used with an adaptive probability, is the only reproduction operator in the technique. An inner loop is used for function minimization without considering constraints. Constraint satisfaction is carried out in an outer loop. Non-feasible solutions in the outer loop are rejected by attaching a penalty to their fitness values.

D.B. Das et al. have proposed two techniques for the solution of RPD. The first, presented in D.B. Das et al. [39], is a Hybrid Stochastic Search technique that uses SA in selection process of GA. The second is the Hybrid Evolutionary Strategy which is an ES based technique with a dominant mutation operator and other improvements presented in D.B. Das et al. [40]. Zhang et al. [41] have proposed a Multi-Agent Systems based approach for optimal reactive power dispatch. Jiang et al.

[42, 43] have proposed the multi-objective approach for reactive power dispatch using techniques based on Evolutionary Programming and Particle Swarm Optimization respectively. Zhao et al. [44] presented another multi-agent based PSO approach for optimal reactive power dispatch.

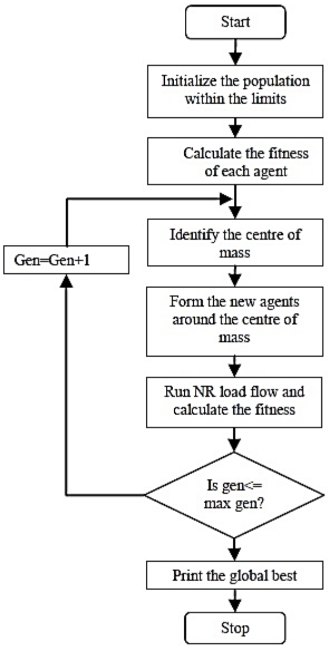

Figure 2. Big Bang-Big Crunch (BB-BC) algorithm for reactive power optimization [8]

Latest development in the field of EAs is Quantum Evolutionary Algorithms (QEA) [45, 46], which synergistically combines the principles of Quantum Computing and EAs. QEA is a population-based probabilistic Evolutionary Algorithm that integrates concepts from quantum computing for higher representation power and robust search. [1] Proposed an alternative approach based on QEA is proposed for the first time for solution of RPD.

In [3] 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. [8] Proposed the nature inspired Big Bang-Big Crunch (BB-BC) algorithm is implemented to solve the multi constrained optimal reactive power flow problem in a power system. The flowchart of this algorithm has shown in Figure 2. [10] Presents Artificial Bee Colony (ABC) based optimization technique is to handle RPO problem as a true multi-objective optimization problem with competing and non-commensurable objectives (Figure 1 for related flowchart).

[12] Proposes an Optimal Reactive Power Flow (ORPF) incorporating static voltage stability based on a multi-objective adaptive immune algorithm (MOAIA). [13] Proposed advanced an Improved Genetic Algorithm Combining Sensitivity Analysis (IGACSA) for reactive power optimization. The new algorithm combined sensitivity analysis to generate initial generation of individuals instead the way of SGA. [14] Proposes a novel heuristic optimization algorithm namely the Mean Variance Mapping Optimization (MVMO) is proposed to handle the ORPD problem (see Figure 3). [18] Presents optimal reactive power dispatch (ORPD) for improvement of voltage stability. This paper uses Differential Evolution method (DE) as approach for solving optimization issues. The flowchart of this algorithm has shown in Figure 4.

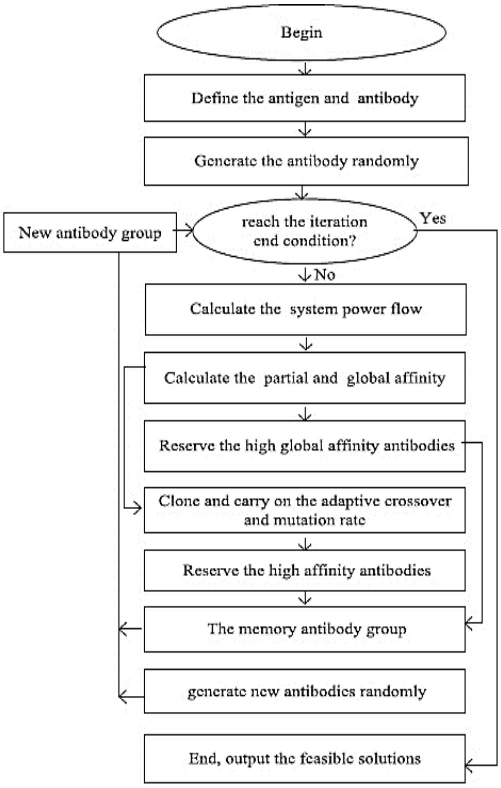

Figure 3. The flowchart of ORPF based on MOAIA [12]

III. PROBLEM DEFINITION

The objectives of reactive power (VAR) optimization are to improve the voltage profile, to minimize system active power losses, and to determine optimal VAR compensation placement under various operating conditions. To achieve these objectives, power system operators utilize control options such as adjusting generator excitation, transformer tap changing, shunt capacitors, and SVC [9].

However, the size of power systems and prevailing constraints produce strenuous circumstances for system operators to correct voltage problems at any given time. In such cases, there is certainly a need for decision-making tools in predominantly fluctuating and uncertain computational environments. There has been a growing interest in VAR optimization problems over the last decade. Most conventional methods used in VAR optimization are based on linear programming and nonlinear programming. Some simplified treatments in these methods may induce local minima. So, there is highly need to find accurate and fast algorithms to use in reactive power optimization problem [9].

IV. RELIABILITY ANALYSIS FOR CRITICAL LINES AND BUSES

Many voltage stability margin indices have been proposed [47]. Ref. [48] proved that the static voltage stability margin could be measured by minimal eigenvalue of the non-singular Jacobian matrix in a multi-generator system. Many articles also have used this index to improve voltage stability margin successfully [49-51]. Some of these indexes are described as follows [12]:

A. Voltage Stability Analysis and Fast Line Flow Index

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 coordinate 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 [3].

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

$$L_{fl} = \frac{4XQ_j}{\left[V_i \sin(\theta-\delta)\right]^2} \qquad (1)$$

where, L_{fl} is Fast Line Flow Index, θ is angle in the impedance angle from impedance triangle, δ is Influence of the vector diagram, angle between sending end and receiving end voltage, X is line reactance, Q_j is reactive power flow at the receiving, V_i is sending end voltage [3].

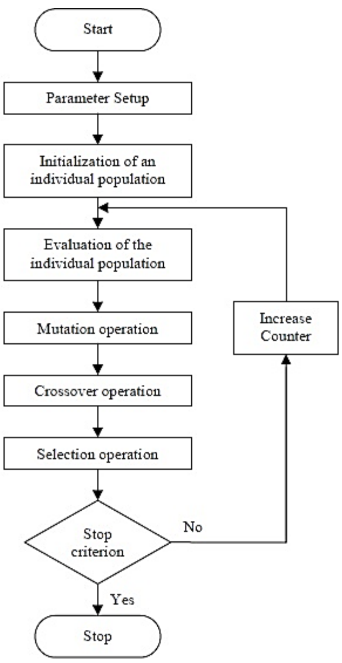

Figure 4. The flowchart of differential evolution

B. 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 [3].

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 [3]:

$$VSA = hV_{act} - \Delta V \qquad (2)$$

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 [3].

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].

C. Reactive Power Control and Voltage Stability Index, *Q*-*V* Analysis

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

$$\begin{bmatrix} J_{P\delta} & J_{PV} \\ J_{Q\delta} & J_{QV} \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta V \end{bmatrix} = \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \qquad (3)$$

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 Jacobean in power flow equation [3].

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 [3].

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

$$\begin{bmatrix} J_1 & J_2 \\ J_3 & J_4 \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta V \end{bmatrix} = \begin{bmatrix} J_{P\delta} & J_{PV} \\ J_{Q\delta} & J_{QV} \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta V \end{bmatrix} = \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \qquad (4)$$

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 [3]:

$$\left[\Delta V\right] = \left[J_R\right]^{-1}\left[\Delta Q\right] \qquad (5)$$

where, J_R is known as reduced Jacobean and is given as follows:

$$J_R = J_{QV} - J_{Q\delta} J_{PV}^{-1} J_{P\partial} \quad (6)$$

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

$$L_k = \frac{\partial Q_k}{\partial V_k} = -\frac{q_{dk}}{V_k} - B_{kk} V_k \quad (7)$$

where, q_{dk} is reactive power demand at nth bus, L_k is voltage stability index at nth bus, B_{kk} is imaginary part of admittance matrix [3].

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

$$\begin{cases} VSI = \dfrac{\partial Q_k}{\partial V_k} \Delta V \\ \Delta V = \left[J_R \right]^{-1} \left[\Delta Q_{inj} \right] \end{cases} \quad (8)$$

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 [3].

$$L_k \approx L_k^f + \sum_{k=1}^{NC} A_{kj} \Delta C_k \quad (9)$$

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].

D. Voltage Stability Index, *L*-Index

For voltage stability bus evaluation uses L-index [52], [53], the indicator value varies in the range between zero (the no load condition) and one (voltage collapse) which corresponds to [18]:

$$I_{bus} = Y_{bus} V_{bus} \quad (10)$$

By segregating the load buses from generator buses, can write as:

$$\begin{bmatrix} I_L \\ I_G \end{bmatrix} = \begin{bmatrix} Y_1 & Y_2 \\ Y_3 & Y_4 \end{bmatrix} \begin{bmatrix} V_L \\ V_G \end{bmatrix} \quad (11)$$

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = H \begin{bmatrix} I_L \\ V_G \end{bmatrix} = \begin{bmatrix} H_1 & H_2 \\ H_3 & H_4 \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \quad (12)$$

where, V_L and I_L are voltages and currents at the load buses, V_G, I_G are voltages and currents at the generator buses, H_1, H_2, H_3, H_4 are sub-matrices of the hybrid matrix H, generated from bus Y partial inversion. From Equations (11) and (12), we can write as [18]:

$$V_L = H_1 I_L + H_2 V_G = Y_1^{-1} I_L - Y_1^{-1} Y_2 V_G \quad (13)$$

$$H_2 = -Y_1^{-1} Y_2 \quad (14)$$

The no load condition, currents at the load buses (I_L) are zero, can be written as:

$$V_{0j} = \sum_{i \in G} H_{2ij} V_i \quad (15)$$

where, V_{0j} is voltages at bus j for no load condition. This representation can then be used to define a voltage stability indicator at the load bus, which is given by [18]:

$$L_j = \left| 1 - V_{0j} / V_j \right| \quad (16)$$

where, L_j is L-index voltage stability indicator for bus j, V_j is voltage for bus j.

The L-index approaches the numerical value 1.0, when a load bus approaches a steady state voltage collapse situation. So if the index evaluated at any bus is less than unity, the system can keep voltage stability [18].

V. PROBLEM FORMULATION

The ORPF formulation includes the objective functions, the variable constraint conditions and the load flow constraint equations [12].

A. Objective Function

The multi-objective functions of the power system ORPF include the technical goal and the economic goal. The economic goal is mainly to minimize the system active power transmission loss. The technical goals are to minimize the load buses voltage deviation from the ideal voltage and to improve the voltage stability margin (VSM). Therefore, multi-objective functions for both the technical and economic goals are considered in this paper as follows [12]:

$$f(x) = \begin{cases} \min(P_L) \\ \min(\Delta V_b) \\ \max(VSM) \end{cases} \quad (17)$$

where, P_L is total real power losses, ΔV_b is voltage deviation, VSM is the voltage stability margin.

B. Voltage Deviation Objective Function

The voltage deviation objective function can be written as the minimum of the total sum of each load bus voltage deviation [12]:

$$\min\left(\sum \Delta V_b\right) = \min\left(\sum_{b=1}^{B} \frac{\phi\left(\left|V_b - V_b^{ideal}\right| - \delta V_b\right)}{V_b}\right) \quad (18)$$

where, V_b is the actual voltage of the system load bus b, V_b^{ideal} is the ideal voltage of the load bus b and δV_b is the maximum permitted voltage deviation of the load bus b.

In this paper, V_b^{ideal} is 1 pu and δV_b is -5% to +5%. When $V_b < V_b^{ideal}$, δV_b = -5%, otherwise δV_b = +5%. The function $\phi(x)$ is:

$$\phi(x) = \begin{cases} 0 & \text{if} \quad x < 0 \\ x & \text{if else} \quad x > 0 \end{cases} \quad (19)$$

In addition, B is the total number of system load buses. When the voltage V_b of load bus b is running at $\left[V_b^{ideal} - \delta V_b, V_b^{ideal} + \delta V_b\right]$, $\phi\left(\left|Vb - V_b^{ideal}\right| - \delta V_b\right) = 0$.

C. System Voltage Stability Margin

As mentioned before, there are many indices for ensuring voltage stability issue. Therefore, we can choose one of them regarding to our problem formulation proportion. In this paper we will use static voltage stability margin can be measured by the minimal eigenvalue of the non-singular Jacobian matrix in a multi-generator system. So, enhancing the minimal eigenvalue of the non-singular Jacobian matrix can be written as [12]:

$$\max(VSM) = \max\left(\min\left|eig(Jacobi)\right|\right) \tag{20}$$

where, *Jacobi* is the Jacobian matrix of the power flow, *eig*(*Jacobi*) is all the eigenvalues of the Jacobian matrix, min(*eig*(*Jacobi*)) is the minimum of the eigenvalues in the Jacobian matrix and max (min(*eig*(*Jacobi*))) is maximizing the minimal eigenvalue in the Jacobian matrix. Thus, the objective function of the ORPF is [12]:

$$\min(F) = \min\left(P_L,\ \sum\Delta Vb,\ -\max(VSM)\right)^T \tag{21}$$

D. System Variable Constraint Conditions

Variable constraint conditions include the control and the state variable constraint conditions. The control variable constraint conditions include the transformer tap changer setting T, the compensating capacitance capacity C and the generator bus voltage U. The state variables include each load bus voltage and each generator bus output reactive power Q. Thus, the variable constraint conditions may be written as [12]:

$$\begin{cases} V_{gk\min} < V_{gk} < V_{gk\max} \\ T_{i\min} < T_i < T_{i\max} \\ C_{j\min} < C_j < C_{j\max} \end{cases} \tag{22}$$

$$\begin{cases} Q_{gk\min} < Q_{gk} < Q_{gk\max} \\ V_{l\min} < U_l < V_{l\max} \end{cases} \tag{23}$$

where, $V_{gk\min}(V_{gk\max})$, $T_{i\min}(T_{i\max})$, $C_{j\min}(C_{j\max})$, $Q_{gk\min}$ $(Q_{gk\max})$ and $V_{l\min}(V_{l\max})$ are the lower (upper) limit values of the generator bus voltage, transformer ratio, capacity of compensation capacitor, generator bus reactive power and each load bus voltage, respectively [12].

E. System Power Flow Constraint Equations

The ORPF must satisfy the system power flow equations, which are written as:

$$\Delta P_i = P_{Gi} - P_{Li} - V_i \sum_{j=1}^{n} V_j \left(G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij}\right) = 0 \tag{24}$$

$$\begin{cases} \Delta Q_i = Q_{Gi} + \sum_{i=1}^{r} \Delta Q_{Ci} - Q_{Li} - \\ -V_i \sum_{j=1}^{n} V_j \left(G_{ij}\sin\delta_{ij} - B_{ij}\cos\delta_{ij}\right) = 0 \end{cases} \tag{25}$$

The system active power loss is:

$$P_L = \sum_{i=1}^{n} V_i \sum_{j\in h} V_j \left(G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij}\right) \tag{26}$$

where, n is the total number of nodes, P_{Gi}, Q_{Gi} are the bus i generator active power and reactive power, respectively, P_{Li}, Q_{Li} are the bus i load active power and reactive power, respectively, V_i, V_j are the buses i and j voltages, respectively, and G_{ij}, B_{ij}, δ_{ij} are the conductance and phase angle between bus i and j, respectively, h is the number of buses connecting with bus i.

At the same time, the system transmission power is limited by the upper capacity of the branch (transformer and transmission line) [12]. In addition, consider that, the mentioned problem formulation can use for all optimization algorithms by a little changes in equation forms. At the following we will note to miscellaneous algorithms test results and comparison between them.

VI. AN EXAMPLE OF REACTIVE POWER OPTIMIZATION USING A HEURISTIC ALGORITHM - GENETIC ALGORITHM

A. Introduction to Genetic Algorithm

A.1. Representation of Design Variables

In GAs, the design variables are represented as strings of binary numbers, 0 and 1. For example, if a design variable x_i is denoted by a string of length four (or a four-bit string) as (0 1 0 1), its integer (decimal equivalent) value will be 1+0+4+0=5. If each design variable x_i, i=1, 2… n is coded in a string of length q, a design vector is represented using a string of total length nq. For example, if a string of length 5 is used to represent each variable, a total string of length 20 describes a design vector with n=4. The following string of 20 binary digits denote the vector (x_1=18, x_2=3, x_3=1, x_4=4) [54-58]:

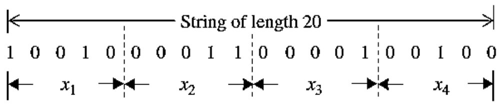

Figure 5. Example of string length

In general, if a binary number is given by $b_q b_{q-1} \ldots b_2 b_1 b_0$, where b_k=0 or 1, k=1, 2…, q then its equivalent decimal number y (integer) is given by:

$$y = \sum_{k=0}^{q} 2^k b_k \tag{27}$$

This indicates that a continuous design variable x can only be represented by a set of discrete values if binary representation is used. If a variable x (whose bounds are given by x^l and x^u) is represented by a string of q binary numbers, as shown in Equation (27), its decimal value can be computed as [54-58]:

$$x = x^l + \frac{x^u - x^l}{2^q - 1} \sum_{k=0}^{q} 2^k b_k \tag{28}$$

Thus if a continuous variable is to be represented with high accuracy, we need to use a large value of q in its binary representation. In fact, the number of binary digits needed (q) to represent a continuous variable in steps (accuracy) of Δx can be computed from relation [54-58]:

$$2^q \geq \frac{x^u - x^l}{\Delta x} + 1 \tag{29}$$

For example, if a continuous variable x with bounds 1 and 5 is to be represented with an accuracy of 0.01, we need to use a binary representation with q digits where $2^q \geq \frac{5-1}{0.01}+1=401$ or $q=9$. Equation (28) shows why GAs are naturally suited for solving discrete optimization problems [54-58].

A.2. Representation of Objective Function and Constraints

Because Genetic Algorithms are based on the survival of the fittest principle of nature, they try to maximize a function called the fitness function. Thus GAs are naturally suitable for solving unconstrained maximization problems. The fitness function, $F(X)$, can be taken to be same as the objective function $f(X)$ of an unconstrained maximization problem so that $F(X) = f(X)$. A minimization problem can be transformed into a maximization problem before applying the GAs. Usually the fitness function is chosen to be nonnegative. The commonly used transformation to convert an unconstrained minimization problem to a fitness function is given by [54-58]:

$$F(X)=\frac{1}{1+f(X)} \tag{30}$$

It can be seen that Equation (30) does not alter the location of the minimum of $f(X)$ but converts the minimization problem into an equivalent maximization problem. A general constrained minimization problem can be stated as: Minimize $f(X)$ subject to $g_i(X) \leq 0$; i=1, 2,…, m and $h_j(X) \leq 0$; j=1, 2,…, p. This problem can be converted into an equivalent unconstrained minimization problem by using concept of penalty function as [54-58]:

$$\text{minimize} \quad \phi(X)=f(X)+\sum_{i=1}^{m} r_i \left\langle g_i(X)\right\rangle^2 + +\sum_{j=1}^{p} R_j\left(h_j(X)\right)^2 \tag{31}$$

where r_i and R_j are the penalty parameters associated with the constraints $g_i(X)$ and $h_j(X)$, whose values are usually kept constant throughout solution process. In Equation (5), the function ‹$g_i(X)$›, called the bracket function, is defined as [54-58]:

$$\left\langle g_i(X)\right\rangle=\begin{cases} g_i(X) & if \quad g_i(X)>0 \\ 0 & if \quad g_i(X)\leq 0 \end{cases} \tag{32}$$

In most cases, the penalty parameters associated with all the inequality and equality constraints are assumed to be the same constants as: r_i=r; i=1, 2,…, m and R_j=R; j=1, 2,…, p, where r and R are constants. The fitness function, $F(X)$, to be maximized in the GAs can be obtained, similar to Equation (30), as [54-58]:

$$F(X)=\frac{1}{1+\phi(X)} \tag{33}$$

Equations (31) and (32) show that the penalty will be proportional to the square of the amount of violation of the inequality and equality constraints at the design vector X, while there will be no penalty added to $f(X)$ if all the constraints are satisfied at the design vector X [54-58].

A.3. Genetic Operators

The solution of an optimization problem by GAs starts with a population of random strings denoting several (population of) design vectors. The population size in GAs (n) is usually fixed. Each string (or design vector) is evaluated to find its fitness value. The population (of designs) is operated by three operators' reproduction, crossover, and mutation to produce a new population of points (designs). The new population is further evaluated to find the fitness values and tested for the convergence of the process [54-58].

One cycle of reproduction, crossover, and mutation and the evaluation of the fitness values is known as a generation in GAs. If the convergence criterion is not satisfied, the population is iteratively operated by the three operators and the resulting new population is evaluated for the fitness values. The procedure is continued through several generations until the convergence criterion is satisfied and the process is terminated. The details of the three operations of GAs are given below [54-58].

A.4. Reproduction

Reproduction is the first operation applied to the population to select good strings (designs) of the population to form a mating pool. The reproduction operator is also called the selection operator because it selects good strings of the population. The reproduction operator is used to pick above average strings from the current population and insert their multiple copies in the mating pool based on a probabilistic procedure. In a commonly used reproduction operator, a string is selected from the mating pool with a probability proportional to its fitness. Thus if F_i denotes the fitness of the string in the population of size n, the probability for selecting the ith string for the mating pool (p_i) is given by [54-58]:

$$p_i=\frac{F_i}{\sum_{j=1}^{n} F_j} \qquad i=1,...,n \tag{34}$$

Note that Equation (34) implies that the sum of the probabilities of the strings of the population being selected for the mating pool is one. The implementation of the selection process given by Equation (34) can be understood by imagining a roulette wheel with its circumference divided into segments, one for each string of the population, with the segment lengths proportional to the fitness of the strings as shown in Figure (5) [54-58].

By spinning the roulette wheel n times (n being the population size) and selecting, each time, the string chosen by the roulette-wheel pointer, we obtain a mating pool of size n. Since the segments of the circumference of the wheel are marked according to the fitness of the various strings of the original population, the roulette-wheel process is expected to select Fi/F copies of the ith string for the mating pool, where $\bar{F}$ denotes the average fitness of the population [54-58]:

$$\bar{F}=\frac{1}{n}\sum_{j=1}^{n} F_j \tag{35}$$

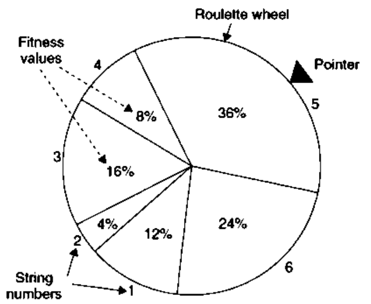

Figure 6. Roulette-Wheel selection scheme

In Figure (5), the population size is assumed to be 6 with fitness values of the strings 1, 2, 3, 4, 5, and 6 given by 12, 4, 16, 8, 36, and 24, respectively. Since the fifth string (individual) has the highest value, it is expected to be selected most of the time (36% of the time, probabilistically) when the roulette wheel is spun n times (n=6 in Figure (5)). The selection scheme, based on the spinning of the roulette wheel, can be implemented numerically during computations as follows [54-58].

The probabilities of selecting different strings based on their fitness values are calculated using Equation (34). These probabilities are used to determine the cumulative probability of string i being copied to mating pool, p_i by adding individual probabilities of strings 1 through i as:

$$P_i = \sum_{j=1}^{i} p_j \tag{36}$$

Thus the roulette-wheel selection process can be implemented by associating the cumulative probability range P_{i-1}-P_i to the ith string. To generate the mating pool of size n during numerical computations, n random numbers, each in the range of zero to one, are generated (or chosen). By treating each random number as the cumulative probability of the string to be copied to the mating pool, n strings corresponding to the n random numbers are selected as members of mating pool [54-58].

By this process, the string with a higher (lower) fitness value will be selected more (less) frequently to the mating pool because it has a larger (smaller) range of cumulative probability. Thus strings with high fitness values in the population, probabilistically, get more copies in the mating pool. It is to be noted that no new strings are formed in the reproduction stage; only the existing strings in the population get copied to the mating pool. The reproduction stage ensures that highly fit individuals (strings) live and reproduce, and less fit individuals (strings) die. Thus the GAs simulate the principle of "survival-of-the-fittest" of nature [54-58].

A.5. Crossover

After reproduction, the crossover operator is implemented. The purpose of crossover is to create new strings by exchanging information among strings of the mating pool. Many crossover operators have been used in the literature of GAs. In most crossover operators, two individual strings (designs) are picked (or selected) at random from the mating pool generated by the reproduction operator and some portions of the strings are exchanged between the strings [54-58].

In the commonly used process, known as a single-point crossover operator, a crossover site is selected at random along the string length, and the binary digits (alleles) lying on the right side of the crossover site are swapped (exchanged) between the two strings. The two strings selected for participation in the crossover operators are known as parent strings and the strings generated by the crossover operator are known as child strings. For example, if two design vectors (parents), each with a string length of 10, are given by [54-58]:

$$\text{(Parent 1)} \quad X_1 = \{010 \,|\, 1011011\}$$

$$\text{(Parent 2)} \quad X_2 = \{100 \,|\, 0111100\}$$

The result of crossover, when the crossover site is 3, is given by:

$$\text{(Offspring1)} \quad X_3 = \{010 \,|\, 0111100\}$$

$$\text{(Offspring2)} \quad X_4 = \{100 \,|\, 1011011\}$$

Since the crossover operator combines substrings from parent strings (which have good fitness values), the resulting child strings created are expected to have better fitness values provided an appropriate (suitable) crossover site is selected. However, the suitable or appropriate crossover site is not known beforehand. Hence the crossover site is usually chosen randomly. The child strings generated using a random crossover site may or may not be as good as or better than their parent strings in terms of their fitness values [54-58].

If they are good or better than their parents, they will contribute to a faster improvement of the average fitness value of the new population. On the other hand, if the child strings created are worse than their parent strings, it should not be of much concern to the success of the GAs because the bad child strings will not survive very long as they are less likely to be selected in the next reproduction stage (because of survival-of-the-fittest strategy used) [54-58].

As indicated above, the effect of crossover may be useful or detrimental. Hence it is desirable not to use all the strings of the mating pool in crossover but to preserve some of the good strings of the mating pool as part of the population in the next generation. In practice, a crossover probability, p_c is used in selecting the parents for crossover. Thus only 100p_c percent of the strings in the mating pool will be used in the crossover operator while 100(1-p_c) percent of the strings will be retained as they are in the new generation (of population) [54-58].

A.6. Mutation

The crossover is the main operator by which new strings with better fitness values are created for the new generations. The mutation operator is applied to the new strings with a specific small mutation probability, p_m. The mutation operator changes the binary digit (allele's value) 1 to 0 and vice versa. Several methods can be used for implementing the mutation operator [54-58].

In the single-point mutation, a mutation site is selected at random along the string length and the binary digit at that site is then changed from 1 to 0 or 0 to 1 with a probability of p_m. In the bit-wise mutation, each bit (binary digit) in the string is considered one at a time in sequence, and the digit is changed from 1 to 0 or 0 to 1 with a probability p_m. Numerically, the process can be implemented as follows. A random number between 0 and 1 is generated/chosen [54-58].

If the random number is smaller than p_m, then the binary digit is changed. Otherwise, the binary digit is not changed. The purpose of mutation is 1- to generate a string (design point) in neighborhood of current string, thereby accomplishing a local search around the current solution, 2- to safeguard against a premature loss of important genetic material at a particular position, and 3- to maintain diversity in the population [54-58].

As an example, consider the following population of size n = 5 with a string length 10:

1 0 0 0 1 0 0 0 1 1
1 0 1 1 1 1 0 1 0 0
1 1 0 0 0 0 1 1 0 1
1 0 1 1 0 1 0 0 1 0
1 1 1 0 0 0 1 0 0 1

Here all the five strings have a 1 in the position of the first bit. The true optimum solution of the problem requires a 0 as the first bit. The required 0 cannot be created by either the reproduction or the crossover operators. However, when the mutation operator is used, the binary number will be changed from 1 to 0 in the location of the first bit with a probability of np_m [54-58].

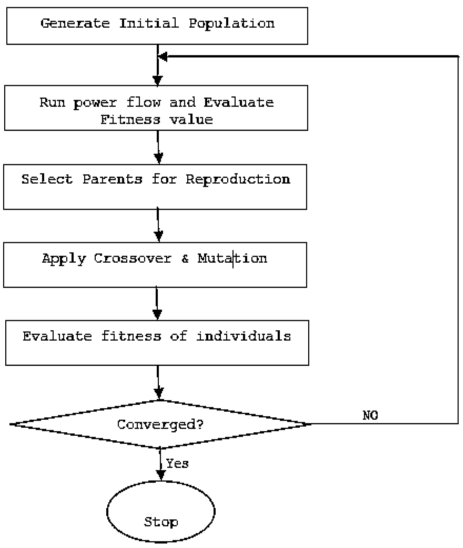

Figure 7. Flowchart of GA based RPD algorithm

Note that the three operator's reproduction, crossover, and mutation are simple to implement. The reproduction operator selects good strings for the mating pool, the crossover operator recombines the substrings of good strings of the mating pool to create strings (next generation of population), and the mutation operator alters the string locally. The use of these three operators successively yields new generations with improved values of average fitness of the population [54-58].

Although, the improvement of the fitness of the strings in successive generations cannot be proved mathematically, the process has been found to converge to the optimum fitness value of the objective function. Note that if any bad strings are created at any stage in the process, they will be eliminated by the reproduction operator in the next generation. The GAs have been successfully used to solve a variety of optimization problems in the literature [54-58].

B. Fitness Function for Implementation of Genetic Algorithm to Reactive Power Optimization Problem

In the RPD problem under consideration the objective is to minimize the total power loss satisfying the constraints in Equations (22) to (25). For each individual, the equality constraints (24) and (25) are satisfied by running Newton-Raphson algorithm and the constraints on the state variables are taken into consideration by adding a quadratic penalty function to the objective function. With the inclusion of penalty function, the new objective function then becomes [16]:

$$\begin{aligned} &\text{minmize } f(V,Q_{gi},T_i,C_i)=P_{loss}+ \\ &+k_v\sum_{i=1}^{N_{PQ}}\left(V_i-V_i^{\lim}\right)^2+k_q\sum_{i=1}^{N_g}\left(Q_{gi}-Q_{gi}^{\lim}\right)^2+ \\ &+k_f\sum_{i=1}^{N_T}\left(T_i-T_i^{\lim}\right)^2+k_l\sum_{i=1}^{N_C}\left(C_i-C_i^{\lim}\right)^2+ \\ &+k_s\sum_{i=1}^{N_C}\left(S_i-S_i^{\lim}\right)^2+k_h\sum_{i=1}^{N_C}\left(L_i-L_i^{\lim}\right)^2 \end{aligned} \tag{37}$$

where, k_v, k_q, k_f, k_l, ks, and k_h are penalty factors, V_i is generator bus voltages, Q_{gi} is reactive power generation via generators, T_i is tap changer transformers tap position, C_i is capacitors reactive power generation, S_i is transmission lines limits, L_i is voltage stability index. In the above objective function $V_i^{\lim}$ and $Q_{gi}^{\lim}$ are defined as [16]:

$$V_i^{\lim}=\begin{cases}V_i^{\min} & \text{if} \quad V_i<V_i^{\min}\\ V_i^{\max} & \text{if} \quad V_i>V_i^{\max}\end{cases} \tag{38}$$

$$Q_{gi}^{\lim}=\begin{cases}Q_{gi}^{\min} & \text{if} \quad Q_{gi}<Q_{gi}^{\min}\\ Q_{gi}^{\max} & \text{if} \quad Q_{gi}>Q_{gi}^{\max}\end{cases} \tag{39}$$

$$T_i^{\lim}=\begin{cases}T_i^{\min} & \text{if} \quad T_i<T_i^{\min}\\ T_i^{\max} & \text{if} \quad T_i>T_i^{\max}\end{cases} \tag{40}$$

$$C_i^{\lim}=\begin{cases}C_i^{\min} & \text{if} \quad C_i<C_i^{\min}\\ C_i^{\max} & \text{if} \quad C_i>C_i^{\max}\end{cases} \tag{41}$$

The value of the penalty factor should be large so that there is no violation for unit output at the final solution. Since GA is designed for the solution of maximization problems, the GA fitness function is defined as the inverse of Equation (37) [58].

$$F_{fitness}=\frac{1}{f} \tag{42}$$

Therefore, we should optimize Equation (37) then reactive power in the power system will be optimized. The flowchart and steps of reactive power optimization by genetic algorithm is shown in Figure 7.

VII. SIMULATION RESULTS

The IEEE 57-bus system are used as the test case to examine the performance of several algorithm and compare them with other heuristic algorithms. For test system, the lower and upper limits of load bus voltages are 0.95 p.u. and 1.05 p.u., respectively. Generator voltages at the high voltage terminal are defined as continuous variables. The lower and upper limits are set to 0.94 p.u. and 1.06 p.u., respectively [14].

Discrete control variables consist of transformer tap positions and the susceptance of shut compensators. All Under-Load Tap Changing (ULTC) transformers are assumed to have 21 discrete taps within ±10% of the nominal voltage (1% for each tap). Each transformer tap is defined by an integer between -10 to 10. These ULTC data are fictitious values. The number of taps and the voltage range in practical cases can be different. All shunt compensators have 11 discrete steps of different ratings (defined by an integer between 0 and 10). The performance of MVMO is compared with following algorithms [14].

1- PSO: A standard PSO version 2007 [59]
2- DE: A basic DE namely "DE/current-to-best/1" [60, 61]
3- JADE: An adaptive DE algorithm [62]
4- JADE-vPS: A modified JADE algorithm [63]

The IEEE 57-bus system consists of seven generators, 80 lines where 15 of which are equipped with ULTC transformers. Shunt reactive power compensators are connected to buses 18, 25 and 53. The limit of these susceptances is [0, 0.2], [0, 0.18] and [0, 0.18], respectively. Therefore, the ORPD search space has 25 dimensions. The population size PS of PSO, DE and JADE and the initial value of PS in JADE-vPS is set to 50 [14].

Table 1. Statistical results for active power loss in MW

	MVMP	PSO	DE	JADE	JADE-vPS
Min.	24.8512	24.8479	24.8360	24.8493	24.8451
Ave.	24.9917	24.9336	24.8701	24.9494	24.9565
Max.	25.2608	25.1642	25.0307	25.2044	25.3768
Standard deviation	0.1029	0.0671	0.0352	0.0666	0.0896

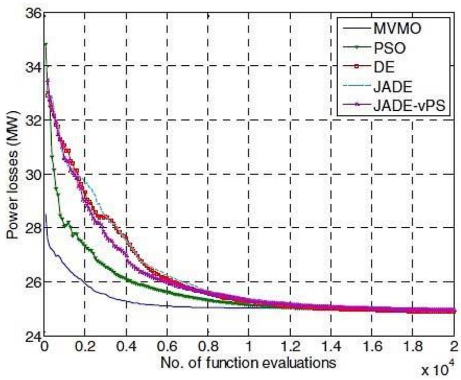

Figure 8. Average convergence characteristics

To fairly compare each algorithms with others, every algorithm is independently run for 50 times. Then statistical values consisting of minimum, average, maximum and standard deviation of active power losses are computed as listed in Table 1 [14].

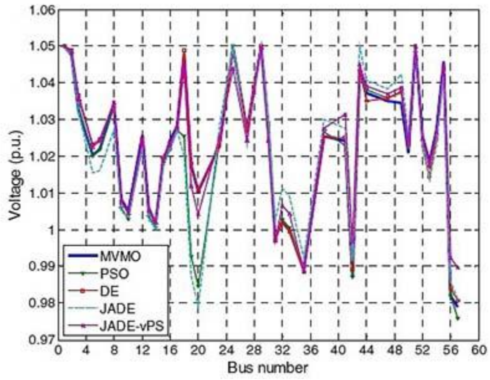

Figure 9. Load bus voltage profiles

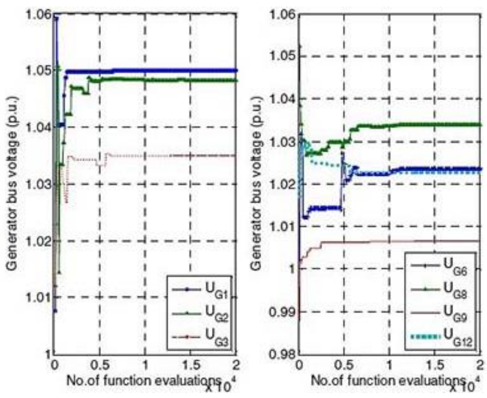

Figure 10. Convergence of generator voltages

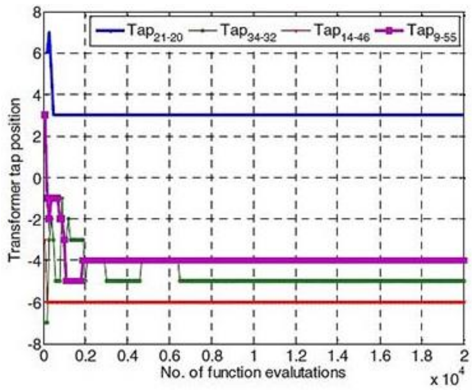

Figure 11. Convergence of selected transformer taps

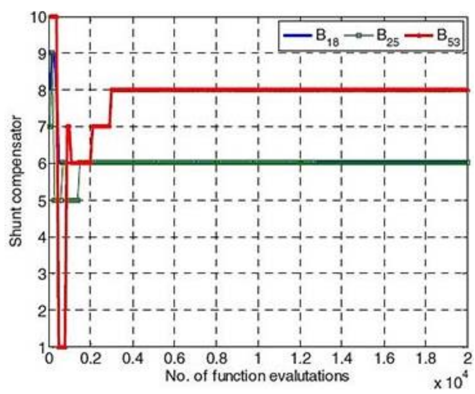

Figure 12. Convergence of shunt compensator

The average convergence of active power losses found by each algorithm is plotted after the first 100 FEs as shown in Figure 8. It is clearly shown that the convergence of MVMO is the fastest. In this test case, the statistical results of MVMO in Table 1 are not outstanding the other algorithms. However, the MVMO results are on average very close to the other techniques. An interesting observation made from Figure 8 is that MVMO is very fast in the global search capability because the lowest power loss has been found after the first 100 Fes [14].

As mentioned in [64] that there are five buses (buses 25, 30, 31, 32 and 33) in this network that the voltages are outside the limits. After the ORPD result given by each method, power flow is calculated to determine bus voltages as shown in Figure 9. It is shown that all bus voltages can be maintained within the limits. These voltage profiles confirm the merits of ORPD in achieving both reduced power losses and voltage security [14].

The convergence of optimized control variables are shown in Figures 10 to 12. From these figures, the control variables change abruptly at the early searching stage. Then, they settle to a steady state at the later stage. At this phase, an optimum has been discovered. The CPU time of all methods is approximately 5 minutes [14].

VIII. CONCLUSIONS

In this paper, reactive power optimization is fully introduced and some studies in this filed introduced too. In recent years, reactive power control problem has been concerned with sciences and researchers due to reactive power highly affect in power system operation and control. Reactive power has direct and non-direct relationship with all parameters of power system, so reactive power optimizations will be a nonlinear and non-convex optimization problem.

In addition, power system stability and reliability indexing have direct relationship by reactive power balance in power system. Reactive power can change and also control voltages of system buses directly and keep them in ideal ranges. Therefore, reactive power balance is very important to satisfying preferred ranges in bus voltages. For checking voltage stability of power system many indices are proposed and each of them have advantages and disadvantages in problem formulation and optimization process.

Classic algorithms cannot reach to global optimum of optimization problems as reactive power optimization due to gradient-based optimization algorithms nature. Therefore, in recent years, efforts to reach to reliable and accurate algorithm to solve this problem have been done and advantages and disadvantages of them introduced. Finally, the IEEE 57-bus test system optimization results have been presented and comparisons between some of them have been done in simulation result section.

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