Voltage Stability in Power System – A Survey

S.Jaisiva1 S.Neelan2 K.Arum Selvi3 R.Vinoth4
1,2,3,4 Assistant Professor 3 Associate Professor
1,2,3,4 Department of Electrical & Electronics Engineering
1,2,3,4 IFET College of Engineering, Villupuram, Tamilnadu, India

Abstract— Reactive power optimization (RPO) is an important issue for providing the secure and economic run of the power systems. The importance of reactive power planning on economic profit and secure running has been increasing, because of the increasing fuel costs and investment funds. It is also quite important for an electric operator to provide voltage in a specified range for the customers. As such, RPO provides voltage control in power systems. Furthermore, it is used for decreasing active power loss and making better power flow by enhancing the voltage stability. The voltage stability index is used to find optimal location of the facts devices in the network. Voltage stability problems usually occur in heavily loaded systems. Nowadays the power demand increases enormously, hence in a large interconnected power system network subject stress condition. This situation can be handled by increasing the generation or reduce transmission losses. Through various uses of FACTS devices in transmission lines, the voltage stability profiles are maintained and by use of algorithms like PSO, GA, SFLA the voltage stability and the profile of the system has been improved in transmission lines.

Key words: Voltage Profile, Voltage Stability, UPFC, TCSC, SVC, STATCOM, Shuffled Frog Leap Algorithm (SFLA), Bacterial Foraging Algorithm (BFA), Genetic Algorithm (GA), Particle Swarm Optimization (PSO)

I. INTRODUCTION

Reactive power optimization is one of the difficult optimization problems in power system operation and control. To improve the voltage profile and to decrease the active power losses along the transmission lines under various operating conditions, power system operator can select a number of control tools such as switching reactive power sources, charging generator voltages and adjusting transformer tap settings. The multi-objective of this paper is to allocate reactive power sources so that the active power transmission loss is to be minimized and the voltage stability margin is to be maximized, while satisfying the number of constraints.

Reactive power optimization (RPO) is an important optimization process in terms of voltage stability, voltage quality and active power loss. The main object function in RPO is the total active power loss function, but in later years, systems were analyzed in terms of reactive supply costs and voltage profile.

Since voltage profile minimizes the deviations between the nominal and bus voltages, the reactive power transferred from the bus will decrease and the lines current will also decrease. As such, these provide supplements for the decrement of active power loss. The effects of the reactive power supplies connected to buses are quite important on reduction of active power loss. However, due to the installation, some extra equipment and devices costs like disjoncteur needs to be addressed from a different perspective. Based on this, cost functions are used in RPO, leading to a multi-objective function. This function is a non-linear function having a lot of variables and constraints. Firstly, this problem was solved with classical methods such as linear, non-linear, quadratic and dynamic programming. Since the problems have a lot of variables, constraints, different local minimum and the possibility of getting trapped in the local minimum, the meta-heuristic methods are preferred as the solution to these problems.

Consumption of electricity is increasing with economic development with deregulated electricity market. Power system stability is defined as the ability of a power system that enables it to remain in stable operating equilibrium under normal operating conditions and to regain an acceptable state of equilibrium after being subjected to a disturbance. Voltage stability depends on generator reactive power limit, load characteristics and transmission lines. The power system voltage is stable if voltages after disturbances are close to voltages at normal operating conditions. As the load varies, the reactive power requirements of the transmission system also vary. Since the reactive power cannot be transferred over long distances and losses also increases. The proper selection and location of the FACTS devices for controlling the reactive power and voltage are major challenges of power system. To overcome voltage instability and power losses, FACTS devices have been implemented in power system. Thus by implementing FACTS devices, the transmission losses were reduced which enhances the voltage profile. Optimization algorithms can be either deterministic or stochastic. The OPF methods are conventional and intelligent and solved by varieties of methods such as successive linear programming, Newton – based nonlinear programming method and with varieties such as recently proposed interior point methods. The use of optimization algorithms in transmission lines makes to know the maximum voltage profile place and through obtaining it, the FACTS devices are used to enhance the voltage profile. By incorporating FACTS devices with best optimal algorithms, the voltage stability enhancement is achieved.

Voltage Stability is becoming an increasing source of concern in stability operation of present day power systems. The problem of voltage instability is mainly considered as the inability of the network to meet the load demand imposed in terms of inadequate reactive power support or active power transmission capability or both. Voltage collapse is a local load bus problem and depends mostly on load conditions in the system. Thus the reactive power support and voltage problems are intrinsically related. Hence this paper formulates the reactive power optimization as a multi-objective optimization problem with loss minimization and voltage stability margin maximization objectives. The static voltage stability margin is primarily associated with the reactive power support. Several tools
have been presented in the literature for the analysis of the static voltage stability of a system.

II. PROBLEM FORMULATION

A multi-objective optimization problem consists of multiple objective functions with equality and inequality constraints to be optimized. The equality constraints represents the typical load flow equations.

A. Voltage stability index:

Voltage stability is an important problem to power system. Voltage Stability is evaluated at each bus of the system by an indicator, L index. At load bus j, L – index can be expressed as

\[ L_j = |L_j| = |1 - \frac{V_j}{V_i} + j\alpha L | \]

Where \( \alpha \) – set of load buses
\( V_j \) – complex voltage at load bus j
\( V_i \) – complex voltage at generator bus i
\( \alpha L \) – elements of matrix C which can be determined as

\[ [C] = [YLL]^{-1}[YLG] \]

The first objective function considering the minimization of Voltage stability Index can be represented as given

\[ F_1 = \text{Voltage Stability Index} = L_{\text{max}} \]

This analysis will be carried out only for the load buses; hence the index that to be obtained is for load buses only. For stability the index L must not be more than 1 for any of the nodes j. The global index for stability of the given power system is defined to be \( L = \text{maximum of Lj for all j (load buses)} \). The index far away from 1 and close to 0 indicates voltage stability. The L index will give the scalar number to each load bus. Among the various indices for voltage stability and voltage collapse prediction (i.e. far away from 1 and close to 1 or >1 respectively), the L index will give more accurate results. The L indices for given loads conditions are calculated for all load buses and the maximum of the L indices gives the proximity of the system to voltage collapse.

B. Power loss (MW):

The second objective function considering the minimization of real power loss can be expressed as,

\[ \sum_{i=1}^{n} P_{\text{loss}} = \sum_{i=1}^{n} \sum_{j=1}^{N} g_{i,j} (V_{i}^2 + V_{j}^2 - 2V_{i} V_{j} \cos(\delta_{i} - \delta_{j})) \]

Where \( V_{i,j} \) – voltage magnitude at bus \( g_{i,j} \) – conductance of line \( i-j \)
\( \delta_{i} \) – voltage angle at bus \( i \)
\( N_j \) – Total no of transmission lines

C. Fuel cost:

The third objective function considering minimization of cost of generation can be expressed as,

\[ F_3 = \min F(\text{Ph}) = \sum_{i=1}^{n} (a_{i} P_{\text{Gi}}^2 + b_{i} P_{\text{Gi}} + c_{i}) \]

Where \( P_{\text{Gi}} \) – Generated power of \( i^{th} \) generator
\( a_{i} \) – cost coefficient of \( i^{th} \) generator
\( b_{i} \) – cost coefficient of \( i^{th} \) generator
\( c_{i} \) – cost coefficient of \( i^{th} \) generator

D. Fitness function:

Considering all the three objective functions from (1) - (6) the Fitness Function(FF) is expressed as,

\[ F = h_1 F_1 + h_2 F_2 + h_3 F_3 \]

Where \( h_1, h_2 \) and \( h_3 \) are weighting factor of minimization of VSI objective function, weighting factor of power loss minimization objective function, weighting factor of generation cost minimization objective function.

\( h_1 F_1 + h_2 F_2 + h_3 F_3 = 1 \)

where \( h_1, h_2 \) and \( h_3 \) are coefficients. By trial and error method, they are optimized to 0.3, 0.3 and 0.4 for SVC and 0.35, 0.35 and 0.3 for TCSC by satisfying the above equation.

III. REVIEW USING FACTS DEVICE

A. Unified Power Flow Controller (UPFC)

The UPFC is a unique device that can provide simultaneous control of all basic power system parameters. The UPFC can independently and very rapidly control both real and reactive power flows in a transmission line. It can fulfill the functions of reactive shunt compensation, series compensation and phase shifting meeting multiple control objectives. UPFC has series and shunt connected converters. The UPSC can control the line’s real power and reactive power and bus voltage where it is connected, by proper injection of voltage magnitude in series and shunt respectively. Here the reactive power will be injected at the lines whenever required. The UPFC operates with constraints on the following variables such as the series – injected voltage magnitude; the line current through series converter; the shunt- converter current the minimum line – side voltage of the UPFC and the real power transfer between the series converter and the shunt converter.

The effect of controlled voltage Vs on system is,

\[ V_{i}^* = V_{s} + V_{i} \]

B. Thyristor Controlled Series Reactor (TCSC)

TCSC is series connected FACT device in which a capacitor is connected in transmission line and a parallel connection of thyristor controlled inductor with capacitor. The power flows in heavily loaded line can be reduced by TCSC through power flow control in the network. When the \( \omega L > 1/\omega C \), the reactance of the FC is less than that of the parallel connected variable reactor and that this combination
provides a variable capacitive reactance are both implied. Moreover, this inductor increases the equivalent capacitance reactance of the LC combination above that of the FC. In the variable capacitive mode of the TCSC, as the inductive reactance of the variable inductor is increased, the equivalent capacitive reactance is gradually decreased. The behaviour of the TCSC is similar to that of the parallel LC combination. The difference is that the LC combination analysis is based on the presence of pure sinusoidal voltage and current in the circuit, whereas in the TCSC, because of the voltage and current in the FC and thyristor – controlled reactor are not sinusoidal because of the thyristor switching.

Fig. 2: Basic model of TCSC

C. Static Var Compensator (SVC)

SVC is a VAR generator whose output is adjusted to exchange capacitive or inductive currents so as to maintain/ control bus voltage. SVC is combination of controllable shunt reactor and a shunt capacitor. The susceptance of SVC can be varied by varying firing angle of thyristor in range of 90° - 180°. The SVC slope substantially reduces the reactive power rating of the SVC for achieving nearly the same control objectives; prevents the SVC from reaching its reactive power limits too frequently; and facilitates the sharing of the reactive power among multiple compensators operating in parallel. When more than one compensator is used at one location, the control action must be coordinated. With additional balancing controls, exact load sharing can be attained. The SVC behaves like a controlled susceptance, and its effectiveness in regulating the system voltage is dependent on the relative strength of the connected ac system.

Fig. 3: Basic model of SVC

D. Static Compensator (STATCOM)

STATCOM is the voltage – source inverter which converts a DC input voltage into AC output voltage in order to compensate the active and reactive power needed by system. STATCOM exhibits constant current characteristics when voltage is low/high under/ over the limit. This allows STATCOM to deliver constant reactive power to system. A STATCOM is a controlled reactive power source. It provides the desired reactive power generation and absorption entirely by means of electronic processing of the voltage

Fig. 4: Basic structure of STATCOM

IV. REVIEW USING OPTIMIZATION ALGORITHM

A. Shuffled frog leap algorithm (SFLA)

The SFLA - based approach for solving the optimal placement and sizing of distributed generation problem to minimize the loss and improve the voltage profile takes the following steps: In SFLA, each possible solution Xi = (xi1, xi2, xi3,……, xiS) that in this paper Xi = l1, l2,……. lbus, x1, x2, ….. x power limit.Where,1 is the number of DG location candidates and x is the number of capacity types of DGs are considered as a frog. The steps of the algorithm are as follows:

- **Step - 1:** Create an initial population of P frogs generated randomly. SFLA population = [X1, X2,……, Xp] pxn where, p= mxn, N is the number of DG, m is the number of memplexes and n is the number of frogs in memplex.
- **Step - 2:** Sort the population increasingly and divide the frogs into m memplexes each holding n frogs such that P = mxn. The division is done with the first frog going to the first memplex, second one going to the second memplex, the mth frog to the mth memplex and the m+1th frog back to the first memplex. Below figure illustrates this memplex partitioning process.
and $X_b$ respectively. Also the frog with the global best fitness $X_g$ is identified, and then the position of the worst frog $X_w$ for the memplex is adjusted. Below figure demonstrates the original frog leaping rule. If the evolutions produce a better frog(solution), it replaces the older frog, otherwise $X_b$ is replaced by $X_g$ and the process is repeated. If no improvement becomes possible in this case a random frog is generated which replaces the old frog.

\[ \text{Fig. 6: The original frog leaping rule} \]

- **Step 3-5**: If $m > m_{\text{max}}$, return to Step 3-2. If $y_1 < y_{\text{max}}$, return to step 3-3, otherwise go to Step 2.
- **Step 4**: Check the convergence. If the convergence criteria are satisfied stop, otherwise consider the new population as the initial population and return to the step 2. The best solution found in the search process is considered as the output results of the algorithm. The flowchart of the SFLA is illustrated in below figure.

B. Particle Swarm Optimization (PSO):

PSO is a well known novel optimization method developed by Kennedy and Eberhart and is being used in different fields for optimization. $W$ can be calculated as:

\[ W = W_{\text{max}} - \frac{W_{\text{max}} - W_{\text{min}}}{x_{\text{iter}}} \]

The range of $W$ is 0.4 to 0.9. The steps to obtain optimal location is,

- **Step 1**: Initial searching points and velocities are randomly generated within their limits.
- **Step 2**: $P_{\text{best}}$ is set to each initial searching points. The best evaluated values among $P_{\text{best}}$ are set to $g_{\text{best}}$.
- **Step 3**: New velocities are calculated using equation

\[ V_g(t+1) = W + V_g(t) + C_1 \times \text{rand}(P_{\text{bestid}} - X_g(t)) + C_2 \times \text{rand}(g_{\text{bestid}} - X_g(t)) \]

- **Step 4**: If $V_g(t+1) < V_{\text{dmin}}$ then $V_g(t+1) = V_{\text{dmin}}$ and if $V_g(t+1) > V_{\text{dmax}}$, then $V_g(t+1) = V_{\text{dmax}}$.
- **Step 5**: New searching points are calculated using

\[ X_g(t+1) = X_g(t) + V_g(t+1) \]

- **Step 6**: Check capacity limits constraints

\[ P_{\text{bestid}}(t+1) > P_{\text{dmax}}, \text{then } P_{\text{bestid}}(t+1) = P_{\text{dmax}} \]

and

\[ P_{\text{bestid}}(t+1) < P_{\text{dmin}}, \text{then } P_{\text{bestid}}(t+1) = P_{\text{dmin}} \]

- **Step 7**: Evaluate fitness values for new searching point. If evaluated value of each agent is better than previous $P_{\text{best}}$ then set to $P_{\text{best}}$. If best $P_{\text{best}}$ is better than $g_{\text{best}}$ then set to $g_{\text{best}}$.
- **Step 8**: If maximum iteration is reached stop process otherwise go to step 3.

C. Bacterial Foraging Algorithm (BFA):

Foraging theory is based on the natural behavior of animal searching for their nutrient which maximize their energy for foraging [10]. This algorithm is based on the searching behavior of E.Coli bacteria. E.coli is a microorganism which has the nature of searching of food more quicker than other. Chemotaxis is the natural foraging behavior of bacteria, which helps to catch the required nutrient. Implementation of chemotaxis steps, the searching process are followed.

Let $j$ be the stepping rate of chemotaxis, $k$ be the reproduction step and $l$ be the index of elimination dispersal event. The length of life time of bacteria $N_c$ is measured by the number of chemotaxis steps. Bacteria swims in the free space to reduce loss, along with maximum number of steps $N_s$. Next to the chemotaxis reproduction is adopted. $N_r$ is the number of reproduction steps to be taken by bacteria for population sorting. In order to make increase of population of bacteria reproduction is carried out. This method provides bacteria with a lot of nutrients and also keeps the population size constant.

For initialization, you must choose $p$, $S$, $N_c$, $N_s$, $N_r$, $N_d$, $ped$, and the $C(i)$, $i = 1,2, K, S$. If you use swarming, you will also have to pick the parameters of the cell-to-cell attractant functions; here we will use the parameters given above. Also, initial values for the $\theta(i,i) = 1,2, K, S$ must be chosen. Choosing these to be in areas where an optimum value is likely to exist is a good choice. Alternatively, you may want to simply randomly distribute them across the domain of the optimization problem. The algorithm that models bacterial population chemotaxis, swarming, reproduction, elimination, and dispersal is given here (initially, $j = k = l = 0$). For the algorithm, note that updates to the $\theta(i,i)$ automatically result in updates to $P$. Clearly, we could have added a more sophisticated termination test than simply specifying a maximum number of iterations. Algorithm were as follows.

- **STEP 1**: Elimination-dispersal loop: $l = l + 1$
- **STEP 2**: Reproduction loop: $k = k + 1$
- **STEP 3**: Chemotaxis loop: $j = j + 1$

For $i = 1,2, K, S$, take a chemotactic step for bacterium $i$ as follows.

Compute $J(i,j,k,l) = J(i,j,k,l) + J_{cc}(\theta(i,j,k,l), p(j,k,l))$ (i.e., add on the cell-to-cell attractant effect to the nutrient concentration).

Let $J$ last = $J(i,j,k,l)$ to save this value since we may find a better cost via a run.

Tumble: Generate a random vector $\Delta(i) \in [−p, p]$ with each element $m(i), m = 1,2,K,p$, a random number on $[−1,1]$.

Move: Let

\[ \delta(i, j, k, l) = \delta(i, j, k, l) + C(i) \frac{\Delta(i)}{\sqrt{n_{(i, j, k, l)}}} \]

This results in a step of size $C(i)$ in the direction of the tumble for bacterium $i$.

Compute $J(i,j+1,k,l)$, and then let $J(i,j+1,k,l) = J(i,j+1,k,l)+J_{cc}(\theta(i,j+1,k,l), p(i,j+1,k,l))$.

Swim (note that we use an approximation since we decide swimming behavior of each cell as if the bacteria numbered $\{1,2,K,i\}$ have moved and $[i+1,i+2, K, S]$ have not; this is much simpler to simulate than simultaneous decisions about swimming and tumbling by all bacteria at the same time).

Let $m = 0$ (counter for swim length).

While $m < N_s$ (if not have climbed down to low enough) Let $m = m + 1$. 
If \( J(i,j+1,k,l) < J_{\text{last}} \) (if doing better), let \( J_{\text{last}} = J(i,j+1,k,l) \) and let
\[
\delta^j (j+1,k,l) = \delta^j (j+1,k,l) + C(i) \frac{\Delta(i)}{\sqrt{A^j (i) A(i)}}
\]
Else, let \( m = N_s \). This is the end of the while statement.

Go to next bacterium \((i + 1)\) if \( i \neq S\) (i.e., go to b) to process the next bacterium.

If \( j < N_c \), go to step 3. In this case, continue chemotaxis, since the life of the bacteria is not over.

1) Reproduction:

a) For the given \( k \) and \( l \), and for each \( i = 1,2,K, S \), let be the health of bacterium \( i \) (a measure of how much of nutrients it got over its lifetime and how successful it was at avoiding noxious substances). Sort bacteria and chemotaxis parameters \( (i) \) in order of ascending cost \( J_{\text{health}} \) (higher cost means lower health).

\[
\sum_{j=1}^{N_c+1} J(i,j,k,l)
\]

b) The Sr bacteria with the highest \( J_{\text{health}} \) values die and the other Sr bacteria with the best values split (and the copies that are made are placed at the same location as their parent).

- **STEP 4:** If \( k < N_e \), go to step 2. In this case, we have not reached the number of specified reproduction steps, so we start the next generation in the chemotaxis loop.

- **STEP 5:** Elimination-dispersal: For \( i = 1,2,K, S \), with probability \( p_{ed} \), eliminate and disperse each bacterium (this keeps the number of bacteria in the population constant). To do this, you eliminate a bacterium, simply disperse one to a random location on the optimization domain.

- **STEP 6:** If \( i \leq N_e \), then go to step 1; otherwise end.

D. Evolutionary Programming (EP)

EP is an artificial intelligence method which is an optimization algorithm based on the mechanics of natural selections-mutation, competition and evolution. The general process of EP is described in [L.L.Lai and J.T.Ma, 1997 ,Kalyanmoy Deb, 2001]. The procedure of EP for RPP is briefed as follows

- **Initialization:** The initial control variable population is selected randomly from \( P_i = [V_{P_i}^1, Q_{P_i}^1, T_{P_i}^1], i=1,2,........m \), where \( m \) is the population size, from the sets of uniform distribution ranging over \( [V_{\text{min}}^1, V_{\text{max}}^1], [Q_{\text{min}}^1, Q_{\text{max}}^1], [T_{\text{min}}^1, T_{\text{max}}^1] \). The fitness score is obtained by running Newton – Raphson power flow.

- **Statistics:** The values of maximum fitness, minimum fitness, sum of fitness and average fitness of this generation are calculated.

- **Mutation:** Each \( p_i \) is mutated and assigned to \( P_{i+m} \) in accordance with the following equation

\[
P_{i+m} = P_i + N[0, \beta (X_{\text{max}} - X_{\text{min}})] / f_{\text{max}}
\]

Where, \( P_{ij} \) denotes \( j^{\text{th}} \) element of the \( i^{\text{th}} \) individual. \( N(u, \sigma^2) \) represents a Gaussian random variable with mean \( u \) and variance \( \sigma^2 \); \( f_{\text{max}} \) is the maximum fitness of the old generation which is obtained in statistics, \( X_{\text{max}} \) and \( X_{\text{min}} \) are the maximum and minimum limits of the \( j^{\text{th}} \) element. \( \beta \) is the mutation scale which is given as \( 0 < \beta \leq 1 \). If any \( P_{i+m,j} \), \( j = 1,2,......n \), variables, exceeds its limit, where \( n \) is the number of control \( P_{i+m,j} \) will be given the limit value. The corresponding fitness \( f_{i+m} \) is obtained by running power flow with \( P_{i+m} \). A combined population is formed with the old generation and the mutated old generation.

- **Competition:** Each individual, \( P_i \) in the combined population has to compete with some other individuals to get its chance to be transcribed to the next generation.

- **Determination:** The convergence of maximum fitness to minimum fitness is checked. If the convergence condition is not met, the mutation and competition processes will run again.

V. RESULTS

In this paper an analysis of Voltage stability in the power system has been taken into account. Here the analysis is based upon incorporating various facts devices and optimization algorithms. The voltage magnitudes of various devices are given as follows and all the voltage magnitudes values are given in per unit (p.u).

A. By using Facts Devices

- UPFC - 1.0600 p.u
- TCSC - 0.9312 p.u
- SVC - 0.9417 p.u
- STATCOM - 0.9957 p.u

B. By using Optimization Algorithms

- SFLA - 0.98637 p.u
- BFA - 1.02998 p.u
- EP - 0.99999 p.u
- PSO - 1.08999 p.u

VI. CONCLUSION

In this paper incorporation of various optimization technique and facts devices to enhance the voltage stability in the power system has been reviewed. Through the optimization techniques the voltage stability in the transmission lines are improved such that the power flow can be enhanced in the system along with better improvement of voltage profile. The facts devices are used in the system on the transmission sector to inject the reactive power whenever the reactive deficiency is occurred due to this voltage profile has improved in a vast manner and voltage stability has been achieved. Still whenever the load is increased, the voltage profile will get affected severely and voltage stability starts decreasing and it can be overcome by incorporating Facts devices along with optimization techniques which is very much useful in improving voltage stability as well as the voltage profile of the power system network.
ACKNOWLEDGEMENT

I would like to express my greatest gratitude to the people who have helped & supported me throughout my journal paper. Special thanks for our chairman Mr.K.V.Raja, vice chairman Mr. A. Mohammed iylas, Secretary Mr.K.Shivram Alva. I extend my thanks to our Principal Dr.G.Mahendran, Vice Principal Prof.S.Matilda, Dean Placement Prof J.Asha, Head - Funded projects Prof P.Pugazhendiran, Head - Electrical & Electronics Engineering Prof P.Nammalvar.

I wish to thank my parents for their undivided support and interest who inspired me and encouraged me to go my own way, without whom I would be unable to complete my journal. At last but not the least I want to thank my friends who appreciated me for my work and motivated me and finally to God who made all the things possible.

REFERENCES