Ain Shams Engineering Journal (2014) 5, 789–801

Ain Shams University
Ain Shams Engineering Journal
www.elsevier.com/locate/asej
www.sciencedirect.com

ELECTRICAL ENGINEERING

Multi-Objective Genetic Algorithm for voltage stability enhancement using rescheduling and FACTS devices

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Received 7 June 2013; revised 27 March 2014; accepted 9 April 2014
Available online 27 May 2014

KEYWORDS
Generation rescheduling;
Voltage stability;
Multi-Objective Genetic Algorithm;
Fuzzy decision making;
FACTS

Abstract This paper presents the application of Multi-Objective Genetic Algorithm to solve the Voltage Stability Constrained Optimal Power Flow (VSCOPF) problem. Two different control strategies are proposed to improve voltage stability of the system under different operating conditions. The first approach is based on the corrective control in contingency state with minimization of voltage stability index and real power control variable adjustments as objectives. The second approach involves optimal placement and sizing of multi-type FACTS devices, Static VAR Compensator and Thyristor Controlled Series Capacitor along with generator rescheduling for minimization of voltage stability index and investment cost of FACTS devices. A fuzzy based approach is employed to get the best compromise solution from the trade off curve to aid the decision maker. The effectiveness of the proposed VSCOPF problem is demonstrated on two typical systems, IEEE 30-bus and IEEE 57 bus test systems.

1. Introduction

Due to economic and environmental constraints, power systems are being operated very near to loadability limit. The rapid increase in load and nonoptimal use of transmission lines adversely affect the stability of the power systems. Under this scenario, maintaining a stable and secure operation of power system is a very challenging issue. Therefore, voltage stability [1] is being regarded as one of the main concerns to maintain system security. Voltage stability is the ability of the power system to maintain acceptable voltage profile under normal conditions and even after being subjected to disturbances. Voltage collapse [2] is the process by which the system voltage falls to a low, unacceptable value as a result of an avalanche of events accompanying voltage instability. The approaches for voltage stability assessment can be classified into static and dynamic approaches. Static voltage stability assessment is suitable for operational scheduling problems. In this work, L-index [3] one of the static voltage stability index is used for assessing voltage stability of the system.

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Peer review under responsibility of Ain Shams University.

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http://dx.doi.org/10.1016/j.asej.2014.04.004

Voltage security enhancement can be achieved through preventive or corrective control. Preventive control is applied so as to ensure that operating point is away from point of collapse in anticipation of incredible contingencies. The corrective control action on the other hand is activated only when the contingency has occurred endangering voltage stability. Corrective control is considered as economic one in the market environment, nevertheless preventive control is also needed to reduce system interruption. In this paper, Optimal Power Flow (OPF) is used for corrective strategies by determining the optimal settings of control variables to minimize generation cost in the transmission system. OPF [4–8] is a large scale, nonconvex, nonlinear static optimization problem with both discrete and continuous variables. To achieve voltage security enhancement, the contingency state voltage stability index is included **as** additional constraint in the formulation of OPF problem [9–11] along with the contingency state constraints. Generation rescheduling [12,13] is necessary to change the real power settings of the generators in contingency state to improve the voltage stability of the system. The generator ramp rates can significantly restrict the speed with which the active power is rerouted in the network. Monticelli et al. [14] describe mathematical programming techniques that allow the iterative solution of economic dispatch and separate contingency analysis with generation rescheduling to eliminate constraint violations. In [15], generation rescheduling was taken to change the system operating conditions to ensure voltage security margins of contingencies above certain minimal value with a multi-contingency sensitivity based approach. Abido [16] proposed an effective scheme involving generation rescheduling by minimizing the real power control variable adjustments for VAR dispatch problem. Mohapatra et al. [17] proposed coordinated preventive and corrective rescheduling actions attempt to make the system correctively secure with respect to line and generator outages. In contingency state, by including voltage stability index in the objective function, voltage stability is achieved at the expense of operating costs. This increase in operating costs can be reduced by generation rescheduling in contingency states. Hence, one of the objectives in the security enhancement problem is to minimize the deviation of control variables in the contingency state from the base case value. To ensure voltage security of the system, Flexible AC Transmission Systems (FACTS) [18] devices based on power electronics technology are a good choice due to their fast and flexible control. A proper co-ordination between FACTS devices and conventional power system control devices is essential to make system voltage secure in addition to economical aspects. However, to obtain good performance from these controllers, proper placement and sizing [19,20] of these devices is crucial. In practical system, suitable allocation of FACTS devices depends on system stability and other factors such as installation cost and conditions also need to be considered [21,22]. In [21], both technical and economic benefits arising from the installation of FACTS devices with the emphasis on generator cost reduction is carried out by solving GA based OPF procedure. Saravanan et al. [23] proposed the application of PSO technique for optimal placement and sizing of FACTS devices with minimum cost of installation and to improve system loadability. Phadke et al. [24] proposed fuzzy performance index based on fuzzy logic and real coded GA to determine the optimal placement and sizing of FACTS devices. This paper investigates modal analysis method [25] to find the optimal location of multi-type FACTS devices namely: SVC and TCSC to enhance voltage stability and reduce system losses considering investment cost of these devices. The issue of optimal settings of the FACTS devices is formulated as an optimization problem taking into account the installation cost along with voltage security enhancement. In this paper, traditional OPF problem is extended to include multi-type FACTS devices for improvement in system stability. This objective along with FACTS investment cost has not been reported in many literatures. Hence in this paper, rescheduling of generators by minimizing the deviation of real power control variables is considered as the other objective in addition to the FACTS installation cost.

In this paper, a new solution method for VSC-OPF problem including FACTS devices taking into account the issues mentioned above is formulated as multi-objective optimization problem and is addressed through two approaches. Firstly, the problem is formulated in corrective control considering minimization of real power control variable adjustment and voltage stability index, L-index in the postcontingency state. Secondly, the problem is investigated in suitable control actions with minimization of investment cost of FACTS devices and voltage stability index along with generation rescheduling.

The OPF problem based on mathematical programming techniques such as linear programming [4], nonlinear programming [5], quadratic programming [6], Newton method [7] and Interior point method [8] in solving large scale problems are not guaranteed to converge to global optimum. Also, the discrete variables related to the tap changing transformer and shunt capacitors cannot be incorporated directly into the general Optimal Power Flow problem. Recently, evolutionary computation techniques such as Genetic Algorithm [26] and Evolutionary Programming [27] have been successfully applied to solve the OPF problems. Evolutionary computation techniques do not require any space limitations such as smoothness, convexity or unimodality of the function to be optimized. They are not largely affected by the size and nonlinearity of the problem, and they can perform well in highly constrained and integer (or mixed integer) optimization problems. This feature makes it suitable for many real world applications including the OPF problem.

This paper proposes Multi-Objective Genetic Algorithm (MOGA) [28] which produces multiple solutions in one single simulation run for solving this complex multi-objective optimization problem. Generally, binary strings are used to represent the decision variables of the optimization problem in the genetic population irrespective of the nature of decision variables. This binary coded GA has hamming cliff problems [29,30] which sometimes causes difficulties in the case of coding continuous variables. Also, for discrete variables with total number of permissible choices not equal to 2^k (k is an integer) it becomes difficult to use fixed length binary coding to represent all permissible values. To overcome the above difficulties, the control variables namely generator active power settings (P_{gi}), generator voltage settings (V_{gi}) are represented as floating point numbers and variable settings of SVC and TCSC (SVC_i and $TCSC_i$) and transformer tap settings (Tap_i) are represented as integers in the genetic population.

2. Modeling and placement of FACTS devices

It is desirable to install series controller in the line where active power control is needed, and shunt controller in buses where reactive power control is needed to support the voltage. This paper focuses on the optimal location and settings of SVC and TCSC for voltage security enhancement.

2.1. Mathematical model of SVC and TCSC

SVC is a shunt Compensator and is modeled as series capacitor bank shunted by thyristor controlled reactor as shown in Fig. 1. It can be used for both inductive and capacitive compensation. In this work, SVC is modeled as ideal reactive power injection at bus i:

$$\Delta Q_i = Q_{svc} \tag{1}$$

The SVC has an operating range between −200 MVAR and 200 MVAR and a reference voltage between 0.95 pu and 1.05 pu.

TCSC is a Series Compensator which consists of series capacitor shunted by Thyristor controlled reactor as shown in Fig. 2. It acts as the capacitive or inductive compensator by modifying the reactance of transmission line. In this work, TCSC is modeled by changing transmission line reactance as follows:

$$X_{ij} = X_{line} + X_{TCSC} \tag{2}$$

$$X_{TCSC} = r_{TCSC} \cdot X_{line} \tag{3}$$

where X_{line} is the reactance of transmission line, r_{TCSC} is the degree of compensation of TCSC.

The level of applied compensation of TCSC varies from 20% inductive and 80% capacitive.

2.2. Placement of FACTS devices

The suitable locations of SVC and TCSC are determined using Modal Analysis [25]. The modal analysis technique provides indications of system conditions with voltage stability problems. In this approach, the location of system buses and branches that have the most effect on the critical modes are identified based on system reduced Jacobian matrix under contingency conditions. The locations of buses and branches are identified using participation factor which are computed using the right and left eigenvectors of the Jacobian corresponding to the zero eigenvalue at the nose point. The size of bus participation in a given mode indicates the effectiveness of remedial action applied at that bus in stabilizing the mode. Branch participation indicates the elements which are critical to the stability of a given mode. A candidate data set is decided, related to the highest participation factors of buses and transmission lines in the system in which the shunt and series FACTS controllers are placed which have the highest bus and branch participation factors.

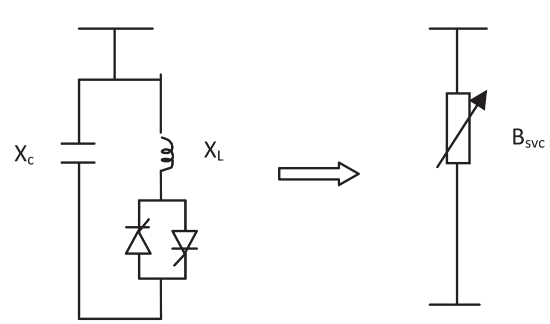

Figure 1 Static VAR Compensator (a) basic structure (b) model.

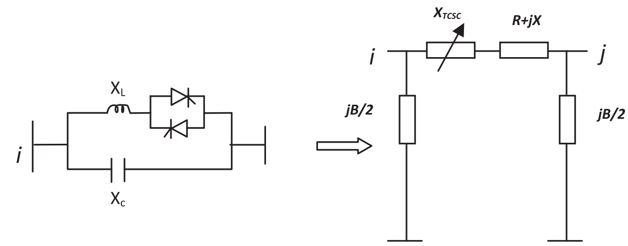

Figure 2 Thyristor Controlled Series Compensator (a) basic structure (b) model.

3. Problem formulation

In this work, the voltage stability enhancement problem is addressed through corrective control strategy. Under this strategy, two different cases are considered. In the first case, minimization of real power control variable adjustment in postcontingency state from base case value and voltage stability index, $L_{\max}$ in the contingency states under stressed conditions are taken as objectives of the optimization problem. In the second case, the minimization of investment cost of FACTS devices and voltage stability index, $L_{\max}$ in the contingency states under stressed conditions along with generation rescheduling are considered as objectives. The above different combinations of objectives for voltage stability enhancement are carried out satisfying system equality and inequality constraints.

3.1. Objective functions

3.1.1. Minimization of voltage stability index, L_{max}

L-index method [3] is an approximate measure of closeness of the system to voltage collapse. The bus with the highest L index value will be the most vulnerable bus in the system. The L-indices for a given load condition are computed for all the load buses and the maximum of the L-indices ($L_{\max}$) gives the proximity of the system to voltage collapse. The L-index has an advantage of indicating voltage instability proximity of current operating point without calculation of the information about the maximum loading point. Hence the minimization of L-index makes the system less prone to voltage collapse. The calculation of L-index is given in Appendix A.

3.1.2. Minimization of real power control variable adjustment

While enhancing the voltage security of the system, it is preferred to have minimum deviation of the generator real power from the base value. This is stated as,

$$F_C = \sum_{i=1}^{N_c} w_i \left(\frac{u_i - u_i^0}{u_i^{\max} - u_i^{\min}} \right) \tag{4}$$

where N_c is the number of control variables, u_i and u_i^0 are the new and initial settings of the ith control variable respectively, w_i is the weighting factor to reflect the relative cost of the ith control variable, $u_i^{\max}$ and $u_i^{\min}$ are the maximum and minimum limits of the ith control variable.

3.1.3. Minimization of FACTS Investment cost

It is important to take the economical aspects of the TCSC devices installed in the power system due to high investment and operating costs. Using database of [31], cost function of SVC and TCSC are modeled as follows:

$$C_{SVC} = 0.0003s^2 - 0.3051s + 127.38\ (\text{US\$/kVAr}) \tag{5}$$

$$C_{TCSC} = 0.0015s^2 - 0.713s + 153.75\ (\text{US\$/kVAr}) \tag{6}$$

where s is the operating range of the FACTS devices in kVAr and C_{svc} and C_{TCSC} are in US$/kVAr

3.2. System constraints

3.2.1. Equality constraint

The real and reactive power balance equations are:

$$P_i - V_i \sum_{j=1}^{N_B} V_j (G_{ij}\text{Cos}\theta_{ij} + B_{ij}\text{Sin}\theta_{ij}) = 0, \quad i = 1,2,\ldots N_{B-1} \tag{7}$$

$$Q_i - V_i \sum_{j=1}^{N_B} V_j (G_{ij}\text{Sin}\theta_{ij} - B_{ij}\text{Cos}\theta_{ij}) = 0, \quad i = 1,2,\ldots N_{PQ} \tag{8}$$

3.2.2. Inequality constraints

AVR constraint:

$$V_i^{\min} \le V_i \le V_i^{\max} \quad i \in N_B \tag{9}$$

Generator reactive power generation constraint:

$$Qg_i^{\min} \le Qg_i \le Qg_i^{\max} \quad i \in N_g \tag{10}$$

Reactive power generation constraint of capacitor banks

$$Q_{Ci}^{\min} < Q_{Ci} \le Q_{Ci}^{\max} \quad i \in N_C \tag{11}$$

Transformer tap setting constraint:

$$t_k^{\min} \le t_k \le t_k^{\max} \quad k \in N_T \tag{12}$$

Transmission line flow constraint:

$$S_l \le S_l^{max} \qquad l \in N_l \tag{13}$$

Reactive power constraint of SVC

$$-200\,\text{MVAR} < Q_{\text{SVC}i} \le 200\text{MVAR} \quad i \in N_{SVC} \tag{14}$$

Reactance constraint of TCSC

$$-0.5\,X_L < X_{\text{TCSC}i} < 0.5X_c \qquad i \in N_{TCSC} \tag{15}$$

The above conflicting objectives are considered in the proposed approach of VSC-OPF problem and are solved using Multi-Objective Genetic Algorithm.

4. Multi-Objective Genetic Algorithm

An optimization problem in which more than one objective is involved is called as multi-objective optimization problem. A Multi-Objective optimization Problem (MOP) can be mathematically stated as,

$$\text{Min}\, F(x) = [f_1(x), \ldots f_m(x)] \tag{16}$$

Subject to:

$$g_j(x) = 0 \quad j = 1, \ldots M$$
$$h_k(x) \leqslant 0 \quad k = 1, \ldots K$$

where $F(x)$ consists of m conflicting objective functions, x is the decision vector, g_j is the jth equality constraint and h_k is the kth inequality constraint.

The improvement of one objective may lead to deterioration of another. Thus, a single solution that can optimize all objective functions does not exist. The best trade-offs solutions called the pareto optimal solutions can be obtained using Evolutionary Algorithms.

Genetic Algorithms (GA) [32] are generalized search algorithms based on the mechanics of natural genetics. A population of candidate solutions or individuals is maintained and they are made to compete with each other for survival. They combine solution evaluation with stochastic genetic operators namely, selection, crossover and mutation to obtain optimality. Being a population based approach, GAs are well suited to solve multi-objective optimization techniques. MOGA [33] was the first multi-objective GA that explicitly used pareto based ranking and niching techniques together to encourage the search toward the true pareto front while maintaining diversity in the population. The flowchart of MOGA is shown in Fig. 3. The details of MOGA are explained below:

The main difference between classical GA and MOGA resides in the assignment of fitness. Once fitness has been assigned, selection can be performed and genetic operators are applied as usual. To a solution i, a rank equal to one plus the number of solutions η_i that dominate solution i is assigned:

$$r_i = 1 + \eta_i \tag{17}$$

The rank one is assigned to nondominated solutions since no solution would dominate a nondominated solution in a population. After ranking, raw fitness is assigned to each solution based on its rank by sorting the ranks in ascending order of magnitude. Then, a raw fitness is assigned to each solution by linear mapping function. Thereafter, solutions of each rank are considered at a time and their averaged raw fitness are called assigned fitness. Thus the mapping and averaging procedure ensures that the better ranked solutions have a higher assigned fitness. To maintain diversity in the population, niching is introduced among solutions of each rank. The niche count is calculated by summing the sharing function value as below:

$$nc_i = \sum_{j=1}^{\mu(r_i)} Sh(d_{ij}) \tag{18}$$

where $\mu(r_i)$ is the number of solutions in a rank and $Sh(d_{ij})$ is the sharing function value of two solution i and j.

The sharing function is calculated by using objective function as distance metric as:

$$Sh(d_{ij}) = \left\{ \begin{array}{cc} 1 - \left(\frac{d_{ij}}{\sigma_{share}}\right)^{\alpha} & \text{if } d \leqslant \sigma_{share} \\ 0 & \text{otherwise} \end{array} \right\} \tag{19}$$

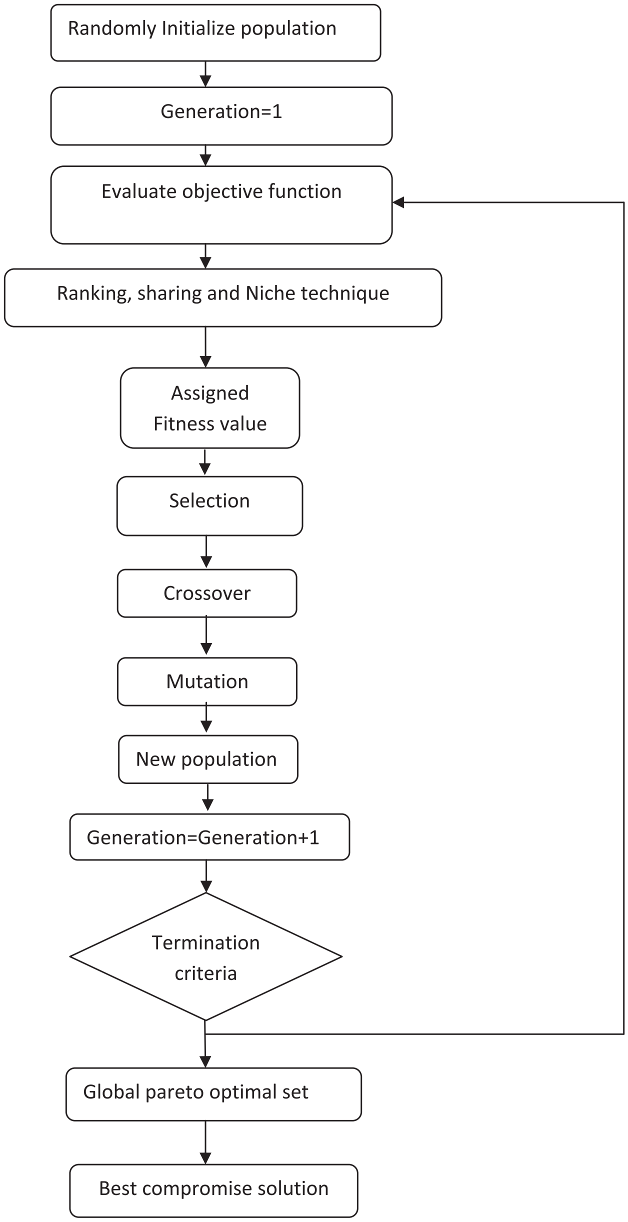

Figure 3 Flowchart of MOGA.

The parameter d is the distance between any two solutions in the population and σ_{share} is the sharing parameter which signifies the maximum distance between any two solutions before they can be considered to be in the same niche. The above function takes a value in $[0,1]$ depending on the values of d and σ_{share}. If $\alpha = 1$ is used, the effect linearly reduces from one to zero.

The normalized distance between any two solutions can be calculated as follows:

$$d_{ij} = \sqrt{\sum_{k=1}^{M}\left(\frac{f_k^{(i)} - f_k^{(j)}}{f_k^{\max} - f_k^{\min}}\right)^2} \tag{20}$$

where $f_k^{\max}$ and $f_k^{\min}$ are the maximum and minimum objective function value of the kth objective.

In MOGA, the shared fitness is calculated by dividing the fitness of a solution by its niche count. Although all solutions of any particular rank have the identical fitness, the shared fitness value of each solution residing in less crowded region has a better shared fitness which produces a large selection pressure for poorly represented solutions in any rank.

As the fitness of the solution is reduced by dividing the assigned fitness by the niche count, to keep the average fitness of the solutions in a rank same as before sharing, the fitness values are scaled. This procedure is continued until all ranks are processed. Thereafter, tournament selection, BLX-α crossover [29] and nonuniform mutation operators are applied to create a new population.

4.1. Best compromise solution

It is often practical to choose one solution from all solutions that satisfy different goals after the pareto optimal set is obtained. Due to imprecise nature of the Decision Maker's (DM) judgement, it is natural to assume that the DM may have fuzzy or imprecise nature of goals of each objective function. Hence in this work, a technique based on fuzzy set theory [34] was applied to extract the best compromise solution. Using linear membership function, a membership function is assigned for each objective functions and is defined as follows:

$$\mu_i = \begin{cases} 1, & F_i \geqslant F_i^{\max} \\ \frac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}}, & F_i^{\min} < F_i < F_i^{\max} \\ 0, & F_i \leqslant F_i^{\min} \end{cases} \tag{21}$$

where $F_i^{\max}$ and $F_i^{\min}$ are the maximum and minimum value of the ith objective function among all non-dominated solutions. The above equation gives a degree of satisfaction for each objective function for a particular solution and maps the objectives in the range of 0 to 1.

The membership function for the nondominated solutions in a fuzzy set is calculated as follows:

$$\mu^k = \frac{\sum_{i=1}^{N_{obj}} \mu_i^k}{\sum_{k=1}^{M}\sum_{i=1}^{N_{obj}} \mu_i^k} \tag{22}$$

where M is the number of nondominated solutions and N_{obj} is the number of objectives. Finally, the best compromise solution is the one achieving the maximum membership function.

5. Results and discussion

The proposed voltage stability enhancement technique is implemented on IEEE 30 bus and IEEE 57 bus test systems and the results are presented. The generators are modeled as PV buses with reactive power limits and the loads are represented by constant PQ loads. The power system is stressed by including the concept of $(N-1)$ contingency analysis and increase in load. $(N-1)$ contingency analysis is performed considering the outage of lines and selecting the worst contingency based on voltage stability index, $L_{\max}$.

The IEEE 30 bus system [35] consists of 6 generators, 24 loads and 4 transformers with off nominal tap ratio and 41 transmission lines. The lower voltage magnitudes at all buses are 0.95 pu for all buses and the upper limits are 1.1 pu for

Table 1 Simulation Results for MOGA- bi objective optimization under corrective control including generation rescheduling considering contingency (28–27)(125% loaded condition).

Control variables		Best minimum control variable adjustment	Best Lmax	Best compromise solution
Real power settings of generators in base case, Pvar	P1	160.2856	162.7092	160.7757
	P2	68.4705	68.8223	68.4143
	P5	34.6984	34.655	34.6833
	P8	19.9052	19.9145	19.8544
	P11	21.5204	21.3407	21.5119
	P13	23.2622	21.6196	22.9246
Real power settings of generators in contingency case, Pcvar	Pc1	160.2599	160.9576	162.2478
	Pc2	67.921	68.3289	67.924
	Pc5	34.4509	34.4554	34.3977
	Pc8	20.0776	20.1719	20.4179
	Pc11	22.2114	26.2394	23.931
	Pc13	23.6058	23.6195	23.6148
Generator voltage magnitudes, Vvar	V1	1.0457	1.0457	1.0457
	V2	1.0319	1.0384	1.0369
	V5	1.0197	1.0207	1.0197
	V8	1.0227	1.0229	1.0228
	V11	1.0999	1.0998	1.0999
	V13	1.0998	1.0998	1.0997
Transformer Tap settings, Tvar	T6-9	1.075	1.075	1.075
	T6-10	0.9	0.9	0.9
	T4-12	0.95	0.95	0.95
	T28-27	0.925	0.925	0.925
Settings of shunt capacitors, Cvar	Qc10	4	4	4
	Qc12	2	2	2
	Qc15	4	4	4
	Qc17	5	5	5
	Qc20	5	5	5
	Qc21	4	4	4
	Qc23	5	5	5
	Qc24	5	5	5
	Qc29	1	1	1
	Objective values			
Lmax		0.517	0.5152	0.5155
Transmission loss (MW)		9.89	10	9.88
Minimum control variable Adjustment		0.2457	1.1953	0.6541

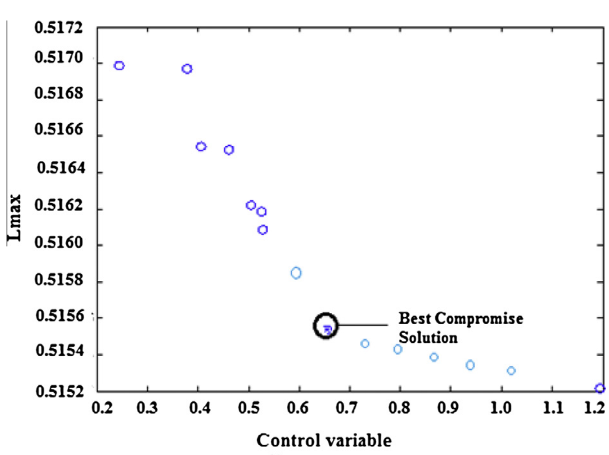

Figure 4 Pareto optimal front of MOGA under corrective control including generation Rescheduling under line outage (28–27) in Case 30 (125% loaded condition).

generator buses and 1.05 pu for remaining buses. The active and reactive powers of system load are 283.4 MW and 126.2 MVAR respectively. As a preliminary computation, the $(N-1)$ contingency analysis is carried out. According to these results, the line outage (28–27) is the most severe contingency in IEEE 30 bus system.

The IEEE 57-bus system [36] was chosen as the second test system to demonstrate the method's usefulness on a large system. IEEE 57-bus system has 4 generators, 3 synchronous condensers, 50 load buses, 80 transmission lines and 16 tap changing transformers. From the contingency analysis, line outage (46–47) is found to be the most severe case with the $L_{\max}$ value of 0.4598. The simulation studies were carried out on Pentium IV, 2.4 GHz system in MATLAB 7.1 environment.

Case 1: Corrective control using generation rescheduling:

In this case, power generation rescheduling is carried out to get more reduction in power flows and hence increase in system security and reliability. The two objective functions considered here are as follows: minimization of L-index and minimization of deviation in real power adjustments control variables from base case to contingency state. The generation cost function is minimized than the approach without generation rescheduling to obtain more economical corrective control action. In the first approach of corrective control including generation rescheduling, the decision variables are real power settings of generators (P_{gi}) and post-contingency state (P_{gc}), voltage magnitudes of generators (V_{gi}), tap settings of transformers (T_{ci}), reactive power settings of capacitor banks (Q_{ci}). The operating range of transformer is between 0 and 8 with step size equal to 0.025 and the capacitor is in the range of 0–5 MVAR. The best solutions of L-index and control variable adjustment optimized individually for IEEE 30 bus system in line outage (28–27) under 125% loaded condition are presented in Table 1. Further, from the fuzzy decision making strategy, the best compromise solution in the overall nondominated solutions is also presented. This demonstrates the effectiveness of the proposed approach as the best solutions of both objectives

Table 2 Simulation Results for MOGA-bi objective optimization under corrective control in case 57 bus system considering contingency (46–47) (150% loaded condition) along with generation rescheduling.

Control variables		Best minimum control variable adjustment	Best Lmax	Best compromise solution
Real power settings of generators in base case, Pvar	P1	480.5551	436.0265	484.2221
	P2	35.0571	35.166	35.1026
	P3	81.5087	107.9117	88.6669
	P6	95.7824	94.7868	95.4347
	P8	361.9684	379.8003	353.4883
	P9	61.0622	60.712	60.1716
	P_{12}	168.2129	168.1368	167.46
Real power settings of generators in contingency case, Pcvar	Pc1	518.7482	514.66	514.6214
	Pc2	34.4832	33.8825	34.3387
	Pc3	49.2665	56.6855	51.8811
	Pc6	65.972	32.2915	87.4182
	Pc8	378.5356	378.5378	378.5533
	Pc9	62.3541	78.7796	62.0098
	Pc_{12}	188.036	396.5799	290.4687
Generator voltage magnitudes, Vvar	V1	1.0464	1.0465	1.0465
	V2	1.0193	1.0188	1.0192
	V3	1.0036	1.0036	1.0036
	V6	1.009	1.0095	1.0087
	V8	1.0151	1.0151	1.0151
	V9	0.9838	0.9838	0.9838
	V_{12}	0.9889	0.9891	0.9889
Transformer Tap settings, Tvar	$T_{4–18}$	1.1	1.1	1.1
	$T_{21–20}$	0.9	0.9	0.9
	$T_{24–25}$	1.1	1.1	1.1
	$T_{24–26}$	0.95	0.95	0.95
	$T_{28–29}$	0.95	0.95	0.95
	$T_{34–35}$	1.1	1.1	1.1
	$T_{22–38}$	0.9	0.9	0.9
	$T_{38–44}$	0.975	0.975	0.975
	$T_{15–45}$	1.05	1.05	1.05
	$T_{14–46}$	1.025	1.025	1.025
	$T_{10–51}$	0.95	0.95	0.95
	$T_{13–49}$	1.025	1.025	1.025
	$T_{11–43}$	0.975	0.975	0.975
	$T_{40–56}$	0.9	0.9	0.9
	$T_{39–57}$	0.95	0.95	0.95
	$T_{9–55}$	0.975	0.975	0.975
Capacitor settings, Cvar	$Cvar_{30}$	1	1	1
	$Cvar_{32}$	3	3	3
	$Cvar_{31}$	2	2	2
	$Cvar_{33}$	3	3	4
		4	3	3
	Objective values			
Minimum control variable adjustment		4.89	18.08	9.5123
Lmax		0.58	0.42	0.45
Transmission loss (MW)		12.29	11.26	12.2

along with a set of nondominated solutions can be obtained in a single run. Fig. 4 depicts the pareto optimal set of case 1 for IEEE 30 bus system. It can be seen that MOGA is more efficient in the point of optimality and distribution of solutions in the trade-off surface. From the best compromise solution, it is worth mentioning that the inclusion of power generation rescheduling in the VSC-OPF problem considerably reduces the production cost by 16.5% in the severe contingency state and L-index by 35% than before optimization.

Similarly in IEEE 57 bus test system, postcorrective control strategy is followed in which the system is 150% overloaded and severe line (46–47) is out of service. Table 2 presents the optimal control settings of VSC-OPF problem including generation rescheduling in corrective control strategy. From this table, it is clear that MOGA has reduced the generation rescheduling cost by 23% and L-index by 45% thereby improving the voltage profile of the system and also considerable reduction in operating cost. Thus by reducing the voltage stability index, the transmission losses are also reduced in the post-contingency condition. The voltage violations that were observed in load buses before optimization have also been corrected after the application of the proposed methods. Fig. 5 depicts the pareto optimal front obtained with voltage stability index and real power control variable minimization for IEEE 57 bus system. The best compromise solution of L_{max} and real power adjustments obtained are 0.45 and 8.51 which shows 46% reduction in L-index and 26% reduction in control variable adjustment. The best compromise is almost close to the optimized values with single objective approach. The pareto optimal front of MOGA for this system presented in Fig. 5 clearly states that search space is well explored by the proposed approach.

Case 2: Corrective control using FACTS devices and generation rescheduling:

The problem was handled as a multi-objective problem where both investment cost of FACTS devices and voltage stability index were optimized simultaneously with the proposed optimization techniques. To reduce the number of location of FACTS devices, computation based on modal analysis was performed to rank the buses and branches according to

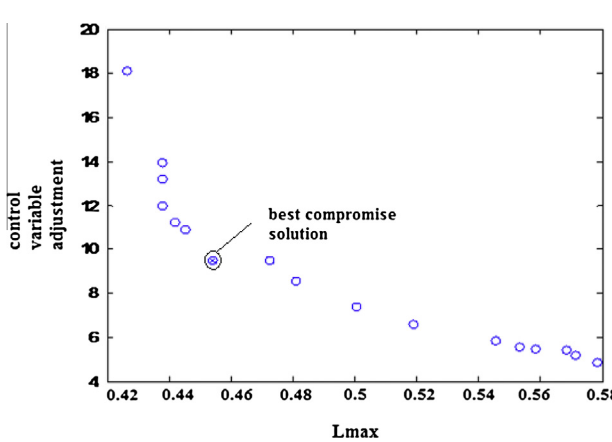

Figure 5 Pareto optimal front of MOGA under corrective control including generation Rescheduling under line outage (46–47) in Case 57 (150% loaded condition).

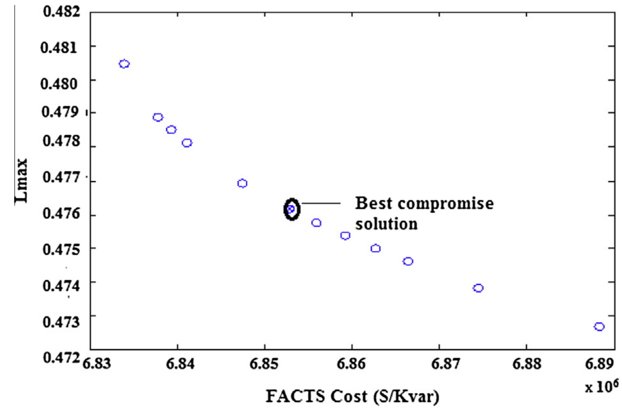

Figure 6 Pareto optimal front of MOGA under corrective control including FACTS devices along with including generation rescheduling under line outage (28–27) in Case 30 (125% loaded condition).

their participation factors out of which best candidate buses and critical lines were selected to site new multi-type FACTS devices namely, SVC and TCSC. In order of priority, the bus candidates for SVC are load buses 30, 29 and 26 while the line candidates to site TCSC are 24–26, 27–29 and 24–25 in IEEE 30 bus system. In the second approach of corrective control approach including generation rescheduling with FACTS devices, the decision variables in the system are real power settings of generators (P_{gi}) and post-contingency state (P_{gc}), voltage magnitudes of generators (V_{gi}), reactive power settings of FACTS devices namely, SVC (SVC_i) and TCSC ($TCSC_i$). The optimal location of SVC and TCSC are decided by modal analysis method. The reactance of TCSC is considered as a continuous variable which varies between 20% inductive and 80% capacitive of the line reactance. Similarly, the SVC is considered as a generator (or absorber) of reactive power which varies continuously between −200 MVAR and 200 MVAR. All MOGA algorithms ran with the population size of 50, generations of 150, crossover probability of 0.9 and mutation probability of 0.015 in two test systems. Fig. 6 shows the pareto-optimal set of corrective control including FACTS devices with generation rescheduling in IEEE 30 bus system. It can be seen that the obtained solutions are well distributed on trade-off surface, except some discontinuity, caused by the discrete decision variables. From this figure, we confirm the superiority of the proposed method, MOGA in point of view of well distribution and optimality of solutions. The optimal solution of each objective and the extreme points given by MOGA in first system are presented in Table 4. The comparison of the extreme points obtained for L-index and installation cost of FACTS devices is almost the same and hence it is concluded that the proposed optimization techniques are robust. From the best compromise solution in Table 3, the maximum L-index has decreased from 0.5155 to 0.4762, a reduction of about 39% and the minimum voltage of the system have been increased from 0.7118 to 0.9674, an improvement of about 26% has been obtained by proposed approach. The voltage profile improvement in the load buses after the inclusion of FACTS devices in IEEE 30 bus system is shown in Fig. 7. Most of the voltage violations buses are eliminated by the installation of multi-type FACTS devices.

Table 3 Simulation Results for MOGA-bi objective optimization under corrective control with FACTS devices considering contingency (28–27) (125% loaded condition) along with generation rescheduling.

Control variables		Best FACTS cost ($/Kvar)	Best Lmax	Best compromise solution
Real power settings of generators in base case, Pvar	P1	128.1	128.04	128.07
	P2	74.58	77.36	76.78
	P5	45.29	44.07	45.61
	P8	31.23	31.01	31.64
	P11	29.85	29.85	29.85
	P13	38.14	38.32	38.14
Real power settings of generators in contingency case, Pcvar	Pc1	137.25	141.76	132.22
	Pc2	69.97	69.83	69.98
	Pc5	42.11	42.11	42.11
	Pc8	33.01	33.4	33.08
	Pc11	26.28	24.39	24.49
	Pc13	32.89	32.75	32.90
Generator voltage magnitudes, Vvar	V1	1.0299	1.0299	1.0299
	V2	1.0137	1.0136	1.0137
	V5	0.9812	0.9811	0.9812
	V8	0.9896	0.9896	0.9897
	V11	1.0608	1.0811	1.0724
	V13	1.0357	1.0357	1.0357
Transformer Tap settings, Tvar	T6-9	1	1	1
	T6-10	0.925	0.925	0.925
	T4-12	0.95	0.95	0.95
	T28-27	1	1	1
SVC settings, SVC	SVC_{30}	0.2416	0.2416	0.2416
	SVC_{29}	1.5541	1.5541	1.5541
	SVC_{26}	0.7118	0.7118	0.7118
TCSC settings, TCSC	$TCSC_{24–26}$	0.0382	0.0382	0.0382
	$TCSC_{27–29}$	−0.5	−0.5	−0.5
	$TCSC_{24–25}$	−0.2216	−0.2216	−0.2216
	Objective values			
FACTS cost ($/h)		6.8339×10^6	6.8882×10^6	6.8529×10^6
Lmax		0.4805	0.4727	0.4762
Transmission loss (MW)		8.59	8.55	8.56
Minimum control variable adjustment		2.4	2.94	2.72

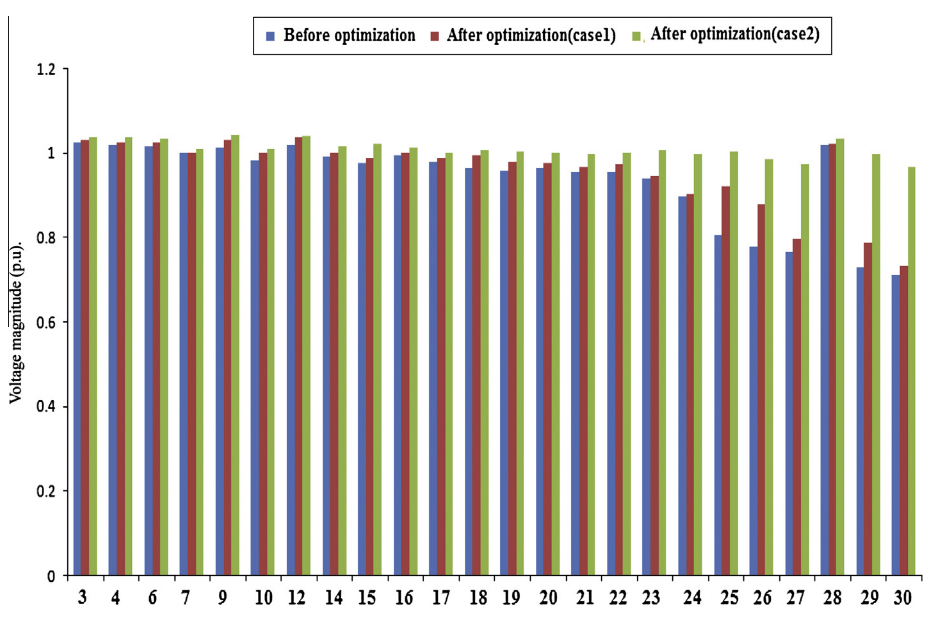

Figure 7 Voltage profile improvement in case 30 for (28–27) line outage (125% loaded condition).

The extreme points of pareto optimal front by MOGA and the best solutions of each functions optimized individually by GA are identical which is given in Table 4. Hence it is verified that the proposed method is capable of exploring more efficient search space. With the proposed method, it is observed that MOGA gives better optimization thereby improving the voltage stability of the system.

In IEEE 57 bus test system, according to modal analysis method, the best locations for installing TCSCs are: lines connected between 14–46, 13–49 and 44–45 and the best three locations for installing SVCs are the buses 31, 33 and 25. The optimal control variable settings of the best FACTS investment cost and best L-index along with best compromise solution after the application of the MOGA for the severe line outage (46–47) under 150% stressed system condition are summarized in Table 5. Corresponding to these control variable settings, there is no limit violations in any of the state variables in the base case and contingency states. The comparison of the extreme points obtained by MOGA indicates that the search space is well explored by the proposed approach. Fig. 8 depicts the pareto optimal front of corrective control including FACTS in the second system. From this figure, it is worth mentioning that proposed MOGA is capable of exploring more efficient noninferior solutions. The improvement of voltage profile of the system after the application of the algorithm under contingency (46–47) is displayed in Fig. 9. From the best

Table 4 Best solution of two functions optimized individually and MOGA solution for IEEE 30 bus system.

	GA		MOGA		
	Best L-index	Best FACTS cost ($/Kvar)	Best L-index	Best FACTS cost ($/Kvar)	Best compromise solution
L_{max}	0.4727	0.4802	0.4727	0.4805	0.4762
FACTS cost	6.8872×10^6	6.8348×10^6	6.8882×10^6	6.8339×10^6	6.8529×10^6

Table 5 Simulation Results for MOGA-bi objective optimization under corrective control in case 57 bus system considering contingency (46–47) (150% loaded condition) including FACTS devices along with generation rescheduling.

Control variables		Best FACTS cost ($/Kvar)	Best Lmax	Best compromise solution
Real power settings of generators in base case, Pvar	P1	211.8251	249.864	239.2783
	P2	41.5905	41.542	41.5947
	P3	134.4559	79.7293	85.9034
	P6	53.8663	70.6601	75.457
	P8	395.8342	395.8366	395.8396
	P9	99.7156	99.8381	99.4393
	P_{12}	330.2349	330.2856	330.1597
Real power settings of generators in contingency case, Pcvar	Pc1	367.3228	367.2566	367.0646
	Pc2	60.3646	60.4223	60.4098
	Pc3	108.0406	76.8928	78.5111
	Pc6	70.9449	72.0092	70.4637
	Pc8	397.4674	397.6531	397.2698
	Pc9	79.2341	79.256	79.2904
	Pc_{12}	220.6049	220.6102	220.6177
Generator voltage magnitudes, Vvar	V1	1.0126	1.0126	1.0126
	V2	1.0025	1.0025	1.0025
	V3	0.9888	0.9888	0.9888
	V6	0.9876	0.9876	0.9876
	V8	1.0005	1.0005	1.0006
	V9	0.9818	0.9818	0.9818
	V_{12}	1.015	1.0149	1.0154
SVC settings, SVC	SVC_{31}	0.4016	0.4016	0.5342
	SVC_{33}	1.276	1.276	1.276
	SVC_{25}	1.7866	1.7866	1.798
TCSC settings, TCSC	$TCSC_{14\text{–}46}$	0.1287	0.1287	0.0983
	$TCSC_{13\text{–}49}$	0.546	0.452	0.356
	$TCSC_{44\text{–}45}$	0.1984	0.1454	0.1104
	Objective values			
Minimum control variable adjustment		5.4	20	10.3
FACTS cost($/h)		6.835×10^6	6.89×10^6	6.852×10^6
Lmax		0.455	0.375	0.41
Transmission loss (MW)		11.98	10.5	10.87

compromise solution in Table 5, the minimum voltage of the system has increased from 0.6795 to 0.9956, an improvement of 32% has been obtained by proposed approach. Hence the improvement in voltage profile of the system after the application of the proposed algorithm is evident from this result. The extreme points of pareto optimal front by MOGA and the best solutions of each functions optimized individually by GA are identical which is given in Table 6. This shows the efficiency of the proposed algorithm in diversity and convergence characteristics in solving the VSCOPF problem.

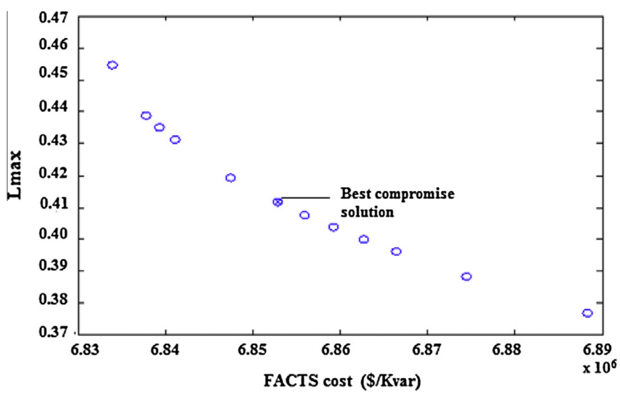

Figure 8 Pareto optimal front of MOGA under corrective control including FACTS devices along with including generation rescheduling under line outage (46–47) in Case 57 (150% loaded condition).

6. Conclusion

In this paper, an optimal procedure to improve voltage stability of the power system during emergency condition through corrective control strategy is proposed. The voltage stability margin of the system is calculated using a suitable indicator, L-index which is a quantitative measure for the estimation of the distance of the actual state of the system to the stability limit and describes the stability of the complete system. The bus with the highest L-index value can represent the stability status of the whole power system which makes the indicator more reliable. The proposed methodology provides techno-economic assessment of multi-type FACTS devices contribution to voltage stability enhancement. A multi-objective formulation of OPF problem has been developed in which candidate solutions are selected for conflicting objectives in two studies: corrective control including generation rescheduling and corrective control with FACTS including generation rescheduling. To improve the efficiency of the Genetic algorithm in the search process, the optimization variables were represented in natural form. As the proposed OPF problem include stability constraints, possible enhancement in steady state and improved results in higher loading condition is achieved. A fuzzy based mechanism is employed to extract the best compromise solution from the pareto front. The method does not impose any limitation in the number of objectives. The proposed approaches have been tested on IEEE 30 bus system and IEEE 57 bus test system under normal and stressed system conditions. The proposed MOGA is

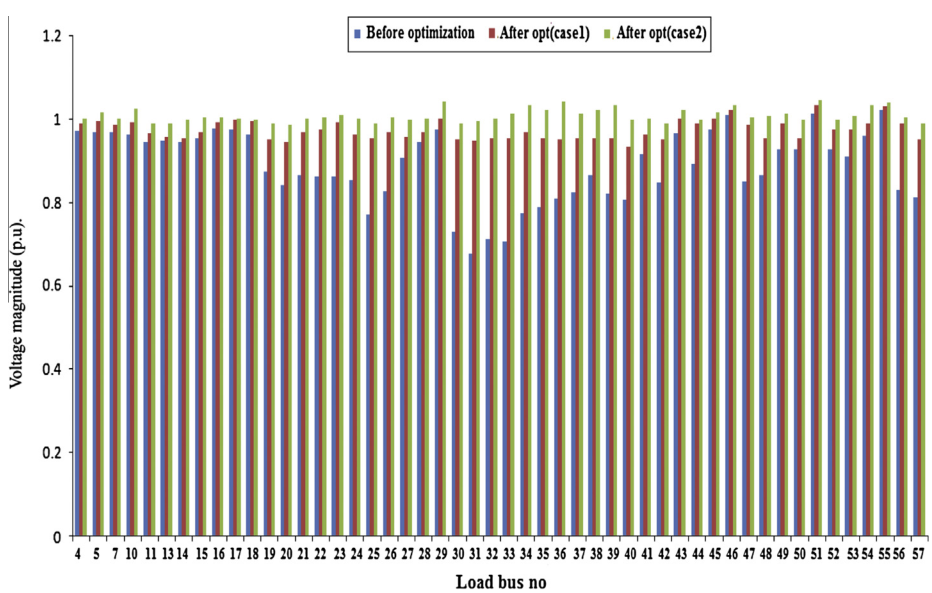

Figure 9 Voltage profile improvement in case 57 for (46–47) line outage (150% loaded condition).

Table 6 Best solution of two functions optimized individually and MOGA solution for IEEE 57 bus test system.

	GA		MOGA		
	Best L-index	Best FACTS cost ($/Kvar)	Best L-index	Best FACTS cost ($/Kvar)	Best compromise solution
L_{max}	0.369	0.443	0.375	0.455	0.41
FACTS cost	6.8872×10^6	6.8348×10^6	6.89×10^6	6.835×10^6	6.852×10^6

better in characterizing the pareto optimal front in solving the multi-objective OPF problem by its well distribution and diversity characteristics.

Appendix A

The L-index calculation for a power system is briefly discussed below:

Consider an N-bus system in which there are N_g generators. The relationship between voltage and current can be expressed by the following expression:

$$\begin{bmatrix} I_G \\ I_L \end{bmatrix} = \begin{bmatrix} Y_{GG} & Y_{GL} \\ Y_{LG} & Y_{LL} \end{bmatrix} \begin{bmatrix} V_G \\ V_L \end{bmatrix} \tag{A1}$$

where I_G, I_L and V_G, V_L represent currents and voltages at the generator buses and load buses.

Rearranging the above equation we get,

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \begin{bmatrix} Z_{LL} & F_{LG} \\ K_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \tag{A2}$$

where

$$F_{LG} = -[Y_{LL}]^{-1}[Y_{LG}] \tag{A3}$$

The L-index of the jth node is given by the expression,

$$L_j = \left| 1 - \sum_{i=1}^{N_g} F_{ji} \frac{V_i}{V_j} \angle(\theta_{ji} + \delta_i - \delta_j) \right| \tag{A4}$$

where

V_i Voltage magnitude of ith generator.
V_j Voltage magnitude of jth generator.
θ_{ji} Phase angle of the term F_{ji}.
δ_i Voltage phase angle of ith generator unit.
δ_j Voltage phase angle of jth generator unit.
N_g Number of generating units.

The values of F_{ji} are obtained from the matrix F_{LG}.

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