Electrical Power and Energy Systems 32 (2010) 1151–1156

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Genetic algorithm based reactive power dispatch for voltage stability improvement

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ARTICLE INFO

Article history:
Received 4 September 2007
Received in revised form 15 March 2010
Accepted 7 June 2010

Keywords:
Voltage stability
L-index
Reactive power dispatch
Genetic algorithm

ABSTRACT

Voltage stability assessment and control form the core function in a modern energy control centre. This paper presents an improved Genetic algorithm (GA) approach for voltage stability enhancement. The proposed technique is based on the minimization of the maximum of *L*-indices of load buses. Generator voltages, switchable VAR sources and transformer tap changers are used as optimization variables of this problem. The proposed approach permits the optimization variables to be represented in their natural form in the genetic population. For effective genetic processing, the crossover and mutation operators which can directly deal with the floating point numbers and integers are used. The proposed algorithm has been tested on IEEE 30-bus and IEEE 57-bus test systems and successful results have been obtained.

1. Introduction

Due to the continuous growth in the demand for electricity with unmatched generation and transmission capacity expansion, voltage instability is emerging as a new challenge to power system planning and operation. Contingencies such as unexpected line outages in stressed system may often result in voltage instability which may lead to voltage collapse. After a voltage collapse, the system becomes dismantled owing to the wide spread operation of protective devices. Unavailability of sufficient reactive power sources to maintain normal voltage profiles at heavily loaded buses are the prime reasons for the voltage collapse. Research efforts have been made in understanding the phenomenon associated with the voltage instability [1–5] and suggesting the remedial measures to protect the power system networks against such failures [6–11]. There are two different approaches to take control action against voltage instability: preventive and corrective control. The preventive control involves taking preventive actions so as to ensure that the operating point is sufficiently away from the point of collapse under a selected set of contingencies. The corrective control, on the other hand is activated when a contingency has occurred endangering voltage stability. The main objective of this work is to study the voltage instability problem in the framework of the short-term operation planning, where the optimal corrective action has to be found to improve the voltage stability by considering just the existing facilities and equipment operational limits.

Several approaches have been proposed in the literature to identify the most effective action to improve the voltage stability. Tiranuchit and Thomas [6] have proposed minimum singular value of the load flow Jacobian as voltage stability index. The sensitivity of the minimum singular value to power adjustments at each bus was used to identify the VAR support needed to maintain the voltage profile when an increase in power flow is required. Bansilal et al. [7] have proposed a non-linear least squares optimization algorithm for voltage stability enhancement. They have used the *L*-index proposed in [1] for voltage stability assessment. A linear programming-based reactive power dispatch algorithm was proposed in [8] for voltage stability improvement. In Ref. [9] two control methods for improving voltage stability based on the concept of Voltage Instability Proximity Index (VIPI) have been proposed. The first method maximizes the value of VIPI by using a Successive Quadratic Programming method to find optimal controls in various system conditions. The second approach determines the controls needed to maintain the specified threshold value, based on the sensitivities of VIPI with respect to control variables. Tare and Bijwe [10] have reported a voltage stability monitoring and enhancement algorithm based on the angle between P and Q gradient vectors at the load bus. In this approach a simple quadratic objective function is formed using sensitivities of the proposed voltage stability index and the minimization of this objective function leads to improvement in voltage stability limit. Sequential primal dual LP algorithm was used in [11] for the improvement of the static voltage stability. Choube et al. [12] presented a corrective scheduling method based on the linear relationship between static voltage stability index and reactive power control variables. The validity of the sensitive approaches is restricted to small incre-

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doi:10.1016/j.ijepes.2010.06.014

ments in reactive power variables only. Although linear programming methods are fast and reliable they have some disadvantages with the piecewise linear cost approximation. Quadratic programming based techniques have some disadvantages with the piecewise quadratic cost approximation.

Recently, evolutionary computation techniques [13] like genetic algorithm and evolutionary programming have been applied to solve the reactive power optimization problems. In [14], a differentially evolutionary algorithm has been proposed for optimal dispatch for reactive power and voltage control in power system operation studies. The inequality operational constraints were handled by penalty parameterless approach. He et al. [15] proposed a multi objective optimization approach to minimize both losses and payment for the reactive power service while maintaining voltage security margin of the system. In this paper, the problem of voltage stability enhancement is formulated as a non-linear optimization problem and a genetic algorithm-based approach is proposed to obtain the optimal settings of reactive power control variables. The algorithm is based on the minimization of an objective function which is the maximum of the *L*-indices at load buses.

Generally, binary strings are used to represent the decision variables of the optimization problem in the genetic population irrespective of the nature of the decision variables. The conventional binary-coded GA has Hamming cliff problems [16] which sometimes may cause difficulties in the case of coding continuous variables. Also, for discrete variables with total number of permissible choices not equal to 2^k (where k is an integer) it becomes difficult to use a fixed length binary coding to represent all permissible values. To overcome the above difficulties this paper proposes a flexible algorithm to solve the optimization problem. The proposed GA-based approach is applied to obtain the optimal control variables so as to improve the voltage stability level of the system under base case and against the critical single line outages in the system. The effectiveness of this algorithm is demonstrated through voltage stability improvement in IEEE 30-bus system and IEEE 57-bus test system.

2. Voltage stability index

Voltage stability analysis involves both static and dynamic factors. As dynamic computations are time consuming, the static approach is generally preferred for stability assessment and control. Static voltage stability analysis involves determination of an index called voltage stability index. This index is an approximate measure of closeness of the system to voltage collapse. There are various methods of determining the voltage stability index. One such method is *L*-index proposed in [1]. It is based on load flow analysis. Its value ranges from 0 (no load condition) to 1 (voltage collapse). The bus with the highest *L*-index value will be the most vulnerable bus in the system. The *L*-index calculation for a power system is briefly discussed below:

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

$$\begin{bmatrix} I_G \\ I_L \end{bmatrix} = \begin{bmatrix} Y_{GG} & Y_{GL} \\ Y_{LG} & Y_{LL} \end{bmatrix} \begin{bmatrix} V_G \\ V_L \end{bmatrix} \tag{1}$$

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,

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \begin{bmatrix} Z_{LL} & F_{LG} \\ K_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \tag{2}$$

Here

$$F_{LG} = -[Y_{LL}]^{-1}[Y_{LG}] \tag{3}$$

The *L*-index of the *j*th node is given by the expression,

$$L_j = \left| 1 - \sum_{i=1}^{N_g} F_{ji} \frac{V_i}{V_j} \quad \angle \quad (\theta_{ij} + \delta_i - \delta_j) \right| \tag{4}$$

where V_i, V_j are the voltage magnitude of *i*th and *j*th generator, θ_{ij} is phase angle of the term F_{ji}, δ_i, δ_j are the voltage phase angle of *i*th and *j*th generator unit.

The values of F_{ji} are obtained from the matrix F_{LG}. 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 indicator $L^{\max}$ is a quantitative measure for the estimation of the distance of the actual state of the system to the stability limit.

3. Problem formulation

We introduce the following notation:

G_{ij}, B_{ij}	conductance and susceptance of transmission line connected between *i*th and *j*th bus
P_i,Q_i	real and reactive power injection of *i*th bus
P_s	real power generation of slack bus
Q_{ci}	Reactive power generation of *i*th capacitor bank
V_{gi}	generator voltage magnitude at bus *i*
t_k	tap setting of transformer at branch *k*
N_l	number of transmission lines
N_C	number of capacitor banks
N_T	number of tap-setting transformer branches
N_{PV}	number of voltage buses
N_B	total number of buses
N_{PQ}	number of load buses
N_{B-1}	total number of buses excluding slack bus

Maintaining the specified voltage stability level under normal and contingency state is a major concern in the operation of power system. The basic idea behind the proposed voltage stability improvement scheme is to minimize the $L^{\max}$ value of the system through rescheduling of reactive power control variables while satisfying the unit and system constraints. This is mathematically stated as,

$$\text{Minimize } (L^{\max}) \tag{5}$$

Subject to

(i) Real power balance equation:

$$P_i - V_i \sum_{j=1}^{N_B} V_j [G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}] = 0; \qquad i = 1, 2, \ldots N_{B-1} \tag{6}$$

(ii) Reactive power balance equation:

$$Q_i - V_i \sum_{j=1}^{N_B} V_j [G_{ij} \cos \delta_{ij} - B_{ij} \sin \delta_{ij}] = 0; \qquad i = 1, 2, \ldots N_{PQ} \tag{7}$$

(iii) Slack bus real power generation limit:

$$P_s^{\min} \leqslant P_s \leqslant P_s^{\max} \tag{8}$$

(iv) Generator reactive power generation limit:

$$Q_{gi}^{\min} \leqslant Q_{gi} \leqslant Q_{gi}^{\max} \qquad i \in N_{PV} \tag{9}$$

(v) Generator bus voltage limit:

$$V_{gi}^{\min} \leqslant V_{gi} \leqslant V_{gi}^{\max} \qquad i \in N_B \tag{10}$$

(vi) Capacitor bank reactive power generation limit:

$$Q_{ci}^{\min} \leqslant Q_{ci} \leqslant Q_{ci}^{\max} \qquad i \in N_C \tag{11}$$

(vii) Transformer tap setting limit:

$$t_k^{\min} \leqslant t_k \leqslant t_k^{\max} \qquad i \in N_T \tag{12}$$

(viii) Line flow limit:

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

From the above formulation it is found that the voltage stability enhancement problem is a combinatorial non-linear optimization problem. The discrete variables appear in the form of transformer tap setting and reactive power generation of capacitor bank. Conventional optimization techniques are not efficient in solving this complex optimization problem. The next section presents the details of the GA-based approach for solving this complex optimization problem.

4. Proposed genetic algorithm

Genetic algorithms (GA) [17] are search algorithms based on the mechanics of natural genetics. They combine solution evaluation with randomized, structured exchanges of information between solutions to obtain optimality. Starting with an initial population, the genetic algorithm exploits the information contained in the present population and explores new individuals by generating offspring using the three genetic operators namely, reproduction, crossover and mutation which can then replace members of the old generation. Genetic algorithms maintain a population of solution structures throughout the process; therefore they are not limited by the selection of initial solution guesses. In this way the entire solution space may be explored and multiple solutions detected. Evaluation of the individuals in the population is accomplished by calculating the objective function value for the problem using the parameter set. The result of the objective function calculation is used to calculate the fitness value of the individual. Fitter chromosomes have higher probabilities of being selected for the next generation. After several generations, the algorithm converges to the best chromosome, which hopefully represents the optimum or near optimal solution.

A number of modifications have been made to the original binary-coded GA in order to improve the effectiveness of the GA to solve the reactive power dispatch problem. First, in the proposed algorithm, the candidate solutions are represented as the combination of floating point numbers and integers instead of binary strings. Each number in the candidate solution represents one variable, whereas in the binary-coded GA, each such value would be a substring. This form of representation has a number of advantages over binary coding. The efficiency of the GA is increased as there is no need to convert the solution variables to the binary type. Moreover, less memory is required. With mixed form of representation, the evaluation procedure and reproduction operator remain the same as that in binary-coded GA, but modifications are necessary in the case of crossover and mutation operators. The details of the genetic operators used in the proposed GA are presented below:

(a) Selection

Selection emphasizes good solutions and eliminates bad solutions while keeping the population size constant. The goal here is to allow the "fittest" individuals to be selected more often to reproduce. There are a number of operators proposed for selection operation [18]. In this work, we use "tournament selection". In tournament selection, 'n' individuals are selected in random from the population, and the best of the n individuals is inserted into the new population for further genetic processing. This procedure is repeated until the matting pool is filled. Tournaments are often held between pairs of individuals (tournament size = 2), although larger tournaments can also be held.

(b) Crossover

The crossover operator is mainly responsible for the global search property of the GA. Crossover basically combines substructures of two parent chromosomes to produce new structures, with the selected probability typically in the range of 0.6–1.0. As each individual in the population consists of two types of variables: real and integer, a "two-point crossover" which takes advantage of the special structure of the problem representation is developed. First, the two parents are cut at the boundary between the float and integer variables. Then separate crossover operators are applied on the floating point and integer parts. The blend crossover operator (BLX-α) [16,18], which is based on the theory of interval schemata is employed in this study for real variables, and simple crossover is applied to the integer part. The features of the BLX-α operator are presented in this section.

For the values $u_i^{(j)}$ and $u_i^{(k)}$ of the variable u_i in the parents j and k, BLX-α operator creates new points uniformly at random from a range extending an amount $\alpha|u_i^{(j)} - u_i^{(k)}|$ on either side of the region bounded by the parents. Fig. 1 illustrates the BLX-α crossover operation for the one dimensional case. In this figure, u_1 and u_2 represent two parents from a particular variable. The value of off springs e_1 and e_2 are given by the expressions:

$$e_1 = u_1 - \alpha I \tag{14}$$

$$e_2 = u_2 - \alpha I \tag{15}$$

where $I = u_2 - u_1$

It is to be noted that e_1 and e_2 will lie between $u_{\min}$ and $u_{\max}$, the variable's lower and upper bound respectively. In a number of test problems, it was observed that $\alpha = 0.5$ provides good results. One interesting feature of this type of crossover operator is that the created point depends on the location of both parents. If both parents are close to each other, the new point will also be close to the parents. On the other hand, if parents are far from each other, the search is more like a random search.

(c) Mutation

The mutation operator is used to inject new genetic material into the population. Mutation randomly alters a variable with a

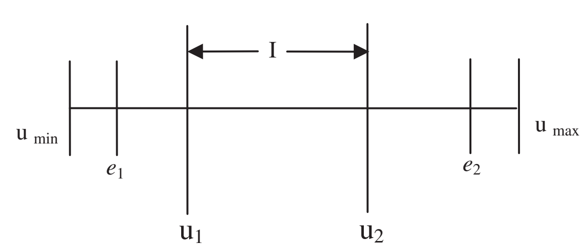

Fig. 1. Schematic representation of BLX-α crossover.

small probability. In this work, "Uniform mutation" operator is applied to the mixed variables with some modifications. First a variable is selected from an individual randomly. If the selected variable is a real number then it is set to a uniform random number between the variable's lower and upper limit. On the other hand, if the selected variable is an integer then the integer is randomly incremented or decremented by one.

5. Genetic algorithm implementation

In solving the reactive power dispatch problem, the following variables need to be determined by the optimization algorithm: generator bus voltages (V_{gi}), reactive power generation of capacitor bank (Q_{ci}), and transformer tap setting (t_k). Hence, each individual in the population consists of a combination of these variables. The fitness value of each string is evaluated by running the power flow algorithm using the control variables represented by the string. Then the genetic operators are applied on the genetic population to improve the solution. This process is continued until the convergence criterion is satisfied. This is pictorially represented in Fig. 2.

While applying GA for the reactive power optimization problem the following issues need to be addressed:

- Problem representation.
- Fitness evaluation.

(a) Problem representation

Each individual in the GA population represents a candidate solution for the given problem. The elements of that solution consist of all the optimization variables of the problem. For the reactive power optimization problem under consideration, generator terminal voltages (V_{gi}), capacitor bank reactive power generation (Q_{ci}) and the transformer tap positions (t_k) are the optimization variables. Generator bus voltages are represented as floating point

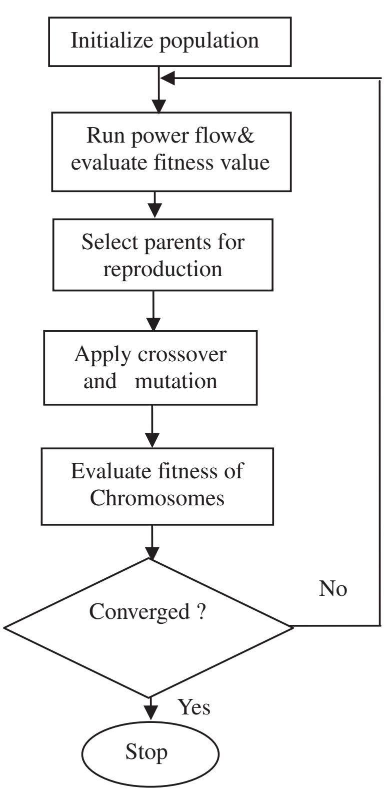

Fig. 2. Flowchart of GA-based algorithm.

numbers, whereas the transformer tap position and the reactive power generation of capacitor bank are represented as integers. The transformer tap setting with tapping ranges of $\pm$ 10% and a tapping step of 0.025 p.u is represented from the alphabet (0,1, ... 8) and the shunt capacitor with limits of 1 and 5 p.u and step size of 1 p.u is represented from the alphabet (0,1, ... 5). With this representation, a typical chromosome of the RPD problem will look like the following:

$$\underbrace{0.981}_{V_1}\ \underbrace{0.970}_{V_2}\ldots\underbrace{1.05}_{V_n}\ \underbrace{4}_{Q_{c1}}\ \underbrace{3}_{Q_{c2}}\ldots\underbrace{1}_{Q_{cn}}\ \underbrace{-2}_{t_1}\ \underbrace{+1}_{t_2}\ldots\ldots\underbrace{+3}_{t_n}$$

This type of representation for the candidate solutions alleviates the problems associated with the binary-coded GA to deal with real variables and integers with total number of permissible choices not equal to 2^k, where k is an integer.

(b) Evaluation function

Genetic algorithm searches for the optimal solution by maximizing a given fitness function, and therefore an evaluation function which provides a measure of the quality of the problem solution must be provided. In the reactive power optimization problem under consideration, the objective is to minimize the $L^{\max}$ of the system satisfying the constraints (6–13). For each individual, the equality constraints are satisfied by running the Newton Raphson power flow algorithm. The inequality constraints on the control variables are taken into account in the problem representation itself, 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 becomes,

$$\text{Min}\, f = L^{\max} + SP + \sum_{j=1}^{N_{PQ}} VP_j + \sum_{j=1}^{N_g} QP_j + \sum_{j=1}^{N_1} LP_j \tag{16}$$

Here, SP, VP_j, QP_j and LP_j are the penalty terms for the reference bus generator active power limit violation, load bus voltage limit violation, reactive power generation limit violation and line flow limit violation respectively. These quantities are defined by the following equations:

$$SP = \begin{cases} K_s(P_s - P_s^{\max})^2 & \text{if} \quad P_s > P_s^{\max} \\ K_s(P_s - P_s^{\min})^2 & \text{if} \quad P_s < P_s^{\min} \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

$$VP_j = \begin{cases} K_v(V_j - V_j^{\max})^2 & \text{if} \quad V_j > V_j^{\max} \\ K_v(V_j - V_j^{\min})^2 & \text{if} \quad V_j < V_j^{\min} \\ 0 & \text{otherwise} \end{cases} \tag{18}$$

$$QP_j = \begin{cases} K_q(Q_j - Q_j^{\max})^2 & \text{if} \quad Q_j > Q_j^{\max} \\ K_q(Q_j - Q_j^{\min})^2 & \text{if} \quad Q_j < Q_j^{\min} \\ 0 & \text{otherwise} \end{cases} \tag{19}$$

$$LP_j = \begin{cases} K_l(L_j - L_j^{\max})^2 & \text{if} \quad L_j > L_j^{\max} \\ 0 & \text{otherwise} \end{cases} \tag{20}$$

where K_s, K_v, K_q and K_l are the penalty factors. The success of the penalty function approach lies in the proper choice of these penalty parameters. Using the above penalty function approach, one has to experiment to find a correct combination of penalty parameters K_s, K_v, K_q and K_l. Since GA maximizes the fitness function, the minimization objective function f is transformed to a fitness function to be maximized as,

$$\text{Fitness} = \frac{k}{f} \tag{21}$$

where k is a large constant.

6. Results and discussion

The proposed GA-based approach was applied to IEEE 30-bus and 57-bus test systems for voltage stability improvement under normal and contingency states. The real and reactive loads are scaled up according to predetermined weighting factors to analyse the system under stressed condition. The *L*-indices for a given load condition are computed for all load buses and the maximum of *L*-indices gives the proximity of the system to voltage collapse. Generator excitation, switchable VAR compensators and transformer tap settings are considered as control variables for voltage stability improvement. The program was written in MATLAB and executed on a PC with Pentium IV processor. The results of the simulation are presented below:

Table 1
Controller settings under base case for IEEE 30-bus system.

S. no	Control variables	Initial setting	Optimal setting
1	V_1	1.0500	1.0500
2	V_2	1.0400	1.0256
3	V_3	1.0100	1.0063
4	V_4	1.0100	0.9895
5	V_5	1.0500	1.0584
6	V_6	1.0500	1.0806
7	t_1	0.9780	1.0500
8	t_2	0.9690	0.9000
9	t_3	0.9320	0.9250
10	t_4	0.9680	0.9500
11	Q_{30}	0	5
12	Q_{29}	0	5
13	Q_{26}	0	5
14	Q_{25}	0	1
15	Q_{24}	0	3
P_{Loss}		10.76	10.55
L_{max}		0.1978	0.1807

Table 2
Results of optimization under contingency state for IEEE 30-bus system.

	Line outage 28–27 (125% loaded condition)		Line outage 27–30 (125% loaded condition)	
	Before optimization	After optimization	Before optimization	After optimization
L^{max}	0.6805	0.04700	0.3432	0.3031
V^{min}	0.7078	0.9214	0.8614	0.9639
P_{loss}	16.1240	13.7018	11.3840	11.2595

(a) IEEE 30-bus system

The IEEE 30-bus system has six generators, 24 load buses and 41 transmission lines, of which four branches (6–9), (6–10), (4–12) and (28–27) are with the tap changing transformer. The initial control variable setting of the system under base load are taken from [19]. The upper and lower voltage limits at all the bus bars except slack bus are taken as 1.10 p.u and 0.95 p.u respectively. The slack bus bar voltage is fixed to its specified value of 1.06 p.u. In order to analyse the system under stressed condition, active and reactive powers of each bus are multiplied by 1.25. Corresponding to this setting, the *L*-indices of all the load buses are computed. From this computation it is found that $L^{max} = 0.1978$ and the five weakest buses are 30, 29, 26, 25 and 24. These five buses have been selected for reactive power injection. The proposed voltage stability enhancement algorithm was applied with generator bus voltage magnitude, reactive power generation of capacitor bank and OLTC position as control variables keeping the generator active power generation fixed except for the slack bus. Generator voltage magnitudes are treated as continuous variables whereas transformer tap-settings and shunt capacitor banks are treated as discrete variables with nine levels and six levels respectively. The GA-based algorithm was tested with different parameter settings and the best results are obtained with the following setting:

No. of generations: 100
Crossover probability: 0.9
Mutation probability: 0.01
Population size: 30

The optimal values of the control variables from the algorithm are given in Table 1 along with the initial control variable setting. From the result of the optimization algorithm it is found that the maximum value of *L*-index has decreased from the initial value of 0.1978–0.1807 in 40.2 s. For comparison, a binary-coded GA with two-point crossover and bit-wise mutation was applied to solve the RPD problem. In this case, the L^{max} obtained is 0.1974 MW and the algorithm took 57.3 s to reach the optimal value. This shows that the proposed algorithm is effective in reaching the optimal solution for the RPD problem.

To analyse the system under disturbance, contingency analysis was conducted at 1.25 times the base load condition. From the contingency analysis, line outages 28–27 and 27–30 have found to be the most severe cases with the L^{max} values of 0.6805 and 0.3432 respectively. The GA-based algorithm was applied to enhance the voltage stability under contingency state. The optimal control variable setting after the application of the proposed algorithm are given in Table 1. The system performance before and after the application of the algorithm for the two contingencies are summa-

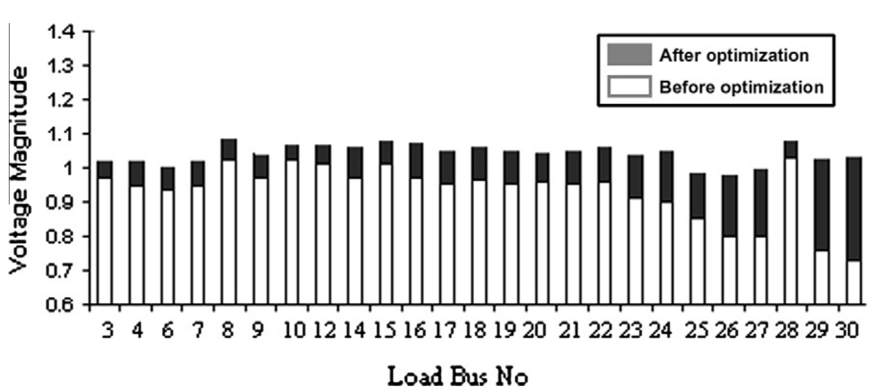

Fig. 3. Voltage profile under line outage 28–27.

Table 3
System performance for IEEE 57-bus test system.

	Line outage 46–47 (125% loaded condition)	
	Before optimization	After optimization
L^{max}	0.5548	0.4499
V^{min}	0.8041	0.9304
P_{loss}	50.43	48.63

Table 4
Improvement of voltage profile for IEEE 57-bus test system.

S. no.	Bus no.	Before optimization		After optimization	
		L-index	Voltage magnitude	L-index	Voltage magnitude
1	25	0.4422	0.8722	0.3712	1.0017
2	26	0.2455	0.8837	0.2201	1.0243
3	30	0.4886	0.8434	0.4042	0.9840
4	31	0.5548	0.8041	0.4499	0.9583
5	32	0.5053	0.8241	0.4189	0.9858
6	33	0.5105	0.8208	0.4223	0.9838
7	34	0.3365	0.8554	0.3049	0.9879
8	35	0.3194	0.8658	0.2909	0.9228
9	39	0.2860	0.8889	0.2626	0.9356
10	57	0.3322	0.8738	0.2960	0.9609

rized in Table 2. From this table, it is found that the value of L^{max} decreases and voltage stability is improved after the application of the algorithm. The voltage profile of the system before and after the application of the algorithm under contingency 28–27 are displayed in Fig. 3. Improvement in the voltage profile of the system after the application of the algorithm is evident from this diagram. Further, before the application of the algorithm voltage violations were present in buses but they are corrected after the control. This shows the effectiveness of the proposed algorithm for voltage stability improvement.

(b) IEEE 57-bus test system:

The IEEE 57-bus system has 7 generators, 5 synchronous condensers and 17 tap changing transformers. The base load of the system is 1272 MW and 298 MVAR. The voltage magnitude limits of all buses are set to 0.94 p.u for lower bound and to 1.06 p.u for upper bound. Based on the contingency study, line outage 46–47 was identified as severe case with L^{max} value of 0.5548. From the weak bus ranking, buses 30, 32, 31, 33 and 34 were selected for reactive power injection. The proposed GA was applied to improve the voltage stability as in the previous case. The result of the simulation is summarized in Table 3. From this table it is found that voltage stability level of the system has improved after the application of the proposed algorithm. Table 4 gives the voltage magnitude and L-index values for a selected list of buses for contingency 46–47. Improvement in voltage profile and reduction in L-index values at the load buses are evident from this result.

7. Conclusion

In this paper, the security enhancement problem is formulated as an optimization problem with minimization of the maximum L-index as the objective function. The weak buses in the system were selected for reactive power injection. An improved genetic algorithm was proposed to identify the optimal control variable setting under normal and contingency state. To improve the efficiency of the genetic algorithm in the search process, the optimization variables were represented in their natural form. Further, to deal with the mixed string used in the genetic population, modifications were made in the crossover and mutation operations. The simulation results on IEEE 30-bus and IEEE 57-bus test systems shows that the proposed algorithm is effective for voltage stability improvement in the normal and contingency states.

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