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A hybrid method for optimal load shedding and improving voltage stability

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Abstract In this paper, a hybrid method is proposed for reducing the amount of load shedding and voltage collapse. The hybrid method is the combination of Genetic Algorithm (GA) and Neural Network (NN). The GA is used by two stages, one is to frame the optimization model and other stage is to generate data set for developing the NN based intelligent load shedding model. The appropriate buses for load shedding are selected based on the sensitivity of minimum eigenvalue of load flow Jacobian with respect to the load shed. The proposed method is implemented in MATLAB working platform and the performance is tested with 6 bus and IEEE 14 bus bench mark system. The result of the proposed hybrid method is compared with the GA based optimization algorithm. The comparison shows that, the proposed method ensures voltage stability with minimum loading shedding.

1. Introduction

As transmission systems, particularly those opening up the electricity sector to competition, across the globe are getting heavily loaded, voltage instability is rising as a novel dispute to the power system planning and operation [1]. Due to the serious use of the transmission networks, voltage stability is turning into one of the most essential problems in the power systems [2]. It is worried with the capability of a power system to sustain acceptable bus voltages under standard conditions and after being subjected to a disturbance [3]. The voltage instability of a power system can be calculated by acquiring the distance of the static power flow equations from the first point of operation to its saddle node bifurcation point, known as the voltage collapse point, in a tangible generation and demand evolution direction. By a scale factor called load margin, this generation and demand evolution are parameterized [4–7].

The process of tripping certain amount of load with lower priority is Load shedding which is to keep up the constancy of the remaining portion of the system [8]. Successful load shedding scheme is required to uphold the power system stability [9]. Lacking of load shedding will cause serious system frequency decay and a stability problem [10]. Conversely, too much load shedding will trip the load too much to cause an unnecessary power outage problem [11]. It is a general practice

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for utility companies to carry out load shedding by applying under-frequency relays to trip the predetermined load with several shedding steps when the frequency drops lower than set values. The transient stability investigates for all the potential fault cases of the external utility power system have to be executed to get an efficient load shedding scheme [12–14].

As a result, the critical load margin obtained is one of the optimization problems which is computed by optimization technique. The optimal load shedding problem formulation has also been growing with shedding constraints. At a particular site, it is providing an appropriate framework for restricting the maximum amount of load to be shed. An early version declared the problem as a minimum load shedding problem. In this approach, the objective was to find the minimum amount of load to shed while gratifying load flow equations and static constraints such as line flows, voltage, angular limits and shedding constraints. Over conventional load flow, the formulation has numerous benefits. One of its strongest points is that it offers an optimization frame for distributing the slack among generation and load throughout the accessible nodes. This is mainly constructive, particularly after disturbances or equipment outages, when corrective action, other than rescheduling, might be required. Transmission limits could get the form of transfer limits or angle differences [15–20].

2. Recent research works: a brief review

In power system, several connected works are already presented in literatures that are based on load shedding with voltage stability. A few of them are reassessed here. A computationally easy algorithm has been progressed by Fu and Wang [21] for studying the load shedding problem in emergencies where an ac power flow solution can never be found for the stressed system. The suggested algorithm was partitioned into two subproblems: restoring solvability subproblem and improving Voltage Stability Margin (VSM) subproblem. To work out each subproblem, Linear optimization (LP)-based Optimal Power Flow (OPF) is used. In restoring solvability subproblem, rather than taking restoring power flow solvability as direct objective function, the objective function of maximization of voltage magnitudes of weak buses is utilized. In VSM subproblem, the traditional load shedding objective is expanded to include both technical and economic effects of load shedding and the linearized VSM constraint was included into the LP based OPF.

Seethalekshmi et al. [22] have offered a load curtailment in the power system necessary for its self-healing under critical contingencies, which may pose a threat to frequency with the voltage stability of the system. Based on the calculated disturbance power with the voltage stability condition of the system, the load shedding requirement in the system has been worked out with the help of real-time data, believed to be accessible from the synchrophasor based wide area monitoring and control system. This idea calculates voltage stability based on a dynamic voltage stability criterion, formulated by means of a Voltage Stability Risk Index (VSRI). Proper locations for the load curtailments have been selected according to the VSRI, computed at each load bus.

Load shedding algorithms for avoiding voltage collapse have been progressed by Sasikala and Ramaswamy [23]. These fuzzy based approaches have been coined to enhance Voltage Profile (VP), in addition to improving Voltage Stability (VS). The results attained on four standard examples over a range of load patterns have been authenticated to bring out its advanced computational ability. The presentation indices that have been calculated brought to light the effectiveness of the algorithm. The fact that the fuzzy strategies have been found to need a considerably lower execution time for larger systems serves to depict its computational competence. Although load shedding has been an accepted methodology for improving VS and enhancing VP, yet the key feature in the suggested formulation was to make certain a minimum load shedding to complete the needed objective.

Arya et al. [24] have offered an algorithm for anticipatory load shedding optimization at chosen load buses of the system accounting voltage stability consideration. Load buses have been graded based on sensitivities of minimum eigenvalue of load flow Jacobian relating to the load. It was pressured that load shedding was executed at current loading condition. Attained results by Differential Evolution (DE) have been compared based on mean, standard deviation, best value, worst value, frequency of convergence, standard error of mean, confidence interval and length of confidence interval of objective function, with PSO and its variant. Advantage of DE algorithm was that its mechanization was easy without much mathematical complexity and global optimized solution. It was examined that DE executes much better than PSO and its variant.

Tang et al. [25] have conversed under frequency load shedding and under voltage load shedding as large disturbances occur more repeatedly than in the past. They suggested a centralized, load shedding algorithm, which uses both voltage and frequency information offered by phasor measurement units. The consideration of reactive power together with active power in the load shedding strategy was the main input of the method. As a result, this technique addresses the combined voltage and frequency stability issues better than the free approaches. In order to compare it with the other techniques, the technique was experimented on the IEEE 39-Bus system. The Simulation effects show that, after large disturbance, this technique can bring the system back to a novel stable steady state that is better from the point of view of frequency and voltage stability, and loadability.

Yan Xu et al. [26] have suggested an alternative approach based on Parallel-Differential Evolution (P-DE) for powerfully and globally optimizing the event-driven load shedding against voltage collapse. Functioning in a parallel structure, the approach contains candidate buses selection, Voltage Stability Assessment (VSA) and DE optimization. Compared with conventional techniques, it fully regards as the nonlinearity of the problem and was able to successfully escape from local optima and not limited to system modeling and unrealistic statements. In addition, any kind of objective functions and VSA methods can be applied. The suggested approach has been checked on the IEEE 118-bus test system regarding two cases for preventive control and corrective control, correspondingly, and compared with the two presented techniques.

Hamid and Musirin [27] have conversed the application of fuzzy logic as a decision maker that has been extensively executed for working out different engineering problems, particularly in the field of voltage stability improvement. They suggested a method for locating the appropriate load buses for the purpose of load shedding considering multi-contingencies, i.e., using stability index tracing. The amount of load power to be shed was found out via an adapted version of fuzzy system, which contains enhanced membership functions by optimization algorithm. Experiment on IEEE 57-bus and 118-bus Reliability Test Systems (RTS) authenticates the possibility of the suggested method.

El-Zonkoly [35] zealously proposed a modified firefly based optimization algorithm devoted for the optimal demand side management (DSM) of various load types as well as the optimal energy resources schedule. The underlying objective behind the proposed modified firefly algorithm (MFA) was invested on significantly scaling down the entire operational cost encompasses the utilized energy cost, generated energy cost, energy loss cost, grid energy cost, unserved energy cost and start-up cost relating to the thermal generating units. A day-ahead unit commitment planning of diesel generators was elegantly performed to ensure the provision of the requisite energy while maintaining the spinning reserve of the units within the threshold bounds concerned. An effective economic dispatch of dedicated units was taken into account with the intention of attaining the least for minimum generation cost.

Abdelaziza et al. [36] amazingly presented a ground-breaking technique intended for the purpose of the optimal planning of a dispatchable distributed generator connected to the distribution networks. They modified the traditional firefly approach endowed with the innate skills of successfully addressing the virtually inhibited optimization hassles by introducing innovative equations for tailoring the technique constraints and for modernizing the equations. They unbendingly evaluated the optimal location and dimension of the distributed generation units with the paramount purpose of considerably cutting back the system power loss devoid of any infringement in the system practical constraints. In addition, they were instrumental in evaluating the optimal distributed generator location and minimum size for attaining a certain specific power loss by means of the proposed method and also analyzed and contrasted the outcomes with those of a heuristic technique.

The transmission networks are more heavily loaded than ever before to meet the growing demand. One of the major problems associated with such a stressed system is voltage collapse or voltage instability. Voltage collapse is characterized by a slow variation in system operating point due to increase in loads in such a way that the voltage magnitude gradually decreases until a sharp accelerated change occurs. The problem of voltage collapse may simply be explained as the inability of the power system to supply the required reactive power or because of an excessive absorption of the reactive power by the system itself. To predict the voltage instability, various approaches are used with different indices.

The main objective of the proposed method is prevention of voltage collapse while the operating state is nearing instability. But, if all the control strategies such as rescheduling of generations, bringing standby generators on line, switching capacitor banks, reduction of MV set point and other reactive power controls are exhausted, the only alternative way is load curtailment at some weak buses to avoid voltage collapse. Therefore, optimization algorithms and artificial intelligence techniques are used to solve this problem subject to stability constraints such as differential evolution, particle swarm optimization, simulated annealing, and fuzzy logic. In this paper, a hybrid method is proposed to minimize the load shedding power with voltage stability. The detailed description of the proposed hybrid method and the problem formulation are explained in the following sections.

3. Problem formulation

In this paper, the objective function is formulated to minimize the total load shed and maximize the voltage stability. Here, the objective function OF is formulated by the combination of OF_1 and OF_2. These two functions are minimizing the total load shedding and voltage instability.

$$\text{Objective function, } OF = \min\{f(OF_1, OF_2)\} \tag{1}$$

$$OF_1 = \min\left\{\sum_{i=NLS}(P_{L_i} - f_i(x_{\min}) - f_i(x_{\max}))\right\} \tag{2}$$

$$OF_2 = \min\left\{\sum_{i=NL}|1 - V_i|\right\} \tag{3}$$

where P_{L_i} is the ith load shedding bus, $f_i(x_{\min})$ and $f_i(x_{\max})$ are the minimum and maximum limits of ith load shedding bus. For reducing the voltage collapse, the Eq. (3) is used which minimizes the total magnitude of voltage variation. For optimizing the above objective functions, the equality and inequality constraints are used such as power flow equation, voltage, eigenvalue of Jacobian matrix, real and reactive power of generator, real and reactive power of load buses respectively. The description of these constraints is detailed by the following equations.

The power flow constraints are used to calculate the power flow under current operating condition in addition to after that determine the loading condition accounting load shed. The equality constraints are real and reactive power balance at each buses load flow equations are given by,

$$P_i = V_i \sum_{j=1}^{NB} V_j (G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) \tag{4}$$

$$Q_i = V_i \sum_{j=1}^{NB} V_j (G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}) \tag{5}$$

where P_i and Q_i are the real and reactive power of ith bus. In Eq. (4), $i = 1, 2, \ldots, NB$, NB is the number of buses and in Eq. (4), $i = 1, 2, \ldots, NPQ$, NPQ is the number of PQ buses, G_{ij} and B_{ij} are real and imaginary part of (i, j)th element of bus admittance matrix.

Then, in the inequality constraints, real and reactive power of generators and loads are considered. To reduce the complexity of optimization problem, the changes in the value of these constraints are selected. Therefore, the objective function of the optimization problem is reached in less convergence time. The inequality constraints are given as follows:

The real power generation inequality constraint is considered for base case condition as well as the change of generator value for loading condition. Similarly, the reactive power generation inequality constraint is considered under base case condition as well as the change of reactive power of generator value for loading condition.

$$P_{G_i}^{\min} \leqslant P_{G_i} \leqslant P_{G_i}^{\max} \quad i = 1, 2, \ldots NG \tag{6}$$

$$\Delta P_{G_i}^{\min} \leqslant \Delta P_{G_i} \leqslant \Delta P_{G_i}^{\max} \tag{7}$$

$$Q_{G_i}^{\min} \leqslant Q_{G_i} \leqslant Q_{G_i}^{\max}\ i = 1, 2, \ldots NG \tag{8}$$

$$\Delta Q_{G_i}^{\min} \leqslant \Delta Q_{G_i} \leqslant \Delta Q_{G_i}^{\max} \tag{9}$$

where NG is number of generator, P_{G_i} is the real power generated by ith generator, ΔP_{G_i} is the real power changes of generation of ith generator, Q_{G_i} is the reactive power generated by ith generator and ΔQ_{G_i} is the reactive changes of generation of ith generator.

The magnitude of all the bus voltages is selected as an inequality constraint which is in the current state as well as the load shed condition.

$$V_i^{\min} \leqslant V_i \leqslant V_i^{\max}\ \ i = 1, 2, \ldots NB \tag{10}$$

In load flow Jacobian matrix, the eigenvalue is selected as a minimum level in the inequality limits at current operating point as well as load shedding conditions.

$$\lambda_{\min(i)}^{initial} \geqslant \lambda_{\min(i)}^{threshold} \tag{11}$$

$$\lambda_{\min(i)}^{shed} \geqslant \lambda_{\min(i)}^{threshold} \tag{12}$$

where $\lambda_{\min(i)}^{initial}$ is the initial minimum eigenvalue of ith load bus at normal operating point, $\lambda_{\min(i)}^{threshold}$ is the threshold of minimum eigenvalue of ith load bus and $\lambda_{\min(i)}^{shed}$ is the minimum eigenvalue of ith load bus at load shedding point. From the value of $\lambda_{\min(i)}^{threshold}$, the change of value of minimum eigenvalue $\Delta\lambda_{\min}$ of ith load bus is calculated from the slop value of change of eigenvalue and the change of load power. The slope representation characteristics of eigenvalue and the load power are represented as follows:

From Fig. 1, the comparison of change of eigenvalue $\delta\lambda_{\min}$ and the apparent load power δS_{Li} is represented. From this performance comparison, the appropriate value of $\Delta\lambda_{\min}$ is selected which bases on the minimum load shedding buses, since, the minimum load shedding depends on the sensitivity of eigenvalue which is based on apparent power of the system. The sensitivity $\lambda_{\min}$ is calculated by the following equation,

$$\Delta\lambda_{\min} = x_i\ \Delta P_{Li} + y_i\ \Delta Q_{Li} \tag{13}$$

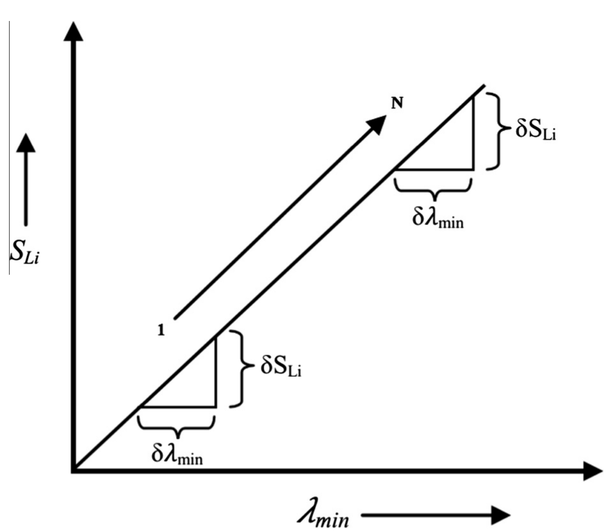

Figure 1 Comparison of eigenvalue and load power.

$$x_i = \frac{\delta\lambda_{\min}}{\delta P_{Li}} \tag{14}$$

$$y_i = \frac{\delta\lambda_{\min}}{\delta Q_{Li}} \tag{15}$$

where x_i is the change of slope characteristics with respect to the eigenvalue and the active power and y_i is the change of slope characteristics with respect to the eigenvalue and the reactive power correspondingly. From the value of Eq. (13), the changes of eigenvalue are calculated which indicate the optimum load bus to shed the load and give the amount of load to shed as per the generation variation. The optimum load bus and the amount of load to be shed are calculated by the proposed hybrid approach. This proposed approach is the combination of Genetic Algorithm (GA) and Artificial Neural Network (ANN). The detailed description of proposed approach is explained in the following section.

3.1. Hybrid approach based load shedding: GA and ANN

In this paper, the load shedding is performed by GA and ANN. The GA is used as two stages: one is to frame the optimization model and other stage is to generate data set for the intelligent load shedding model. The first state of GA is formulated by the Eq. (1) subject to the constraints. In the second stage, the GA is used to generate the fit data set and the neural network model is trained with this data set. Therefore, the performance of load shedding model is enhanced. From the neural network model, the shedding load is predicted for the given input eigenvalue. The detailed explanation of the hybrid approach is given in the next section.

3.2. Genetic Algorithm (GA) to minimize load shedding and to generate training data set

GA is one of the optimization algorithms performed based on the natural selection process of creatures [28]. In load shedding, GA plays a significant role to search the optimal supply restoration strategy [29,30,19]. Here, GA is used for minimizing the variation of real power of the load and voltage deviation. For minimizing the load shed and the voltage deviation, the GA is applied by two stages. In the first stage, minimum eigenvalue of Jacobian matrix is calculated that gives minimum load shedding buses. Then, the amount of load shed value is selected by reducing the voltage deviation using second stage of GA. From the results of these two stages GA, the optimal training data set is generated.

The GA consists of five steps which are population initialization, fitness evaluation, crossover, mutation and termination respectively. The details of these steps are discussed as follows,

Step 1: The first step of GA is the initialization of population for the optimization. Now, the minimum eigenvector is initialized randomly as per the range of eigenvalue. The range of eigenvalue is selected from the initial eigenvalue of the Jacobian matrix.

$$\lambda_{\min} = [\lambda_{\min}^{(1)}, \lambda_{\min}^{(2)}, \lambda_{\min}^{(3)}, \ldots \lambda_{\min}^{(i)}];\ i = 1, 2, \ldots n. \tag{16}$$

where, $\lambda_{\min}^{(i)}$ is the minimum eigenvalue of gene ith load bus.

Step 2: Then the fitness function is calculated for the initialized load bus. In the first stage of GA, the fitness function is calculated by using Eq. (2). The fitness function is calculated for second stage using Eq. (3). The purpose of second objective function is to ensure the voltage stability of the system.

$$\lambda_{\min}^{fit} = [\lambda_{\min}^{fit(1)}, \lambda_{\min}^{fit(2)}, \lambda_{\min}^{fit(3)}, \ldots \lambda_{\min}^{fit(i)}] \tag{17}$$

$$P_{L(shed)}^{fit} = [P_{L(shed)}^{fit(1)}, P_{L(shed)}^{fit}, P_{L(shed)}^{fit(3)}, \ldots P_{L(shed)}^{fit(i)}] \tag{18}$$

where, $\lambda_{\min}^{fit(i)}$ is the fitness value of the minimum eigenvalue of ith load bus which is calculated by Eq. (2). $P_{L(shed)}^{fit(i)}$ is the fitness value of the load power of ith load bus which is calculated by Eq. (3).

Step 3: Then, the crossover operation is performed between the chromosome of fitness value and generated new chromosome. Subsequent to generating new chromosome, a fitness function is applied to the new chromosome. The formula for calculating the crossover rate is described as follows.

$$Crossover\ Rate = \frac{Number\ of\ Gene\ Crossovered}{Length\ of\ Chromosome}$$

Step 4: In the mutation operation, the genes are mutated randomly based on the given mutation rate. The mutation rate is calculated by the given formula,

$$Mutation\ Rate = \frac{Mutation\ point}{Length\ of\ Chromosome}$$

Step 5: In the termination stage, the best solution is chosen based on the fitness function. The best value of the optimization process is denoted as $\lambda_{\min}^{(i)best}$ and $P_{L(shed)}^{(i)best}$. The flowchart of the genetic algorithm procedure is given in Fig. 2. Then, the best fit value is applied to neural network and the intelligent load shedding model is developed.

3.3. Neural Network (NN) based intelligent load shedding model

NN is one of the artificial intelligence techniques that are used to predict the minimum load shed for the given eigenvalue. In load shedding, the training data set of NN is generated by the actual system stability behavior [31]. But in this paper, the training data set is generated from the best solution of GA i.e. $\lambda_{\min}^{(i)best}$ and $P_{L(shed)}^{(i)best}$. From the best value, the input of the network is $\lambda_{\min}^{(i)best}$ and the output is $P_{L(shed)}^{(i)best}$. The feed forward network model is used which consists of three layers named as

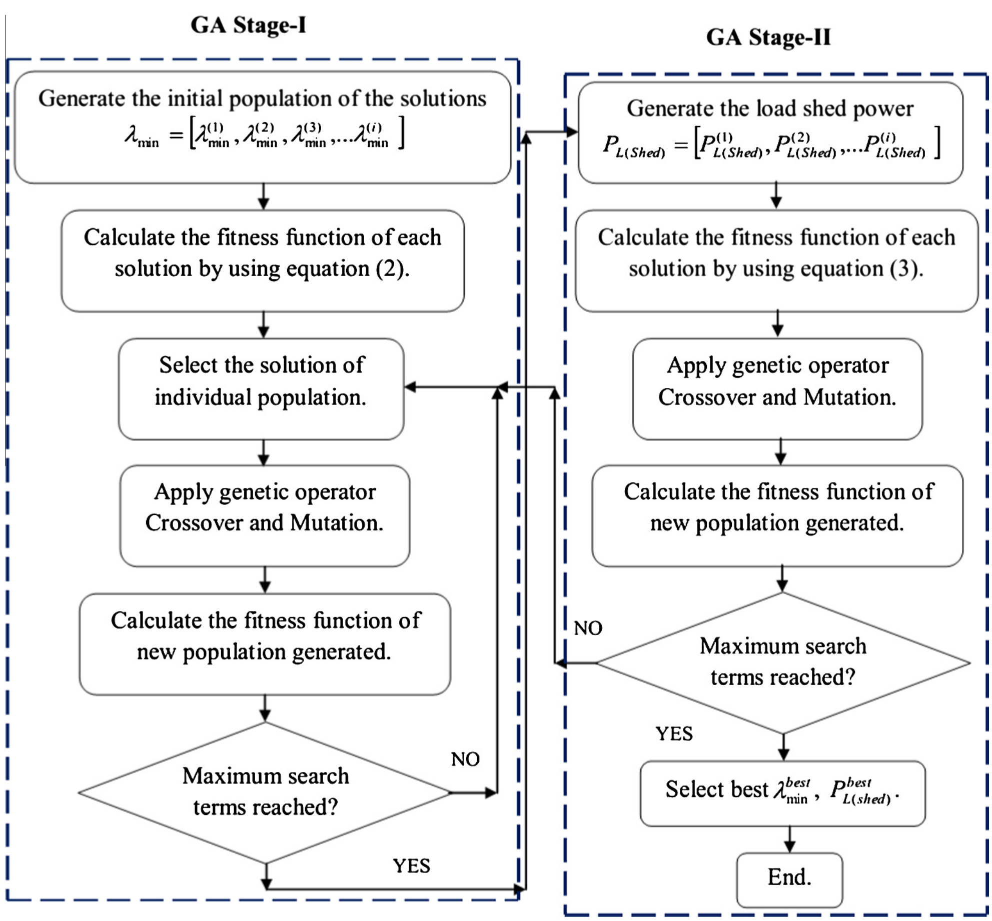

Figure 2 Flowchart of GA for the proposed approach.

input, hidden and output layer respectively. The training date set of the network is given as in Eqs. (19) and (20).

$$\text{Input training data, } \lambda_{\min}^{best} = \begin{bmatrix} \lambda_{\min}^{(1)best} \\ \lambda_{\min}^{(2)best} \\ \lambda_{\min}^{(3)best} \\ \vdots \\ \lambda_{\min}^{(i)best} \end{bmatrix} \tag{19}$$

$$\text{Output training data, } P_{L(shed)}^{best} = \begin{bmatrix} P_{L(shed)}^{(1)best} \\ P_{L(shed)}^{(2)best} \\ P_{L(shed)}^{(3)best} \\ \vdots \\ P_{L(shed)}^{(i)best} \end{bmatrix} \tag{20}$$

Using these data set, the network is trained and output of the network is denoted as $P_{L(shed)}^{NN}$. The structure of network is given in Fig. 3.

The Back Propagation (BP) training steps involved in the neural network are explained below,

Step 1: Initialize the input, output and weight for each neuron. Here, $\lambda_{\min}^{best}$ is the input of the network and $P_{L(shed)}^{NN}$ is the output of the network.

Step 2: These data sets are given to the classifier and determine the BP error as follows,

$$BP_{error} = P_{L(shed)}^{best} - P_{L(shed)}^{NN} \tag{21}$$

Eq. (21), $P_{L(shed)}^{best}$ is the target output and $P_{L(shed)}^{NN}$ is the output of the network.

Step 3: The output of the network is calculated as,

$$P_{L(shed)}^{NN} = \varphi + \sum_{n=1}^{N} w_{2n1} P_{L(shed)}^{NN}(n) \tag{22}$$

$$P_{L(shed)}^{NN}(n) = \frac{1}{1 + \exp(-w_{1n}\lambda_{\min}^{best})} \tag{23}$$

Eqs. (22) and (23) denote the activation function of output layer and hidden layer respectively.

Step 4: Vary the weights of neurons by $w_{new} = w_{old} + \Delta w$, where, Δw is the change in weight, which can be determined as,

$$\Delta w = \chi . P_{L(shed)}^{NN} . BP_{\text{error}} \tag{24}$$

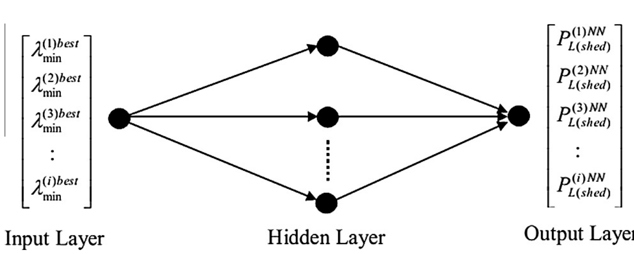

Figure 3 Structure of Neural Network.

where χ is the learning rate which varies from 0.2 to 0.5.

Step 5: Repeat the process from step 2, until BP_{error} gets minimized to a least value i.e.,

$$BP_{\text{error}} < 0.1 \tag{25}$$

Once the process gets completed, the network will be suitable for providing the load shed $P_{L(shed)}^{NN}$ values for any minimum eigenvalue.

4. Results and discussion

The proposed GA-NN load shedding method is implemented in MATLAB working platform. The performance of proposed hybrid method is tested with IEEE benchmark system. In this paper, two systems are used one is 6 bus system and other is 14 bus system. From the testing system, the results of minimum eigenvalue of load, bus voltage, and the active power of load are evaluated. The result of hybrid method is compared with GA and normal case results. The results and analysis of 6 and 14 bus systems are given below.

4.1. Six-bus system

First, the result of proposed method is tested with 6 bus system. The bus data and the line data of 6 bus system are referred in [32]. The testing system consists of 2 generator buses and four load buses. In this paper, the load shedding problem is formed randomly by creating generation shortage. For reducing this generation shortage, the sensitivity of eigenvalue of load bus is calculated which is varied by the range of load power. The proposed hybrid technique is selected and the sensitivity eigenvalue and the voltage stability are improved. Then, the real power of the load buses that have higher sensitivity value is shed. In Table 1–3, the minimum eigenvalue of load buses, the voltage magnitude and the load values are tabulated.

In 6 bus system, the buses 3, 4, 5 and 6 are load buses. Initially, the eigenvalues are calculated from the Jacobian matrix. As per the calculated eigenvalue, the range of eigenvalues is indexed for these load buses based on the real power limits. Then, the sensitivity of this load bus is calculated and the load shed buses are selected based on the maximum sensitivity eigenvalue. In Table 1, the bus numbers 3, 5 and 6 have maximum sensitivity eigenvalue. After that, the load power is shed and the magnitude of bus voltage, the real power and the load values are calculated which are tabulated in Table 2 and 3.

Table 1 Minimum Eigenvalue and sensitivity of minimum eigenvalue of six-bus system.

Bus number	Minimum eigenvalue for load bus at normal load	Sensitivity eigenvalue calculated by GA	Sensitivity eigenvalue calculated by hybrid method
3	0.1849	0.2221	0.2138
4	0.0041	0.0075	0.0069
5	0.1441	0.1698	0.0946
6	0.0741	0.0145	0.0723

From the results, it is observed that the proposed hybrid technique has achieved good voltage stability and minimum load shedding values.

Then, the performance of proposed hybrid method is analyzed by line chart that is compared with base case and GA results. The performance comparison of six bus system is illustrated in Fig. 4. In Fig. 4(a), the minimum eigenvalue and the sensitivity of eigenvalues are compared. It is seen that, the hybrid method is optimized by minimum eigenvalue and the minimum load shedding is achieved. In Fig. 4(b), the magnitude of voltage is compared and it is observed that, the hybrid method has achieved maximum voltage stability by minimizing the total voltage deviation. In Fig. 4(c), the load power is compared before and after the load shedding. The comparison shows that, hybrid method has less load variation to the base case after load shedding.

4.2. IEEE 14-bus system

Then, the performance of the proposed method is tested with 14 bus system. The bus data and the line data of 14 bus system are referred into [33,34]. This system consists of two generators in bus number 1 and 2 and condensers in buses 3, 6 and 8. The desired range of load bus voltage is 0.95 pu to 1.06 pu. The load shedding problem is formed randomly by creating generation shortage in the main generators. To minimize this generation shortage, the sensitivity of eigenvalue of load bus is calculated. The sensitivity of eigenvalue is varied as per the range of load power. Then, the real power of the load buses of 14 bus system that have higher sensitivity value is shed. The minimum eigenvalue of load buses, the voltage magnitude and the load values are tabulated in Table 4–6.

In the beginning, the eigenvalues of load buses are calculated from the Jacobian matrix. With the calculated eigenvalues, the range of eigenvalues is indexed for these load buses based on the real power limits. Then, the sensitivity of the load bus is calculated and load shed buses are selected based on the maximum sensitivity of eigenvalue. From Table 4, the bus numbers 4, 3 and 14 have maximum sensitivity of eigenvalue and based on the sensitivity of these values, the load shed problem is solved. The load power is shed and the magnitude of bus voltage, the real power and the load values are calculated which are tabulated in Table 5 and 6. The results of 14 bus system show that, the proposed hybrid technique attained excellent voltage stability and minimum load shedding values.

Table 2 Bus voltage of 6-bus system before and after load shed.

Bus number	Normal bus voltage (pu)	Voltage after generation change (pu)	Voltage after load shed by GA (pu)	Voltage after load shed by hybrid method (pu)
1	1.0870	1.0870	1.0870	1.0870
2	1.6800	1.6600	1.6600	1.6600
3	0.8120	0.9331	0.9659	0.9936
4	0.8350	0.9585	0.9933	1.0241
5	0.8050	1.1169	1.1100	1.1422
6	0.7990	0.9400	0.9658	0.9970

Table 3 Real power of load before and after load shed for IEEE 6 bus system.

Bus number	Normal load (pu)	Load shed by GA (pu)	Load shed by hybrid method (pu)
3	0.8970	0.8291	0.8321
4	0.0000	0.0000	0.0000
5	0.5550	0.5334	0.5398
6	0.7930	0.6336	0.6473

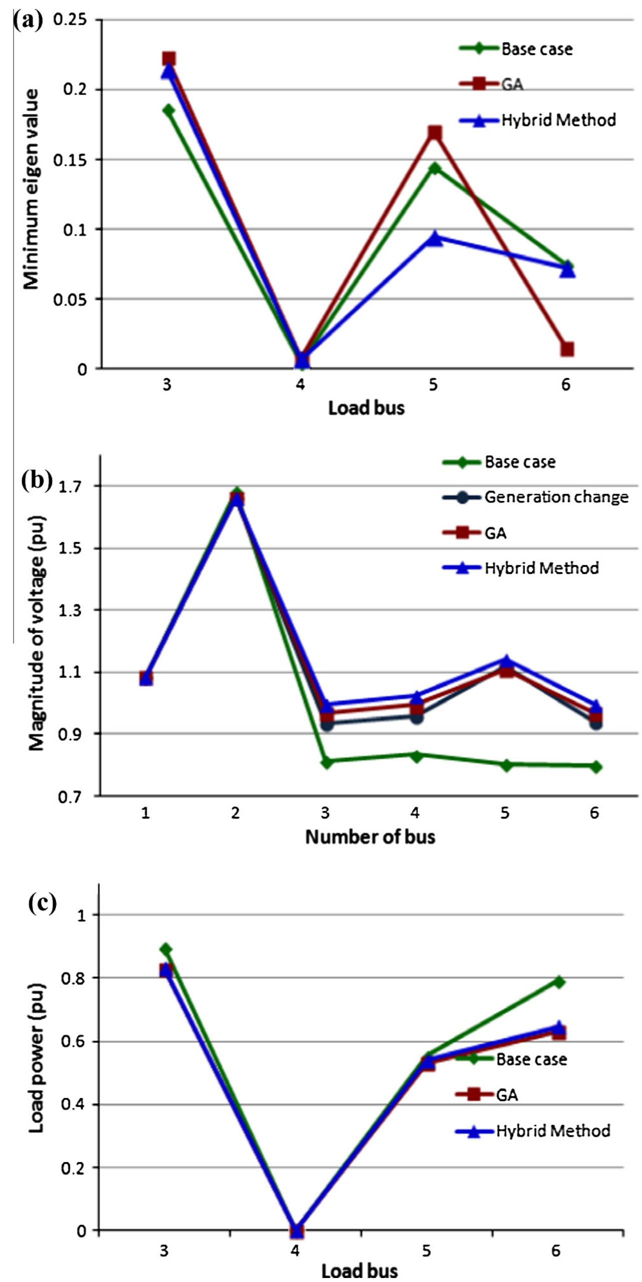

Figure 4 Six bus system performance comparison: (a) minimum eigenvalue, (b) magnitude of voltage (pu) and (c) load power (pu).

The performance comparison of IEEE 14 bus system is illustrated in Fig. 5. In Fig. 5(a), the minimum eigenvalue and the sensitivity of eigenvalues are compared. In Fig. 5

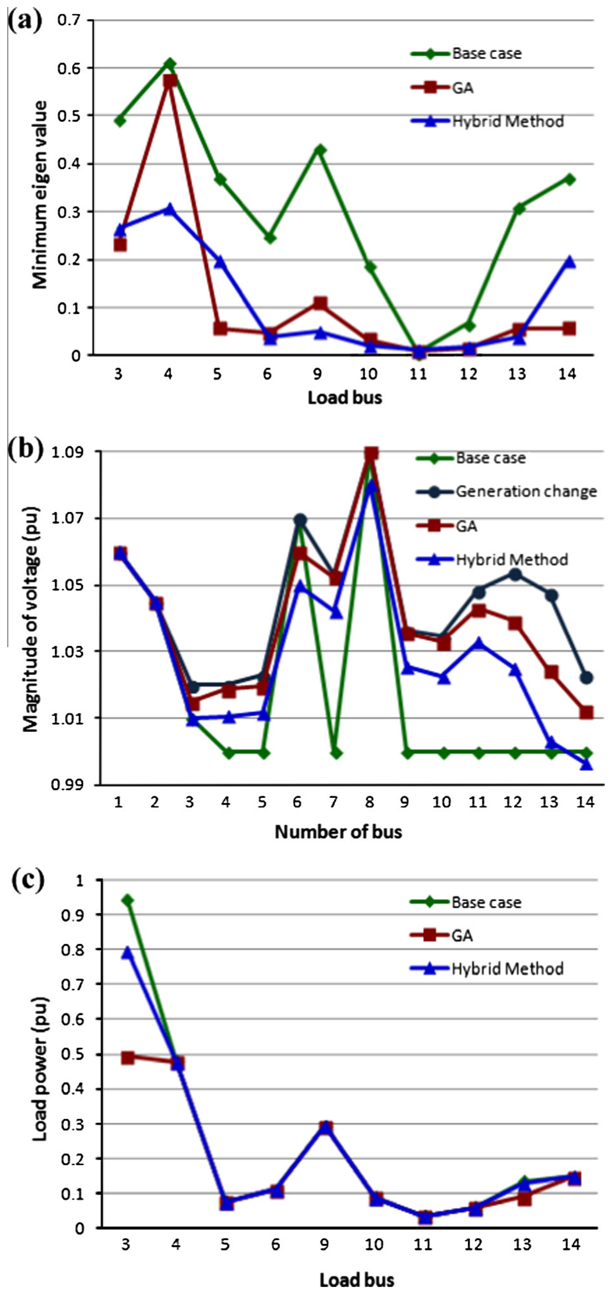

Figure 5 IEEE 14 bus system performance comparison: (a) minimum eigenvalue, (b) magnitude of voltage (pu) and (c) load power (pu).

(b), the magnitude of voltage is compared. It shows that, the hybrid method has achieved maximum voltage stability by minimizing the total voltage deviation. In Fig. 5(c), the load power is compared before and after load shedding. In bus number 3 and 4, the GA is shedding large amount of load when compared with hybrid method. The comparison shows that, hybrid method has less load variation to the base case after load shedding. All these comparison results have ensured that the hybrid method has achieved minimum load shedding.

Table 4 Minimum eigenvalue and sensitivity of minimum eigenvalue of 14-bus system.

Bus number	Minimum eigenvalue for load bus at normal load	Sensitivity eigenvalue calculated by GA	Sensitivity eigenvalue calculated by hybrid method
3	0.4936	0.2332	0.2663
4	0.6117	0.5745	0.3071
5	0.3716	0.0566	0.1978
6	0.2496	0.0461	0.0388
9	0.4326	0.1099	0.0494
10	0.1886	0.0343	0.0211
11	0.0056	0.0083	0.0117
12	0.0666	0.0146	0.0180
13	0.3106	0.0553	0.0373
14	0.3716	0.0566	0.1978

Table 5 Bus voltage of 14 bus system before and after load shed.

Bus number	Normal bus voltage (pu)	Voltage after generation change (pu)	Voltage after load shed by GA (pu)	Voltage after load shed by hybrid method (pu)
1	1.0600	1.0600	1.0600	1.0600
2	1.0450	1.0450	1.0450	1.0450
3	1.0100	1.0200	1.0150	1.0100
4	1.0000	1.0199	1.0186	1.0105
5	1.0000	1.0228	1.0195	1.0115
6	1.0700	1.0700	1.0600	1.0500
7	1.0000	1.0530	1.0524	1.0422
8	1.0900	1.0900	1.0900	1.0800
9	1.0000	1.0362	1.0356	1.0254
10	1.0000	1.0346	1.0329	1.0225
11	1.0000	1.0485	1.0430	1.0328
12	1.0000	1.0537	1.0392	1.0251
13	1.0000	1.0475	1.0244	1.0033
14	1.0000	1.0229	1.0123	0.9966

Table 6 Real power of load before and after load shed for IEEE 14 bus system.

Bus number	Normal load (pu)	Load shed by GA (pu)	Load shed by hybrid method (pu)
3	0.9420	0. 494	0.895
4	0.4780	0.4780	0.4780
5	0.0760	0.0760	0.0760
6	0.1120	0.1120	0.1120
9	0.2950	0.2950	0.2950
10	0.0900	0.0900	0.0900
11	0.0350	0.0350	0.0350
12	0.0610	0.0610	0.0610
13	0.1350	0.0915	0.128
14	0.1490	0.1490	0.1490

5. Conclusion

A hybrid technique is proposed for minimizing the load shedding and voltage deviation. In the hybrid method, the GA is used in two stages viz, for framing the optimization model and for generating the data set for training the network. The appropriate buses for load shedding are selected based on the sensitivity of minimum eigenvalue of the load flow Jacobian matrix. The proposed algorithm is applicable for nonlinear problems because its mechanization is simple without much mathematical complexity and global optimized solution. The proposed method is implemented and the effectiveness is tested with 6 bus and IEEE 14 bus systems. The result of the proposed hybrid method is compared with GA based optimization algorithm. The comparison shows that, proposed method has achieved less load shedding and minimum voltage deviation.

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