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Corrective action planning considering FACTS allocation and optimal load shedding using bacterial foraging oriented by particle swarm optimization algorithm

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Abstract

Reactive power planning (RPP) involves optimal allocation and determination of the type and size of new reactive power (VAR) supplies to satisfy voltage constraints during normal and contingency states. The RPP issue is in fact an optimization of large scale mixed integer nonlinear programming problem, so it is proper to use an evolutionary algorithm to solve the problem. In this paper, in order to solve the RPP problem for corrective action of power systems, the bacterial foraging (BF) oriented by particle swarm optimization (PSO) algorithm (BF-PSO) is proposed. In the algorithm, the VAR control has been carried out by using flexible AC transmission systems (FACTS) devices, in order to minimize the installation costs of these devices. In order to determine the saving rate in the costs, corrective control is also performed by the utilization of load shedding algorithm. The IEEE 57-Bus system is used to test the proposed method. The simulation results of the proposed algorithm are compared with PSO and genetic algorithms (GA) to show the efficiency of this method in the RPP problem.

Key Words: *FACTS Devices, Reactive Power Planning, Load Shedding, BF Algorithm, PSO Algorithm.*

1. Introduction

One of the most important problems in power systems is the violation of constraints and total system stability. The state in which the system constraints violate their limits is called a contingency state, and the operations required for the correction of this state are called contingency control or corrective control. There is more probability of voltage collapse and instability in the systems with no fast reactive power supplies. So, the utilization of the fast momentary reserves of VAR devices can be considered as one of corrective action control [1]. Other functions performed for corrective control are the utilization of distributed generation [2], corrective switching in transmission systems [3], and load shedding [4–6]. The problem of corrective control by the utilization of reactive power reserve supplies is very close to reactive power planning problems consisting of contingency analysis in which the analysis of the supplies of reactive power reserves for the power system secure operation is performed. Two groups of constraints have been utilized in the conventional reactive power planning problems as follows:

a) the constraints of voltage feasibility, which guarantee bus voltages within permissible limits;

b) the voltage stability constraints which guard the system against voltage collapse.

Reactive power planning involves optimal allocation and determination of types and sizes of new reactive power supplies to satisfy the voltage constraints in normal and contingency states. This problem is a large scale mixed integer non-linear optimization programming which can be solved by many of the optimization techniques [8].

To overcome problems related to the conventional optimization methods and avoid leading to the local optimum, the utilization of algorithms based on heuristic methods for the solution of these problems were taken into consideration. Genetic algorithm [9, 10] and particle swarm optimization (PSO) algorithm [11, 12] have been applied for the reactive power planning. The neural networks have been also utilized for the solution of this problem [13].

The BF-PSO algorithm is one of the metaheuristic algorithms which is a suitable method for the solution of this problem due to its high accuracy and convergence speed. In this paper, corrective control strategies based on allocation of FACTS devices are presented by using BF-PSO algorithm with the goal of minimization of the total costs of these devices. Moreover, the proposed method with the goal of minimization of load shedding costs is carried out by the utilization of BF-PSO algorithm and corrective control action. In order to show the efficiency of the proposed algorithm, simulations with PSO and GA algorithms are also done and the results of the comparison are presented. The acceptable results show the effectiveness of the proposed algorithm.

To achieve these goals, the RPP problem is first described in section 2, and the problem formulation including cost calculation and definition of the problem constraints are presented in section 3. The candidate sites selection of FACTS devices will be specified in section 4. In sections 5 and 6, a description of BF-PSO algorithms are presented and section 7, explains how solution methods have been applied in RPP problem. Finally in section 8, the numerical examinations are carried out using IEEE 57-Bus system to demonstrate the effectiveness of the proposed method.

2. Corrective control action in power systems

In reactive power planning problems, the aim is to optimize a specific objective function by considering different operational conditions of the power system. The power system which is operating with specified power generation and permissible voltage levels is at its normal state. In this state, if the system makes a contingency such as overloading, line tripping, and generation outage, it will be in the emergency state. In this state a corrective control should be performed on the system as soon as possible, otherwise; the system will move to voltage collapse [14]. A system on which corrective control is performed proceeds to a corrective state. In this state, when the system is voltage stable, but load margins are too small, the preventive control is carried out on the system to obtain system stability. So the system returns to a preventive state. After that, the system will quickly return to its normal operation state. Figure 1 clearly represents the transition states described above.

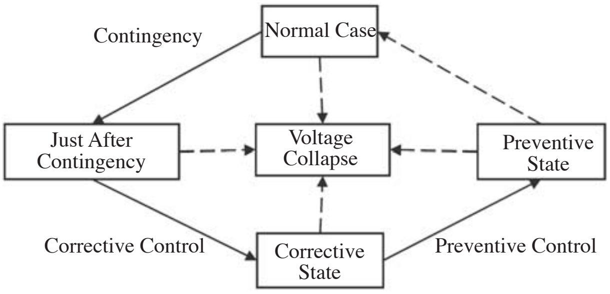

Figure 1. System transition states.

The constraints of operational states are defined in different forms, which the most common is voltage constraints (presenting the permissible limits in ranges 0.9 to 1.1 p.u.) [7]. The violation of these constraints leads to emergency state which necessitates the corrective controls.

3. Problem formulation

When the power system encounters emergency state, it should return to the normal state as soon as possible. Therefore, it is required that FACTS devices could be applied for the aim of corrective control. The purpose of this paper is the allocation of these devices for corrective control actions, in order to minimize the investment cost. For this purpose, the annual cost of the FACTS devices is calculated and utilized as an objective function.

3.1. Investment cost of FACTS devices

The survey of practical documents about reactive power supplies leads us to the conclusions that first, cost of slow devices is cheaper than fast devices; secondly, for low-power rating, it is increased, while for high-power rates the cost is reduced. In this regard, Figure 2 depicts the fast devices investment costs (such as static Var compensator and static compensator – SVC and STATCOM). These results are extracted from Siemens data center [15].

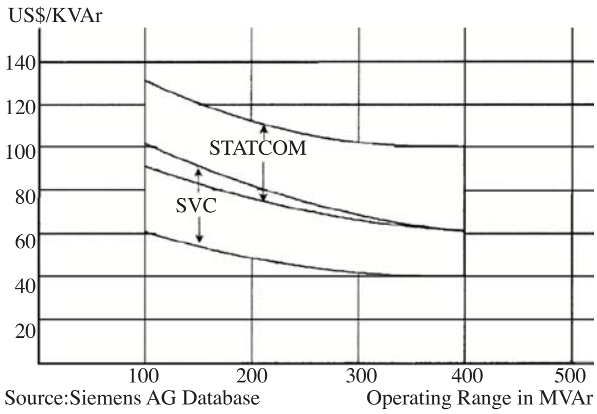

Figure 2. Investment costs of fast devices [15].

To apply Figure 2 in the problem formulation, it is assumed that the investment costs for FACTS devices are represented by the quadratic function

$$\mu_i = k_2 \cdot c_i^2 + k_1 \cdot c_i + k_0. \tag{1}$$

Here, μ_i is the investment costs in terms of \$/KVAR and c_i is the sizes of the installed VAR sources in terms of MVAr. The coefficients of equation (1) for static Var compensator (SVC) and static compensator (STATCOM) are given in Table 1, which are achieved by using a curve fitting technique on Figure 2 [15].

Table 1. Cost function coefficients for SVC and STATCOM devices.

k_0	k_1	k_2	
127.38	0.3051	0.0003	SVC
188.2	0.2691	0.0003	STATCOM

3.2. Optimization model

The initial investment cost expressed by equation (1), is presented as equation (2) for the purpose of its application in the problem:

$$F_{It0} = \sum_{i \in \Omega} (\mu_i \cdot c_i \cdot d_i), \tag{2}$$

where d_i is an integer with values of 1 or 0 representing the presence or absence of VAR device in bus i, and Ω is a set of all candidate sites of FACTS devices.

Also, the annual investment costs (F_{It}) are obtained as

$$F_{It} = \frac{i_r (1 + i_r)^{D_y}}{(1 + i_r)^{D_y} - 1} F_{It0}, \tag{3}$$

where i_r and D_y are equal to the interest rate and the life period of VAR devices, respectively.

Therefore, the reactive power planning problem can be formulated with the objective function of minimization annual investment costs of FACTS devices, and considering the constraints of different operational states of the power system in the following manner:

$$\begin{array}{l} \text{Minimize } F_{\text{total}} = F_{It} \\ \quad Subject\_To: \\ \qquad 0 \leq C_{It,i} \leq C_{It,\max} \\ \qquad V_{\min,i} \leq V_i \leq V_{\max,i} \end{array} \tag{4}$$

Here, $C_{It,i}$ is the capacity of the installed FACTS device in bus i, and $C_{It,\max}$ is the permissible maximum VAR compensation of FACTS device; and $V_{\max,i}$, $V_{\min,i}$ are the maximum and minimum permissible voltage on bus$i$, respectively. In addition to these constraints, the power flow equations should be considered as

$$\begin{array}{l} 0 = P_{Gi} - P_{Di} - V_i \sum\limits_{j \in N_i} V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) \\ 0 = Q_{Gi} - Q_{Di} - V_i \sum\limits_{j \in N_i} V_j (G_{ij} \sin\theta_{ij} + B_{ij} \cos\theta_{ij}) \end{array} \tag{5}$$

where:

$P_{G,i}$, $Q_{G,i}$ are the active and reactive powers generation at bus i (p.u)

$P_{D,i}$, $Q_{D,i}$ are the active and reactive powers load bus i (p.u)

G_{ij}, B_{ij} are real and imaginary parts of the admittance ij of the admittance matrix (p.u)

θ_{ij} is the phase angle difference between voltage buses i and j (radian)

4. Candidate sites selection of FACTS devices

An important step in reactive power planning problem is the site selection of candidates for the installation of new reactive power devices. It is ideal that unlimited FACTS devices should be installed in all the buses, so that the required value of reactive power could be injected in each bus. Of course, it is not economically cost-effective, as there is a limited number of candidate buses for the placement of FACTS devices. Since the employed FACTS devices are voltage control ones, the participation factors are applied as the voltage indexes for the determination of candidate sites to install the above devices. These factors are calculated by the Jacobian matrix

$$\begin{bmatrix} \delta \\ V \end{bmatrix} = \begin{bmatrix} J_{11} & J_{12} \\ J_{21} & J_{22} \end{bmatrix}^{-1} \cdot \begin{bmatrix} P \\ Q \end{bmatrix}. \tag{6}$$

Ignoring the effect of active power on the magnitude of bus voltage, the voltage of each bus shall be equal to

$$V_i = \alpha_{1i}.Q_1 + ... + \alpha_{ni}.Q_n, \tag{7}$$

where α's are participation factors.

Finally to determine the candidate sites, after performing load flow, the number of bus with the minimum voltage is selected. Then by applying sensitive analysis, equation (7) is formed. It should be noted that the candidate sites are the buses with higher participation factors in equation (7).

5. Bacterial Foraging Algorithm

A recent evolutionary computation technique, called BF scheme has been proposed by Passino in 2002. The idea in this algorithm was adopted from biological and physical living behavior of E.coli bacteria existing in human intestine. Chemotaxis is basically a behavior to earn a living that performs a type of optimization in which bacteria try to reach the nutrients and avoid noxious materials and find a way to exit the neutral and noxious nutrient environment [16–17]. The control system of these bacteria that dictates how foraging should proceed, can be subdivided into four sections namely Chemotaxis, Swarming, Reproduction, and Elimination and Dispersal. These operations among the bacteria are used for searching the total solution space. Brief descriptions of these operations are given below, then followed by a flowchart for solving the optimization problems will be presented.

5.1. Chemotactic step

This process is achieved through swimming and tumbling via Flagella. Depending upon the rotation of Flagella in each bacterium, it decides whether it should move in a predefined direction (swimming) or altogether in different directions (tumbling). Figure 3 shows the bacterium movement.

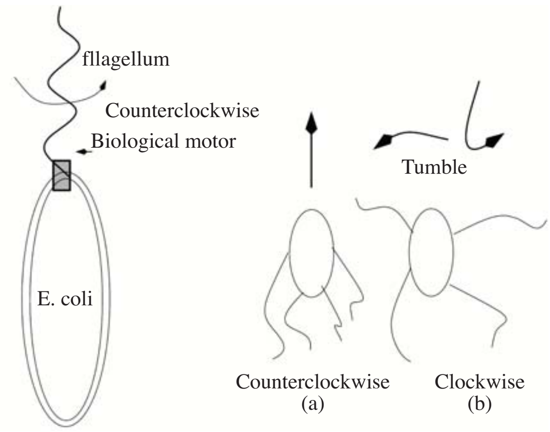

Figure 3. Schematic diagram of E. coli cell movement behavior.

In BF algorithm, one moving unit length with random directions represents "tumbling," and one moving unit length with the same direction relative to the final step represents "swimming." The chemotactic step consists of one tumbling along with another tumbling, or one tumbling along with one swimming. This movement is can be described as

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}, \tag{8}$$

Where $\theta^i(j,k,l)$ denotes the position of i^{th} bacterium at j^{th} chemotaxis, k^{th} reproduction, and l^{th} elimination and dispersal, respectively. Also, $C(i)$ and $\Delta(i)$ are the movement length and direction random vector, respectively.

5.2. Swarming step

The discussion of section (5.1) was for cases when bacteria behaved individually (without producing signal for other bacteria), but there is an exchange of signals between the bacteria here (through absorbing materials). So, the group movement for every bacterium (J^i_{cc}) is defined as

$$J^i_{cc}\left(\theta_{gm}\left(j,k,l\right),\theta^i\left(j,k,l\right)\right), i=1,2,...,S, \tag{9}$$

where $\theta_{gm}\left(j,k,l\right)$ is the location of the global minimum bacterium till the j^{th} chemotactic, k^{th} reproduction, and l^{th} elimination stage. Based on this equation, the group movement for all bacteria (J_{cc}) is calculated as follows:

$$\begin{aligned} &J_{cc}\left(\theta_{gm}\left(j,k,l\right),\theta\left(j,k,l\right)\right) = \sum_{i=1}^{s} j^i_{cc}\left(\theta_{gm}\left(j,k,l\right),\theta^i\left(j,k,l\right)\right) = \\ &\sum_{i=1}^{s}[-d_{attract}\exp(-\omega_{attract}\sum_{m=1}^{P}(\theta_{m_{gm}}-\theta^i_m)^2]+ \\ &\sum_{i=1}^{s}[h_{repellant}\exp(-\omega_{repellant}\sum_{m=1}^{P}(\theta_{m_{gm}}-\theta^i_m)^2] \end{aligned} \tag{10}$$

Here, $d_{attract}$, $h_{repellant}$, $w_{attract}$, and $w_{repellant}$ are the parameters which are to be selected appropriately. Of course, it is appropriate that $d_{attract} = h_{repellant}$. Meanwhile, $\theta_{m_{gm}}$ represents the m^{th} parameter of the global minimum bacteria. It should be noted that $J_{cc}\left(\theta_{gm}\left(j,k,l\right),\theta\left(j,k,l\right)\right)$ is the combined cell-to-cell attraction and repelling effects and $\theta = [\theta_1, \ldots \theta_P]^T$ are points on the optimization domain.

5.3. Reproduction step

After certain steps of chemotactic, the least healthy bacteria die and the other healthiest bacteria each split into two bacteria, which are placed in the same location. This makes the population of bacteria constant.

5.4. Elimination and dispersal step

Swimming prepares the environment for local foraging and speeds up convergence in the process of reproduction. However, only by swimming and reproduction, a large space cannot be enough for searching the global optimal point. In BF algorithm, the dispersal event takes place after a definite number of reproduction processes. First, a bacterium with regard to a P_{ed} prearranged probability is selected to move and disperse to another position in the environment. These events can effectively prevent trapping in local optimal points. Also, N_{ed} is the number of elimination and dispersal event and P_{ed} is defined for every bacterium (which is the probability of elimination and dispersal).

Assume that the frequency of the moving steps is more than the frequency of the reproduction steps and the frequency of reproduction is also more than the elimination and dispersal event. Therefore, many movement steps take place before reproduction, and many regeneration steps also occur before the elimination and dispersion [16–17]. Figure 4 shows the flowchart of specific application of this algorithm.

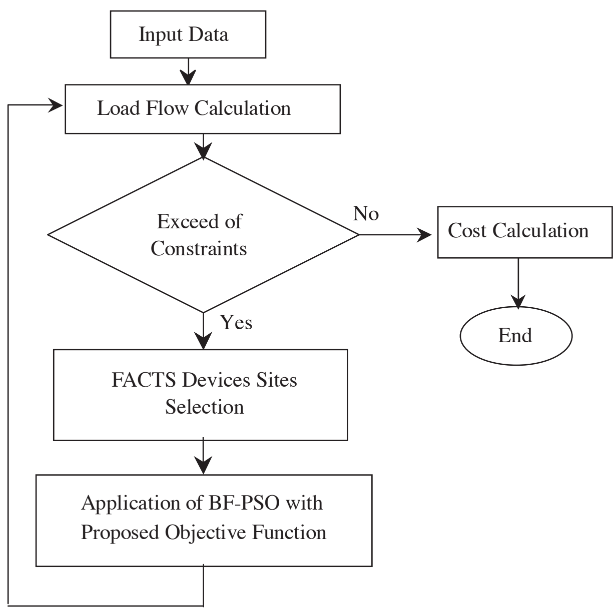

Figure 4. Bacterial foraging algorithm Flowchart.

6. Bacterial foraging oriented by PSO algorithm

The BF algorithm depends on random direction which slows down the optimal solution process. Particle swarm optimization (PSO) algorithm might also converge to local optimal solutions. Therefore, in the BF-PSO algorithm, it is tried to benefit from the advantages of these two algorithms in the process of optimization. So, the application of PSO in BF algorithm for solving the above problem is discussed in this section.

6.1. A survey of PSO algorithm

The PSO algorithm models the behavior of a group of particles whose initial values are specified with a group of proposed random solutions [18]. These particles repeatedly search the environment of the problem to reach new solutions. The position and the velocity of each particle are specified by X_k^i and V_k^i of particle i at iteration k in the searching space, respectively. Every particle conserves its best P_{lbest}^i global position. Also, the vector of the best position of the particle is conserved in P_{global}^i global best position. Then, the velocity of particle i at iteration $k+1$ (V_{k+1}^i) can be updated according to the following equation:

$$V_{k+1}^i = w \cdot V_k^i + C_1 \cdot R_1(P_{lbest}^i - X_k^i) + C_2 \cdot R_2(P_{global}^i - X_k^i), \tag{11}$$

where R_1 and R_2 are two random functions that produce random number in the range of 0 to 1. Also, w is the inertia weight factor and C_1 and C_2 are learning factors. It should be noted that the factor w has decreased and varied linearly from 0.9 to 0.4 [18]. In general w can be determined from the relation

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{k_{\max}} * k, \tag{12}$$

where $k_{\max}$ and k are the maximum and current number of iteration (or generation), respectively.

In the end of each iteration, the new position of each particle is also obtained by the addition of the previous position and the new speed via the relation

$$X_{k+1}^i = X_k^i + V_{k+1}^i. \tag{13}$$

6.2. Application of PSO in BF algorithm

As it was mentioned in equation (8), each movement step of BF algorithm is dependent on the random parameter of Δ, which slows down the searching process. For this purpose, by considering PSO parameters expressed in section 6.1, the new direction for the movement of every bacterium is calculated as follows:

$$V_{k+1} = w \cdot V_k + C_1 \cdot R_1(P_{lbest} - P_{current}) + C_2 \cdot R_2(P_{global} - P_{current}). \tag{14}$$

Based on this equation, V parameter is updated at each iteration. It should be noted that in BF algorithm, the V parameter is utilized in place of Δ parameter to orient every bacterium [18].

7. The BF-PSO algorithm for the proposed method

In this section, the proposed design procedure of FACTS allocation and load shedding algorithms based on the BF-PSO process is discussed. Based on the basic conception proposed in section 3, the fitness function is considered as the following equation for the placement of FACTS devices:

$$J = F_{It} + J_1 + J_2. \tag{15}$$

In this equation, J_1 and J_2 are the cost functions related to violations of minimum and maximum limits in voltage constraints, which can be presented by the functions

$$\begin{array}{l} J_1 = pf_1 * abs(sign(V_{\min} - 0.95) - 1) \\ J_2 = pf_2 * abs(sign(V_{\max} - 1.05) + 1) \end{array}, \tag{16}$$

where penalty factors pf_1 and pf_2 are considered for the satisfaction of the constraints in these equations, so that if they violate the permissible constraints, the fitness function increases and the possibility of bacterium elimination related to its solution is raised in regeneration process.

Moreover, the corrective action control is performed by the utilization of optimal load shedding for determination and comparison of the saving value in total cost. Load shedding by BF-PSO algorithm is performed in such a manner that the load power factor remains constant and the load shedding costs are minimized. Therefore, the fitness function considered for optimal load shedding is as follows:

$$J = F_{L.Sh} + J_1 + J_2, \tag{17}$$

where J_1 and J_2 are defined based on equation (16).

Finally, the saving cost done due to the utilization of FACTS devices is calculated as follows:

$$F_{saving} = F_{L.Sh} - F_{It}. \tag{18}$$

For this purpose, the general flowchart for the proposed method is presented as Figure 5. On the left of flowchart shown in Figure 5, the FACTS devices allocation is performed. In this part, an initial population is randomly generated by BF-PSO algorithm. Every bacterium in this population is applied for the calculation of the fitness function. In other words, each bacterium is a combination of reactive power sources which are considered as a response to the problem. Each bacterium consists of several numbers equal to the number of candidate sites for FACTS devices. These numbers which are between the minimum and maximum permissible limits of reactive power of FACTS devices, represent the generation of VAR devices in the intended sites.

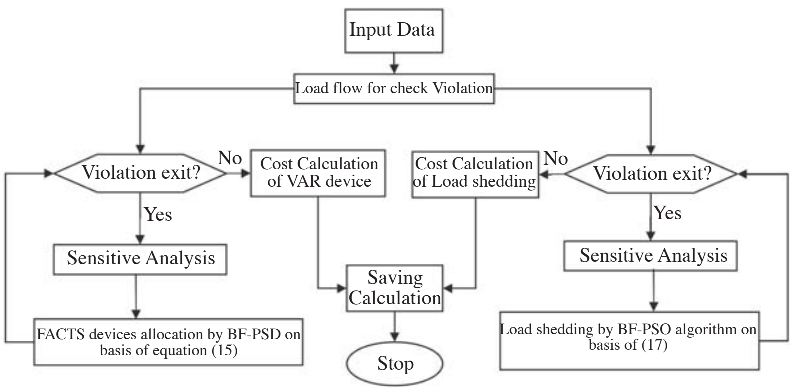

Figure 5. The general flowchart for the proposed method.

On the right of flowchart shown in Figure 5, every bacterium consists of several numbers equal to the number of the candidate sites in order to perform the load shedding problem by BF-PSO algorithm. The amount of these numbers represent the value of loads to be shed in each of these sites.

8. Simulation results

For the evaluation of the effectiveness and efficiencies of the proposed algorithm in this section, the IEEE 57-Bus test system is used [19]. The single-line diagram of the system is shown in Figure 6. Also, the parameters utilized in simulation are shown in Table 2.

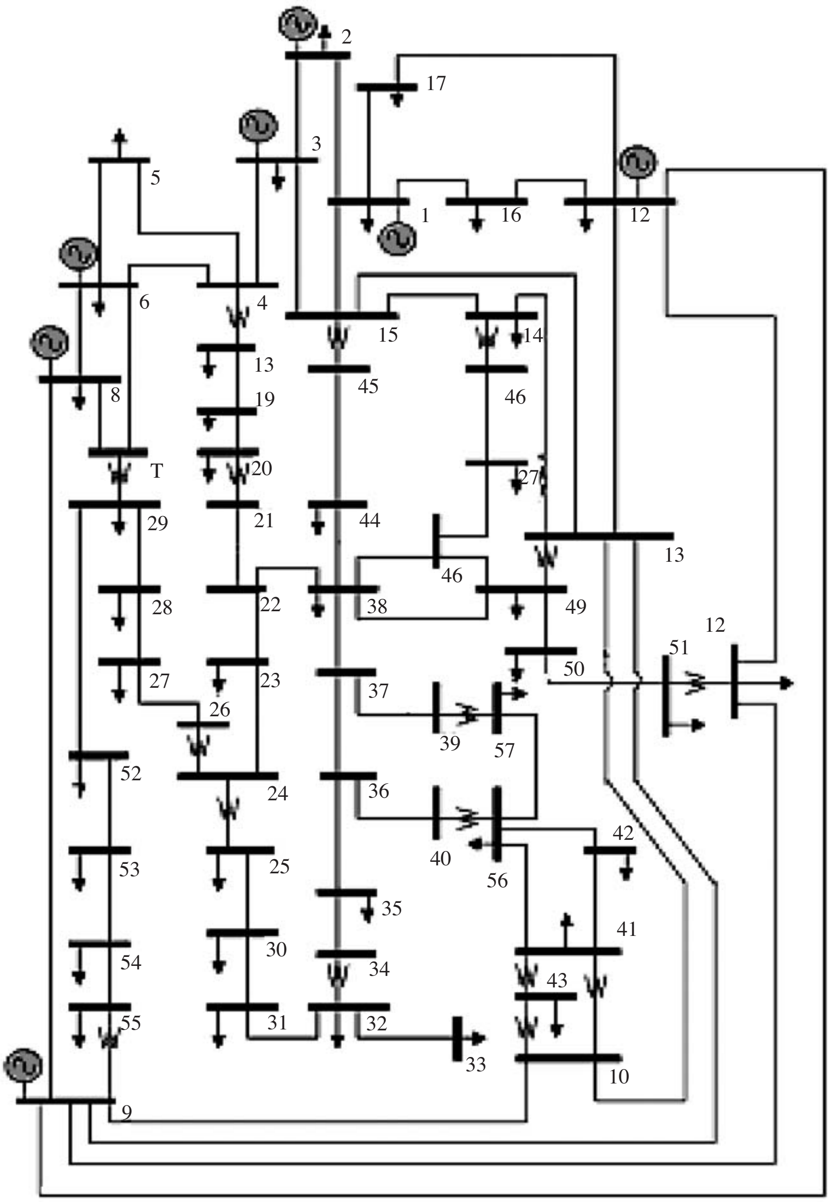

Figure 6. The single-line diagram of IEEE 57-Bus system.

Table 2. Simulation data.

D_y	i_r	$C_{It,\max}$	$V_{\min}$	$V_{\max}$	Parameter
10	0.04	0.6	0.95	1.05	Value

Figure 7 shows the voltage profile in normal state of the system, where all the voltages are within their permissible limits.

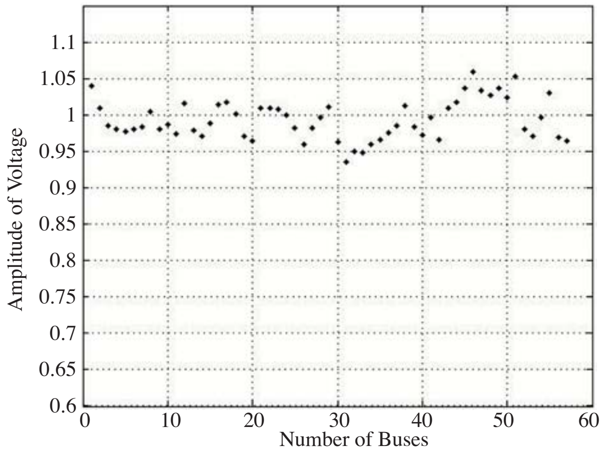

Figure 7. System voltage profile in the normal state.

With regard that one of the widespread faults in power system is overloading, it is assumed that the system load increased to 20%. In this case, the voltage profile is depicted in Figure 8 after this fault. As it is observed, the least voltage is apparent in Bus-31 with a value of 0.88 per unit (p.u.), violating its permissible limits. Therefore, corrective control should be performed on this system.

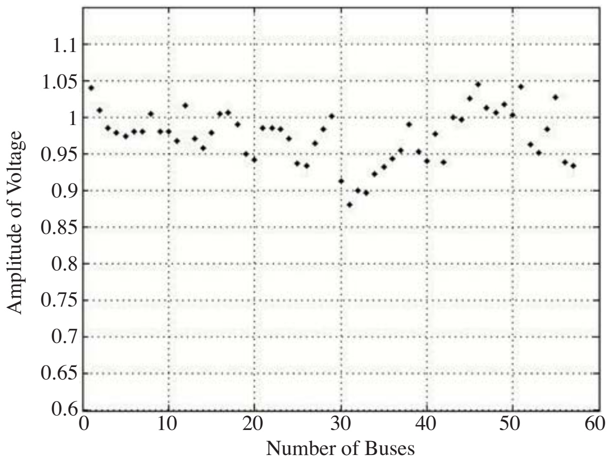

Figure 8. Voltage profile after the implementation of fault.

It should be noted that the correction of voltage in the bus with the least voltage will result in voltage correction in other buses, also violating the limits. So, based on the flowchart of the proposed method, the sensitivity analysis is only performed for Bus-31. The results of this analysis are presented in Table 3 for 15 buses with the most values of participation factors.

Table 3. Sensitivity analysis results.

Participation factor	Bus number	Participation factor	Bus number
0.0579	10	0.1054	31
0.0576	8	0.0696	20
0.0571	34	0.065	18
0.0546	40	0.0643	22
0.0531	6	0.064	16
0.0501	4	0.0637	14
0.0494	32	0.0632	12
		0.0629	24

The optimal locations and suitable values of FACTS devices in the 15 buses with the most sensitivity in participation factors by the use of BF-PSO algorithm are shown in Tables 4. Also, to demonstrate the efficiency and capability of proposed algorithm, the results are compared with PSO and GA algorithms. It has to be mentioned that load conditions and parameters setting are the same as before and parameters of PSO and GA algorithms are according to reference [20].

As can be seen in Table 4, total injected reactive power for corrective control by using proposed BF-PSO, PSO and GA algorithms are 293.2 MVAR, 333.7 MVAR and 349.3 MVAR, respectively. So, by applying the BF-PSO algorithm, the total injected reactive power of FACTS devices is less than using PSO and GA algorithms.

Table 4. Table 4. Optimal location and size of the injection reactive power.

Bus number	Injected Reactive Power (MVAR)		
	BF-PSO algorithm	PSO algorithm	GA algorithm
31	19.1	23.7	22.5
20	0	0	0
18	45	38.2	50.4
22	0	16.9	0
16	26	25.4	31.9
14	0	0	0
12	29.2	17.8	21.4
24	0	0	0
10	0	23.6	0
8	0	0	0
34	26.7	27.3	29.2
40	50.7	67.4	70.6
6	0	34.5	0
4	49.4	0	56.7
32	47.1	58.9	66.6
Total injected reactive power	293.2	333.7	349.3

By injecting these values of reactive powers, obtained from the BF-PSO algorithm, the voltage profile is improved in an appropriate manner, as shown in Figure 9. Comparing Figures 8 and 9, it is realized that the minimum voltage improves from 0.88 to 0.95.

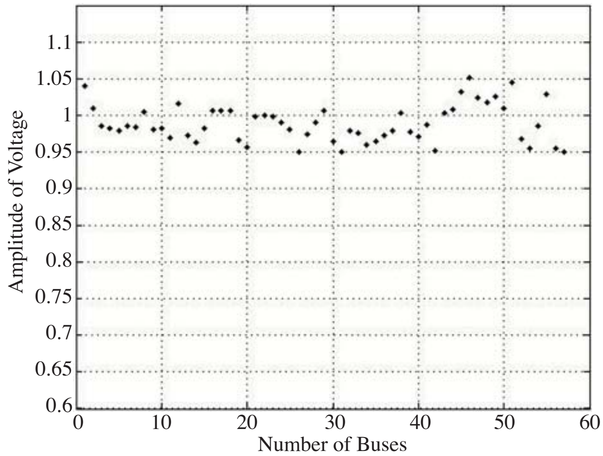

Figure 9. Voltage profile after the reactive power injection.

As mentioned in section (7), the corrective control is also performed by using a load shedding algorithm to compare and calculate the costs. Notice that the candidate buses for load shedding algorithm are those very same buses obtained in sensitivity analysis. The value of loads to be shed in different buses are shown in Table 5.

Table 5. The value and site of loads to be shed.

Reactive power (MVAR)	Active power (MW)	Bus number
16.7	33.5	31
37.2	74.5	32

Voltage profile following load shedding will be as shown in Figure 10. With regard to the cost of load shedding (which is considered to be 1000$ per 100 MW [21]), the corrective control cost by performing the optimal load shedding algorithm in this system will be equal to

$$F_{L.Sh} = 1080\$.$$

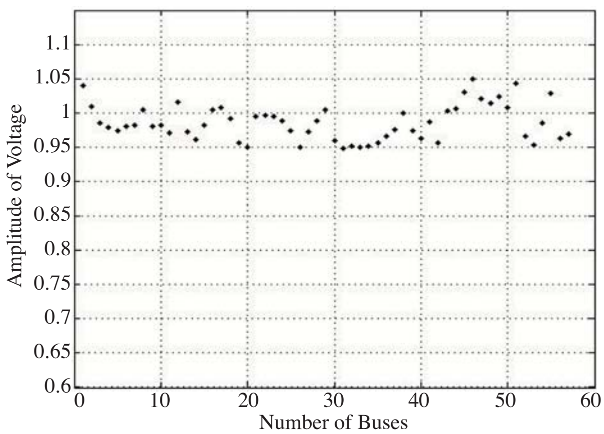

Figure 10. Voltage profile after performing load shedding algorithm.

Table 6 shows a comparison of system voltages in different states representing the efficiency of the proposed method. Also, Table 7 shows the annual corrective control cost (F_{It}) and annual saving cost (F_{Saving}) by the utilization of all of the algorithms. The annual saving cost is obtained from equation (17). From this table it can be seen that using FACTS devices for corrective control increased cost saving compared with optimal load shedding. The total annual saving cost resulted from proposed BF-PSO, PSO and GA algorithms are 622$, 599$ and 593$, respectively, which represent the capability of the proposed method comparing with the other ones in the network cost reduction.

Table 6. Comparison of the voltage of the buses in different cases.

Max Voltage in system		Min Voltage in system		State
Value	Bus Number	Value	Bus Number	
1.051	46	0.936	31	Normal
1.040	46	0.880	31	Emergency
1.051	46	0.950	26	Using FACTS devices with BF-PSO algorithm
1.050	46	0.953	26	Using FACTS devices with PSO algorithm
1.046	46	0.951	26	Using FACTS devices with GA algorithm
1.049	46	0.949	31	Employing Load Shedding

Table 7. Comparison of annual cost saving for different algorithms.

Corrective control	Load shedding cost ($F_{L.Sh}$)	Annual corrective control cost (F_{It})	Annual cost saving (F_{Saving})
Load shedding	1080$	0	0
Using BF-PSO	0	458$	622$
Using PSO	0	481$	599$
Using GA	0	487$	593$

9. Conclusion

A new application of BF-PSO algorithm for a reactive power planning problem with a view to the system transition states was presented in this paper. The occurrence of a fault in power systems can lead to an emergency state, with the voltages violating their permissible limits; such a state therefore requires imposition of corrective control on the system. Fast VAR devices should be utilized for corrective control, although the investment cost of these devices are higher than for slow VAR devices. Optimal placement of FACTS devices in the emergency state of the system was obtained by using the BF-PSO algorithm. The proposed method was compared to PSO and GA algorithms via simulations, with results showing the presented method can have significant savings in total costs, as well as conditioning to satisfactory voltage levels.

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