Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2013) 21: 913 – 923

doi:10.3906/elk-1105-32

Biogeography-based optimization for voltage stability improvement and reactive reserve management

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Received: 18.05.2011 • **Accepted:** 10.08.2011 • **Published Online:** 03.06.2013 • **Printed:** 24.06.2013

Abstract: This paper proposes a biogeography-based optimization algorithm to enhance the voltage stability of a power system. It computes the optimal quantity of reactive power support with a view to place the static VAR compensator at the most appropriate nodes. The scheme inflicts an effective management of VAR resources in the process of improving the voltage profile and reducing the network losses. It includes the results of IEEE 30-node system to illustrate the feasibility of the approach.

Key words: Voltage stability, biogeography-based optimization, real power loss minimization, static VAR compensator, FACTS devices

1. Introduction

Voltage instability, characterized by a monotonic voltage drop that is slow initially and becomes abrupt after some time, is triggered either by some kind of disturbances or an increase in reactive power demand that is beyond the capability of the system. It has been realized that major blackouts were caused by voltage instability. It is therefore necessary to predict the occurrence of voltage instability and carry out corrective measures with a view toward ensuring stable operation [1,2].

Static VAR compensators (SVCs) and other flexible alternating current transmission system (FACTS) devices have been installed in power systems to provide reactive power support. The determination of the node location for such devices and the amount of reactive power support is of great significance for reducing the real power losses in addition to enhancing voltage stability (VS). It also increases the available transfer capacity of the transmission lines, thereby improving the feeder voltage profile. Several methods for solving this problem have been suggested in the literature [3–11].

Numerous methods for prevention of voltage instability using FACTS devices in power systems were surveyed in [3]. An operation strategy involving SVCs for improving voltage profile and minimizing real power loss reduction was suggested in [4]. A bacterial foraging-based algorithm was used to improve the voltage stability limit and to reduce the loss by optimally placing the unified power flow controller (UPFC) in [5]. An operation scheme based on a UPFC in order to ensure security through the line over load control and low voltage control was given in [6]. A method for installing a UPFC with the view of enhancing the VS margin under contingent conditions was presented in [7]. A strategy for maintaining reactive power reserve with the view of

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avoiding voltage collapse was presented in [8]. An analytical procedure for minimizing voltage deviations in order to indirectly enhance VS was proposed through reactive power compensation in [9]. A particle swarm optimization (PSO)-based algorithm was suggested in [10] to ensure voltage security by controlling the reactive power and node voltages. An adoptive immune algorithm for the reactive power optimization was outlined in [11].

Recently, a biogeography-based optimization (BBO) algorithm was suggested for solving optimization problems [12]. It was developed based on the theory of biogeography, studying the geographical distribution of biological species. In this approach, the islands or habitats are modeled to represent problem solutions, and the immigration and emigration of species between islands denote sharing of features between solutions. It has been applied to several optimization problems, such as optimal reactive power control [13], economic load dispatch [14], and power flow [15].

A novel BBO-based algorithm for enhancing VS in power systems through optimal placement of SVCs is detailed in this paper. The algorithm has been tested on the IEEE 30-node system and the results are offered. The paper is divided into 4 segments. Section 1 gives the introduction, Section 2 explains the BBO algorithm, Section 3 explains the proposed strategy, Section 4 discusses the results, and Section 5 gives the conclusions.

2. Biogeography-based optimization

BBO, as suggested by Dan Simon in 2008 [12], is a stochastic optimization technique for solving multimodal optimization problems. It is based on the concept of biogeography, which deals with the distribution of species that depend on different factors such as rainfall, diversity of vegetation, diversity of topographic features, land area, and temperature. A larger number of species are found in favorable areas compared with those in a less favorable area. An island that is geographically isolated from other areas is defined as a habitat and is said to have high habitat suitability index (HSI) if it is suited as a residency for living organisms. The problem variables that define islands are called suitability index variables (SIVs). A large number of species on high HSI islands emigrate to neighboring islands with fewer numbers of species and share their characteristics with those islands. For this reason, habitats with low HSI have a high species immigration rate. The immigration and emigration process helps the species in the area with low HSIs to gain good features from the species in the area with high HSIs and makes the weak elements into strong. It also allows the retaining of good features of species in the areas with high HSIs. The rates of immigration (λ) and emigration (μ) are the functions of the number of species in the habitat. Figure 1 shows the immigration and emigration curves indicating the movement of species in a single habitat.

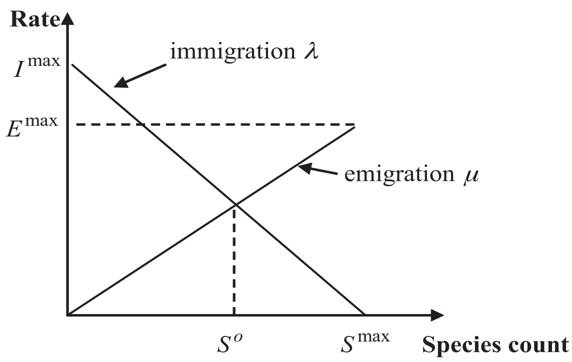

Figure 1. Species model of a single habitat.

In BBO, an island with high HSI represents a good solution and vice versa. The poor solutions for islands with low HSIs accept many new features from good solutions of islands with high HSIs and improve their quality. However, the shared features of the good solution still remain in the high HSI solutions. The concept of immigration and emigration is mathematically represented by a probabilistic model, which relates the probability $P_s(t)$ such that a habitat contains exactly S species at time t with that of the probability $P_s(t+\Delta t)$ at time $(t+\Delta t)$, as:

$$P_s(t+\Delta t) = P_s(t)\,(1-\lambda_s\,\Delta t - \mu_s\,\Delta t) + P_{s-1}\,\lambda_{s-1}\,\Delta t + P_{s+1}\,\mu_{s+1}\,\Delta t. \tag{1}$$

In case the time Δt turns out to be small, the probability of more than one immigration or emigration can be ignored, in which case the limit of Eq. (1) as $\Delta t \to 0$ yields the following equation.

$$\dot{P}_s = \begin{cases} -(\lambda_s+\mu_s)P_s + P_{s+1}\,\mu_{s+1}; & S=0 \\ -(\lambda_s+\mu_s)P_s + P_{s+1}\,\mu_{s+1} + P_{s-1}\,\lambda_{s-1}; & 1 \le S \le S^{\max} \\ -(\lambda_s+\mu_s)P_s + P_{s-1}\,\lambda_{s-1}; & S = S^{\max} \end{cases} \tag{2}$$

The equation for emigration rate μ_k and immigration rate λ_k for k number of species is developed from Figure 1 as follows.

$$\mu_k = \frac{E^{\max}}{n} \tag{3}$$

$$\lambda_k = I^{\max}\left(1-\frac{k}{n}\right) \tag{4}$$

When $E^{\max} = I^{\max}$, the immigration and emigration rates can be related as:

$$\lambda_k + \mu_k = E^{\max}. \tag{5}$$

The concept of BBO is based on the mechanisms of migration and mutation, as discussed below.

2.1. Migration

A population of islands, each denoting a candidate solution, can be represented as vectors of SIVs, which are used to compute the HSI. An island with low HSI indicates an inferior solution and vice versa. The immigration and emigration rates of each island probabilistically control the sharing of features between islands through a habitat modification probability, P^{mod}. The λ is probabilistically used to decide whether or not to modify each SIV of the chosen island. μ is then used to select which of the islands among the population of islands will migrate randomly chosen SIVs to the selected island. The principle of elitism is used for retaining the islands with the highest HSI from entering the next generation with a view toward avoiding the damaging of the best islands.

2.2. Mutation

The cataclysmic events of any island are modeled through mutation of SIVs, whose mutation rates are determined from species count probabilities. The likelihood of the existence of a solution for a given problem is indicated by the probability of each species count, P_s, of Eq. (2). An island mutates with other islands if the respective P_s is very low and vice versa. An island with a very high or very low HSI has less chance to produce a more improved solution, but with a medium HSI it has a better chance to produce a more improved solution in the later stage. The mutation rate of each island can be evaluated using the following equation:

$$m(S) = m^{\max}\left(\frac{1-P_s}{P^{\max}}\right). \tag{6}$$

This mutation scheme tends to increase diversity among the population, avoids the dominance of highly probable solutions, and provides a chance of improving the low HSI solutions even more than they already have been.

3. Proposed strategy

The proposed BBO-based strategy determines the optimal locations and the amount of reactive power support required to enhance the VS by maintaining the voltage profile near 1.0 per unit and minimizing the system's real power loss. The problem control variables are the node locations for SVC placement and the amount of VAR support. This section describes the formulation of the problem and a BBO-based solution procedure for enhancing VS.

3.1. Problem formulation

The node currents and voltages of a power system can be related through node impedance matrix as:

$$\begin{bmatrix} V_1 \\ V_2 \\ \vdots \\ V_k \\ \vdots \\ V_{nb} \end{bmatrix} = \begin{bmatrix} Z_{11} & Z_{12} & \cdots & Z_{1k} & \cdots & Z_{1nb} \\ Z_{21} & Z_{22} & \cdots & Z_{2k} & \cdots & Z_{2nb} \\ \vdots & \vdots & & \vdots & & \vdots \\ Z_{k1} & Z_{k2} & \cdots & Z_{kk} & \cdots & Z_{knb} \\ \vdots & \vdots & & \vdots & & \vdots \\ Z_{nb1} & Z_{nb2} & \cdots & Z_{nbk} & \cdots & Z_{nbnb} \end{bmatrix} \begin{bmatrix} I_1 \\ I_2 \\ \vdots \\ I_k \\ \vdots \\ I_{nb} \end{bmatrix}. \tag{7}$$

The current injection at node-k can be computed from the specified node powers as

$$I_k = \left(\frac{P_k + jQ_k}{V_k}\right)^*, \tag{8}$$

where

$$P_k = P_{Gk} - P_{Lk},$$

$$Q_k = Q_{Gk} - Q_{Lk}.$$

Substituting Eq. (8) into the kth row of Eq. (7),

$$V_k = Z_{k1}\left(\frac{P_1 + jQ_1}{V_1}\right)^* + \cdots + Z_{kk}\left(\frac{P_k + jQ_k}{V_k}\right)^* + \cdots + Z_{knb}\left(\frac{P_{nb} + jQ_{nb}}{V_{nb}}\right)^*. \tag{9}$$

If the SVCs are connected at multiple node locations given by a set of nodes Φ, then Eq. (8) can be modified as:

$$V_k = \sum_{i\in\Phi} -j\alpha_{ki}\, Q_i^{svc} + \beta_k, \tag{10}$$

where

$$\alpha_{ki} = \frac{Z_{ki}}{V_i^*} \text{ and } \beta_k = \sum_{i=1}^{nb} Z_{ki} \left(\frac{P_i + jQ_i}{V_i} \right)^*. \tag{11}$$

Using the load flow solution as the initial solution, Eq. (10), which relates the state variables and control variables, can be iteratively solved for new node voltages and for additional reactive power support Q^{svc} to be provided in the network. The reactive power injection of each SVC is constrained by its capacity as:

$$Q_k^{svc-\min} \le Q_k^{svc} \le Q_k^{svc-\max}. \tag{12}$$

The location and the quantity of VAR support by SVCs are so adjusted that the net voltage deviation of all nodes with respect to nominal node voltage of 1.0 per unit is minimum besides reducing the system loss. The net voltage deviations and system loss can be mathematically expressed as:

$$\Delta V = \sum_{i=1}^{nb} (|V_i| - 1)^2, \tag{13}$$

$$P_{loss} = \sum_{i=1}^{nl} G_i \left(|V_m|^2 + |V_n|^2 - 2\ |V_m|\ |V_n| \cos\theta_{mn} \right), \tag{14}$$

where

$$\theta_{mn} = \angle V_m - \angle V_n.$$

The HSI function of the proposed strategy can be formulated by blending Eqs. (13) and (14) as:

$$Max\ HSI = 1/(\Delta V + \eta\ P_{loss}). \tag{15}$$

3.2. Representation of BBO variables

If there are nc SVCs to be placed, then the problem variables can be represented in matrix form as shown in Figure 2. BL_k values are so generated that they represent load nodes, as SVCs are not placed at PV nodes.

BL_1	BL_2	BL_3	$\cdots$	BL_{nc}
Q_1^{svc}	Q_2^{svc}	Q_3^{svc}	$\cdots$	Q_{nc}^{svc}

Figure 2. Representation of control variables.

The problem variables contain both integer value for representing BL_k and real values to denote Q_k^{svc}, but the BBO algorithm deals with real numbers. Therefore, the BL_k value is rounded off to the nearest integer value to represent a node location.

3.3. Repair algorithm

It is undesirable to fix 2 or more SVCs at a node. During the iterative process, there is a possibility that a solution point contains the same node number for 2 or more SVCs. If this happens, it may be corrected by the following repair mechanism.

- Alter any 1 SVC's node location by generating a random number to represent another load node.
- Repeat the above step until no 2 SVCs' node locations are the same.

3.4. Fitness function

The BBO searches for the optimal solution by maximizing a fitness function, denoted by HSI, which is formulated from the objective function, Eq. (8), involving net voltage deviations and system loss as shown below.

$$MaxHSI = \frac{1}{1+\Phi} \tag{16}$$

3.5. Stopping criterion

The process of generating a new population can be terminated either after a fixed number of iterations or if there is no further significant improvement in the global best solution.

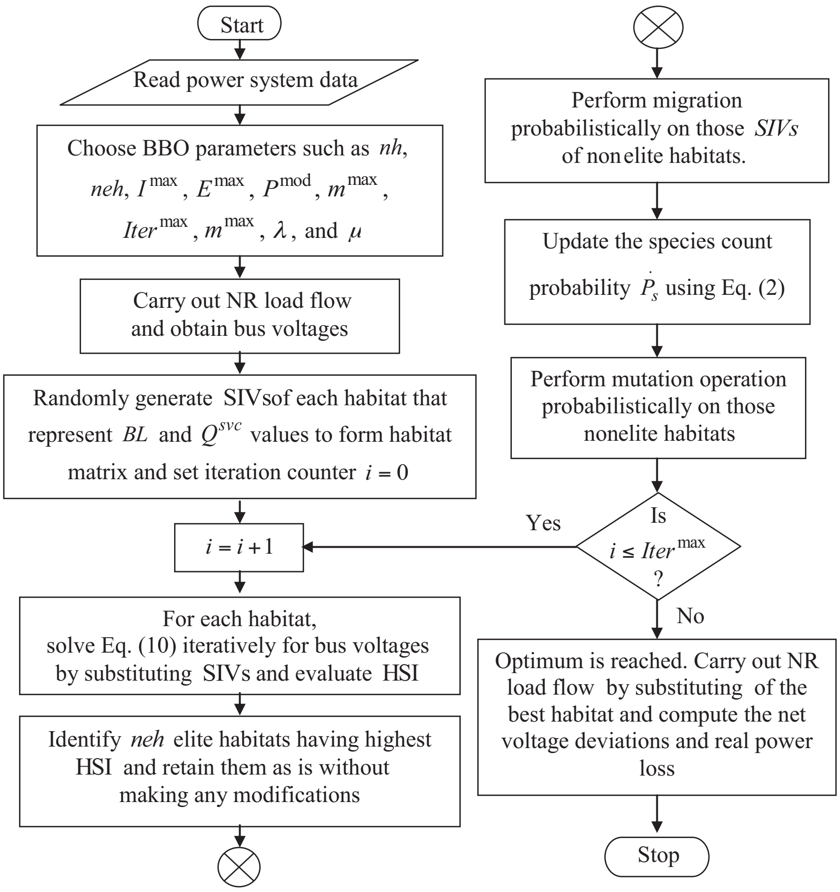

Figure 3. Flow chart of the proposed method.

3.6. Solution process

An initial population of habitats is generated by assigning a random vector that contains BL and Q^{svc} within their respective limits to every individual in the population. The HSI is calculated by considering SIVs of each habitat and the migration and mutation operations are performed for nonelite habitats with a view toward maximizing the HSI. The iterative process is continued until convergence. The flow of the proposed strategy is shown in Figure 3.

4. Simulations

The proposed BBO-based strategy is tested on the IEEE 30-node test system with SVCs, whose lower and upper limits are –100 and 150 MVAR for different load levels, which are obtained by multiplying the base load power by a constant multiplication factor. NR load flow technique [16] is used to obtain node voltages before the optimization process. The results are compared with those of genetic algorithm (GA)- and PSO-based approaches (see Appendix) using the same fitness function of Eq. (16) in respect to the net voltage deviation, system real power loss, node location, and quantity of reactive power support. The various parameters used in the BBO algorithm are listed in Table 1.

Table 1. BBO parameters.

Parameters	Chosen value
nh	50
neh	2
P^{mod}	1
Maximum values forλ and μ	1
Mutation probability	0.005

The node voltages after optimization by BBO, PSO, and GA at base load and at 110% and 120% of base load are graphically displayed in Figures 4, 5, and 6, respectively. It is clearly indicated that the proposed method provides a better voltage profile. The system loss incurred by the 3 methods at the different load levels are compared in Figures 7, 8, and 9, which show that the proposed method offers the lowest power loss when compared to that of GA- and PSO-based strategies.

The net voltage deviations at 3 load levels, realized after optimization by the 3 methods, are given in Table 2. It is interesting to note that the proposed method offers lower net voltage deviations than the other 2 methods. Among the other 2, the PSO-based method is better in view of minimizing the net voltage deviations.

The node location for placement of SVCs, the amount of VAR support, and the execution time by the 3 methods at 120% load level are compared in Table 3. Though all 3 methods choose different nodes for SVC placement, the proposed method gives the optimum location, which requires the lowest VAR support of the methods and the lowest computation time.

The converging characteristics of the 3 methods are shown in Figure 10. It is clear from the curves that the proposed method quickly converges and the performance is better than that of GA- and PSO-based strategies.

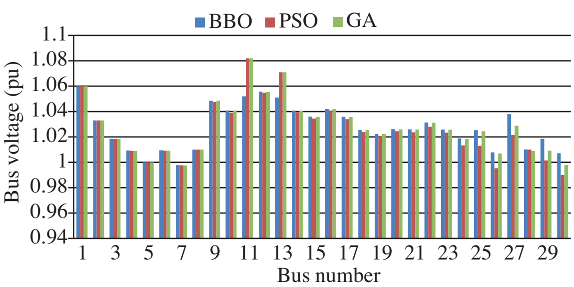

Figure 4. Voltage profile at base load.

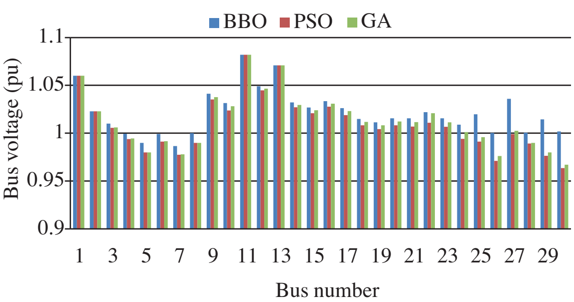

Figure 5. Voltage profile at 110% of base load.

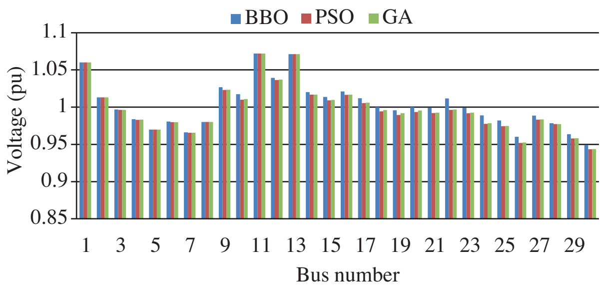

Figure 6. Voltage profile at 120% of base load.

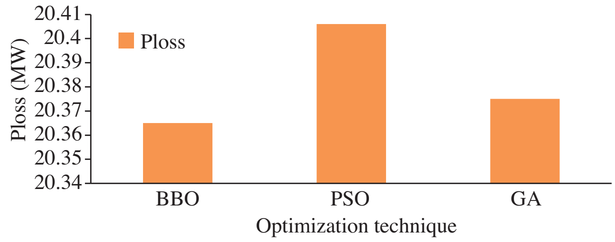

Figure 7. Comparison of real power loss at base load.

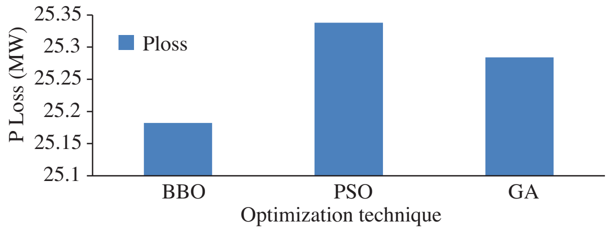

Figure 8. Comparison of real power loss at 110% of base load.

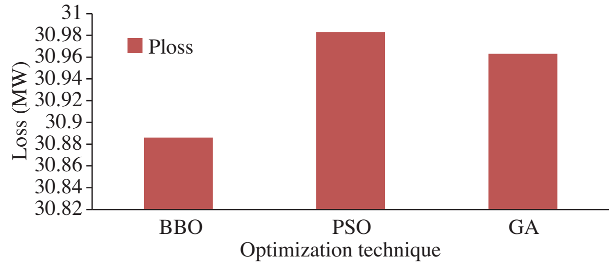

Figure 9. Comparison of real power loss at 120% of base load.

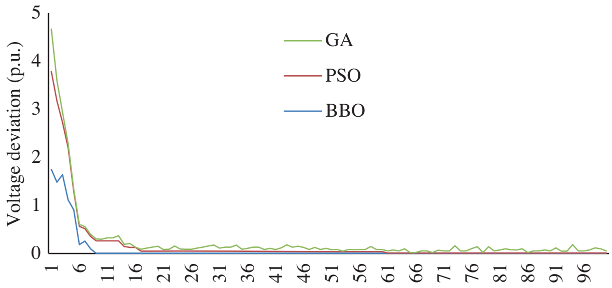

Figure 10. Convergence characteristic of BBO, PSO, and GA.

Table 2. Comparison of voltage deviations.

Type	Net voltage deviation (per unit)		
	Base load	110% load	120% load
BBO	0.001	0.095	0.002
PSO	0.066	0.138	0.142
GA	0.1068	0.142	0.15

Table 3. Comparison of results at 120% of base load.

Type	SVC size (MVAR)	Location	Execution time (s)
BBO	143	4	1.52077
PSO	150	21	1.555065
GA	149	6	1.543682

5. Conclusion

A new BBO-based algorithm for enhancing voltage stability by placing the SVC at the most appropriate node and computing the optimal quantity of reactive power support has been proposed. The simulation results have clearly illustrated that the proposed strategy requires the lowest VAR support, minimizes net voltage deviations, reduces system losses, offers better a voltage profile, and takes the lowest computation time and makes it suitable for practical implementations as compared to the other 2 methods.

Appendix

A.1. Genetic algorithm

The GA is a heuristic optimization technique based on the process of natural evolution involving the mechanics of natural selection and natural genetics. A chromosome in binary form is usually used to represent a candidate solution. A set of chromosomes, called a population, migrates towards a better set of solution by simulating "the survival of the fittest" criterion of Darwinian evolution among chromosome structures. The evolution usually starts from a population of randomly generated individuals and proceeds in generations. In each generation, the fitness of every individual in the population is evaluated, after which multiple individuals are stochastically selected from the current population and modified to form a new population through reproduction, crossover, and mutation operators [17]. The process is continued by treating the new population as the current population until either a maximum number of generations is reached or there is no change in the fitness for a specified number of generations. The GA-based strategy used in this article encodes the variables given in Figure 2 in binary form to represent chromosomes and uses the fitness function given by Eq. (9).

A.2. Particle swarm optimization

Particle swarm optimization (PSO) is a population-based naturally inspired optimization technique based on swarm intelligence [18]. A candidate solution can be represented as particle $X(t)$ in an n-dimensional search space. A population of m particles is initialized with random guesses in the search space. These particles fly around in a multidimensional search space with velocity $V(t)$. There are 2 best positions, denoted as particle best, $X^*(t)$, and global best, $X^{**}(t)$. Particle best is the best position each particle has achieved so far and global best is the best position the swarm has seen achieved so far. These particles communicate with other particles in the swarm and adjust their positions and velocity based on the 2 good positions using the following function.

$$\begin{aligned} V_j(t) \quad = \quad & w(t).V_j(t-1) \\ & +k_1\sigma_1\left\{X_j^*(t-1)-X_j(t-1)\right\} \qquad j=1,2,\cdots,n \\ & +k_2\sigma_2\left\{X^{**}(t-1)-X_j(t-1)\right\} \end{aligned} \tag{A.1}$$

$$X(t)=X(t-1)+V(t) \tag{A.2}$$

Here, $j=1,2,\cdots,n$ and k_2 are constants, and σ_1 and σ_2 are random numbers in the range (0,1).

The inertia constant $w(t)$ is gradually decreased during the iterative process using the following relation.

$$w(t)=\eta\cdot w(t-1) \tag{A.3}$$

The iterative procedure is continued up until the desired conditions are satisfied. However, the process can be terminated either if there is no appreciable change in the global best solution in the successive iterations or the maximum number of iterations are reached. The PSO strategy used in this article represents each particle to denote the control variables given in Figure 2 and uses the fitness function given by Eq. (9).

Nomenclature

BBO	Biogeography-based optimization
BL_k	Node location for the placement of the k*th* SVC
$E^{\max}$	Maximum emigration rate
FACTS	Flexible AC transmission systems
GA	Genetic algorithm
I_k	Current at node k
$I^{\max}$	Maximum immigration rate
$Iter^{\max}$	Maximum number of iterations

$m^{\max}$	Mutation probability
nh	Number of islands
n	Total number of species in the islands
nc	Number of compensators (SVCs)
nb	Number of nodes
neh	Number of elite islands
nl	Number of lines
PSO	Particle swarm optimization
$P_s(t)$	Probability that the islands contain exactly S species at time t
$P_k \& Q_k$	Real and reactive power injection, respectively, at node k
$P_{Gk} \& Q_{Gk}$	Real and reactive power generation, respectively, at node k
$P_{Lk} \& Q_{Lk}$	Real and reactive load, respectively, at node k
$\dot{P}_s$	Species count probability
$P^{\bmod}$	Islands modification probability
P_{loss}	System real power loss
Q_k^{svc}	Reactive power support by kth SVC
$Q_k^{svc-\min}$	Lower reactive power limit of kth SVC
$Q_k^{svc-\max}$	Upper reactive power limit of kth SVC
SVC	Static VAR compensator
S	Species in the islands
t and Δt	Time and change in time, respectively
UPFC	Unified power flow controller
VS	Voltage stability
V_k	Voltage at node k
Z_{kj}	Element of node impedance matrix corresponding to kth row and kth column
λ and μ	Immigration and emigration rates, respectively
η	Constant weight
Subscripts m and n	Terminal nodes of line i
ΔV	Net voltage deviations

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