IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received December 3, 2018, accepted December 7, 2018, date of publication December 18, 2018, date of current version June 7, 2019.

Digital Object Identifier 10.1109/ACCESS.2018.2887266

Adaptive Evolutionary Algorithm Applied to the Voltage Stability Problem in Power Systems

SIDNEI NASCIMENTO, ROSE M. S. BATALHA, AND MAURY M. GOUVÊA, Jr.
Department of Electrical Engineering, Pontifical Catholic University of Minas Gerais, Belo Horizonte 30.535-901, Brazil

Corresponding author: Maury M. Gouvêa, Jr. (maury@pucminas.br)

This work was supported in part by the Coordination for the Improvement of Higher Education Personnel (CAPES) and in part by the Pontifical Catholic University of Minas Gerais (PUC Minas).

ABSTRACT In recent years, research studies have sought methods and devices which enhance the performance of power systems, since the more these systems are expanded, the greater the economic and environmental constraints. With the development of the power electronics applied to power systems, flexible alternating current transmission systems (FACTSs) have sprung up. A problem related to the use of a FACTS device is where best to install and adjust its parameters in order to improve the performance of the system. This paper sets out a method for automatically allocating FACTS devices in power systems for which an adaptive evolutionary algorithm (EA) is used. The proposed method seeks to determine not only where best to install FACTS devices and to supply them with reactive power but also to adjust other decision variables of a power system in order to enhance the voltage stability while taking some indicators into account. The method was tested in experimental studies by using standard IEEE systems, and comparing the results from these with those of the probabilistic and heuristic optimization methods, including the standard EA. The results showed that the proposed method enhanced the voltage stability of the systems and outperformed the other methods.

INDEX TERMS Voltage control, reactive power control, evolutionary computation.

I. INTRODUCTION

In recent years, population based optimization algorithms have been used in several engineering areas due to their global search features and interactions between solutions [1], [2]. Evolutionary algorithm (EA) is a powerful population based mechanism for search and optimization [3], [4]. The use of EAs to solve complex problems has become a research topic of great interest [5], [6].

The multimodality of the fitness landscape is certainly a factor that generates complexity since it creates trends of premature convergence [7]–[9]. In evolutionary process, premature convergence means lack of diversity. The population diversity expresses how different the individuals are from each other. Diversity maintenance or control of the population of evolutionary algorithms may benefit the evolutionary process in several ways, such as preventing premature convergence to local optimums and considering different niches for solutions of multimodal problems [10].

Optimization in power systems is an important example of multimodality and complexity since these systems normally operate near to their constraints due to the continuous demand increase. The voltage instability is the main cause of constraint violations and voltage collapse. Voltage instability and voltage collapse were responsible for several major blackouts throughout the world, since 1970, in New York, until 2003, in North America and Europe [11]. The voltage stability is related to the control of the reactive power.

In recent studies of modern power systems, the Flexible Alternating Current Transmission System (FACTS) becomes the control of the reactive power flow more dynamic, since it provides flexibility on the transmission system [12]–[14]. However, the optimum location of FACTS devices is a very important issue in power systems, since the weakest busbar and/or transmission line need(s) to be identified.

The optimum reactive power flow is an important problem in power systems, since the complexity and dimension of the power flow equations. Thus, the use of the evolutionary algorithm is an attractive alternative due to its probabilistic and global search features. Classical optimization methods generally are based on local search and require well-defined analytic functions. Evolutionary algorithm only compares the quality of solutions solved by a power flow algorithm.

This paper presents an adaptive evolutionary algorithm applied to the reactive power flow problem by controlling the population diversity. The proposed method optimizes the following stability indicators of power systems: the voltage profile, the total reactive power loss, and the voltage collapse margin. The use of an adaptive evolutionary algorithm in large and complex systems, such as a power system can lead to a number of favorable contributions, as follows:

- the proposed method avoids premature convergence and maintains the global search, thereby overcoming drawbacks of population-based methods;
- this is the first time that the adaptive evolutionary algorithm [10] is applied in a realistic application, in the context of power systems;
- this approach allocates FACTS devices automatically, thus supplying the power system with reactive power. This is difficult regarding the use of FACTS devices, since they are expensive pieces of equipment and need to be efficiently installed to obtain their best performance; and
- in addition, the proposed method adjusts the decision variables of the system in order to enhance voltage stability.

Several experiments were conducted in IEEE 14, 57, and 118 busbar systems by using the proposed method and other probabilistic and heuristic optimization methods. The results showed that the adaptive evolutionary algorithm enhanced the voltage stability and outperformed the other methods.

The rest of this paper is organized as follows: Section II presents a literature review which includes very recent studies on voltage stability. Section III describes the reactive power flow problem and its implications on voltage stability. Section IV describes the general concepts on FACTS devices and details of two of them used in this work. Section V addresses the adaptive methodology for evolutionary algorithms. Section VI presents the results obtained in simulation with the standard IEEE busbar systems. Section VII concludes the paper.

II. RELATED WORKS ON VOLTAGE STABILITY

This section presents a literature review on voltage stability, which concerns several recent works on the identification of the stability level [11], [15]–[19] and stability enhancement [5], [12]–[14], [20]–[23].

Parizad *et al.* [15] and Esmaeili and Esmaeili [16] evaluated the voltage stability according to the L-index indicator and the parameters and locations of FACTS devices with a hybrid genetic algorithms and harmony search. Mohamed and Venkatesh [17] presented the bus-wise and line-wise Newton–Raphson method, which uses square of voltage magnitude and linear terms for active and reactive power. The voltage collapse index can be derived to identify lines that interconnect buses subject to collapse. A global sensitivity analysis (GSA) method for power systems with renewable energy integration was presented by Xu *et al*. [18]. GSA identifies the correlation variables between renewable energy and load range for system voltage stability. A strategy for online proximity analysis of an electrical system to voltage collapse was proposed by Liu *et al*. [19], where the non-iterative holomorphic inclusion method determines the loading limit for each load bar based on the estimated online throughout the load area. A new voltage stability index, called P-index, was developed by Kamel *et al.* [11]. The method in which is extended to indicate the distance to collapse and the effectiveness was compared to the L-index in IEEE 14, 57, and 118 busbar systems.

In the works of Nireekshana *et al.* [22] and Gupta and Sharma [5], a genetic algorithm was used to determine the parameters and location of Static Var Compensator (SVC), Thyristor Controlled Series Compensator (TCSC), and Unified Power Flow Controller (UPFC) to improve the voltage stability and to reduce active power losses. Esmaili *et al.* [23] performed a modified augmented e-constraint method to determine the best location and adjustment of a FACTS device to enhance the voltage stability. In order to enhance the voltage stability of power systems, Wibowo *et al*. [21] proposed an approach for planning by allocating multiple FACTS devices and evaluating their impact on operation problem to minimize the annual total cost. The method implies to minimize devices investment cost, and to maximize benefit due to the devices installation. Mohseni-Bonab and Rabiee [20] presented a comprehensive review of recent researches carried out in the area of optimal reactive power dispatch (ORPD). The authors also studied a stochastic multiobjective ORPD (SMO-ORPD) model under load and wind power generation uncertainties. A two-stage stochastic model was employed for dealing with the uncertainties. The considered objective functions were the real power losses and the operation and maintenance cost of wind farms. Eladany *et al.* [14] developed a new algorithm for optimal allocation of TCSC as well as the amount of these devices to increase the transient stability of electrical systems, the algorithm is structured by combining particle swarm optimization, clustering techniques and catastrophe theory. Kapetanaki *et al*. [12] developed a probabilistic methodology to maximize the wind capacity of installed units. The study showed that the use of various reliability indicators, such as SVC and TCSC devices, allows to integrate more wind sources into the system. Ugranli and Karatepe [13] showed a study of planning and expansion of power systems and integration of wind units in which is possible to reduce the generation costs and the investments in transmission lines by introducing TCSC devices.

III. REACTIVE POWER FLOW PROBLEM

When voltage level in power systems deviates from the reference value laid down, the performance of the industrial equipments degrades and their life expectancies tend to drop. For instance, the torque of an induction motor is proportional to the square of the terminal voltage. Thus, it is important to control the voltage level in power system. This control in the power system is performed in an interval which specifies the tolerance of voltage variations.

In a power system, the voltage control in load buses is achieved by acting in the following [25], [26]:

- excitation control of generators, which maintains good voltage control at the generator buses;
- switched shunt capacitors and/or reactors, which provide the capability of controlled reactive power injection into a bus; and
- tap-changing of transformers.

These control actions is motivated by the fact that the bus voltages are strongly related to the reactive power injection at the buses. An particular way to maintain the voltage levels of the load buses into an specific tolerance interval is to minimize the voltage deviation

$$F(\mathbf{X}) = \sum_{V_i \in S_{PQ}} (V_i - 1)^2, \tag{1}$$

where $\mathbf{X}$ is the vector of decision variables, the voltage bus V_i belongs to the set of load buses, S_{PQ}, and the constant 1 means 1 pu (nominal voltage).

The voltage stability is also associated with reactive power flow. The loadability of a bus depends on the reactive power support that the bus can receive from the system as the system approaches to the voltage collapse point [27]. In voltage stability, the changes in the power system due to load increase or contingencies can lead to a shortage of reactive power and decline voltages at the load buses. This effect can be seen in power transferred versus the voltage at receiving end bus. The critical point is reached when any increase in active power transferred leads to rapid decline in bus voltage [26]–[28]. In this point, a heavy reactive power loses occur.

A way to analyze the voltage stability is to calculate the voltage collapse margin. For instance, L-index method is used for evaluating the voltage stability in power systems through the voltage collapse margin [29], [30]. This index, in [0, 1], that identifies the proximity to the voltage collapse can be defined as

$$L_j = \left| 1 - \sum_{V_i \in S_G} C_{ji} \frac{V_i}{V_j} \right|, \tag{2}$$

where S_G is the set of generation buses, V_i is the i-th generation bus voltage in complex form, V_j is the j-th load bus voltage in complex form, and C_{ji} is an element of the matrix

$$[C] = -\left[Y_{LL}\right]^{-1}\left[Y_{LG}\right], \tag{3}$$

where $[Y_{LL}]$ and $[Y_{LG}]$ are submatrices of the admittance matrix Y_{bus}.

This index L_j ranges from 0, where the system is stable, to 1, where the system approaches to voltage collapse. Another important reason for voltage control is that the real line losses also depend to the reactive power flow. It is possible to minimize these losses by selecting an optimum (real and reactive) power flow. The reactive power flow through the line depends greatly upon the receiving end voltage, which may control the line losses.

IV. FACTS DEVICES

The concept of Flexible AC Transmission system (FACTS) refers to control and adapt the parameters of power systems, reactive power flow, bus voltages, and transmission line impedance [24]. The following subsections present two FACTS devices used by the method presented in this paper.

A. STATIC VAR COMPENSATOR

Static Var Compensator (SVC) is shunt connected to a bus and provides an adjustable reactance [31], [32]. The reactive power supplied by SVC in the i-th bus can be modeled as

$$Q_{SVC} = -B_{SVC}\, V_i^2, \tag{4}$$

where V_i is the voltage magnitude at i-th bus and B_{SVC} is the SVC susceptance. Thus, the modified admittance matrix, for addition of a SVC, is expressed as

$$Y^{mod} = Y + \begin{array}{cl} \begin{bmatrix} 0 & 0 & \dots & 0 & 0 \\ 0 & Y_{SVC} & \dots & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 \end{bmatrix} & \begin{array}{l} \\ i_{line} \\ \\ \\ \\ j_{line} \\ \\ \end{array} \\ \begin{array}{ccccc} \quad & i_{row} & \quad & j_{row} & \quad \end{array} & \end{array} \tag{5}$$

B. THYRISTOR CONTROLLED SERIES COMPENSATOR

Thyristor Controlled Series Compensator (TCSC) is series connected to a transmission line in order to control its impedance [33]. TCSC uses thyristor-controlled reactor in parallel to a capacitor bank. The series reactance is automatically adjusted to satisfy an amount of active power flow throughout the transmission line. The modified admittance matrix, for addition of a TCSC, is expressed as

$$Y^{mod} = Y + \begin{array}{cl} \begin{bmatrix} 0 & 0 & \dots & 0 & 0 \\ 0 & \Delta_{ij} & \dots & -\Delta_{ij} & 0 \\ 0 & 0 & \dots & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & 0 & 0 \\ 0 & -\Delta_{ij} & \dots & \Delta_{ij} & 0 \\ 0 & 0 & \dots & 0 & 0 \end{bmatrix} & \begin{array}{l} \\ i_{line} \\ \\ \\ \\ j_{line} \\ \\ \end{array} \\ \begin{array}{ccccc} \quad & i_{row} & \quad & j_{row} & \quad \end{array} & \end{array} \tag{6}$$

where

$$\Delta y_{ij} = y_{ij}^{mod} - y_{ij} = \left(g_{ij}^{mod} + jb_{ij}^{mod}\right) - \left(g_{ij} + jb_{ij}\right) \tag{7}$$

$$g_{ij} = \frac{r_{ij}}{\sqrt{r_{ij}^2 + x_{ij}^2}} \tag{8}$$

$$b_{ij} = -\frac{x_{ij}}{\sqrt{r_{ij}^2 + x_{ij}^2}} \tag{9}$$

$$g_{ij}^{mod} = \frac{r_{ij}}{\sqrt{r_{ij}^2 + \left(x_{ij} + x_{TCSC}\right)^2}} \tag{10}$$

and

$$b_{ij}^{mod} = -\frac{x_{ij} + x_{TCSC}}{\sqrt{r_{ij}^2 + \left(x_{ij} + x_{TCSC}\right)^2}}. \tag{11}$$

V. ADAPTIVE EVOLUTIONARY ALGORITHM

This section presents the proposed method for the adaptive evolutionary algorithm applied to reactive power flow problem. In this approach, the evolutionary algorithm is handle as a control process, which its output is controlled in order to maintain a desired level of population diversity. The method consists of an evolutionary process and a diversity evaluator, which provides the diversity of the current population. The controller supplies the control signal for the process as a function of the mutation rate, which is based on the error between the process output (population diversity) and the desired level of diversity. The following subsections present the structure of the proposed method.

A. DIVERSITY MEASURE

In Nature, diversity loss, caused by the extinction of a species, might cause serious ecological disturbance that has irreversible consequences for an ecosystem. High diversity might provide abilities that individuals, populations, and species need so as to respond to adversities, such as diseases, parasites, and predators, and to adapt themselves to changes in the environment [34].

Several models were proposed to calculate the population or species diversity. For example, a diversity measurement based on a finite set of species [35], a function to calculate the loss of diversity when a species becomes extinct [36], a function that uses the Euclidean distance between species [37], and a function from the theory of communication [38]. Our model was based on the heterozygosity, H_e, proposed by Simpson [39]. Replacing H_e with Γ, our diversity function becomes

$$\Gamma = 1 - \sum_{i=1}^{n_a} p_i^2, \tag{12}$$

where n_a is the number of alleles and p_i is the occurrence rate of the i-th allele in the population. In an EA approach, the number of alleles depends on the representation of the problem: for binary-coded EA, $n_a = 2$, for integer-coded EA, n_a is measurable, and for real-coded EA, we calculate the number of alleles by dividing the gene length into a given number of subintervals (n_a).

Equation (12) is used to measure the population diversity because of its simplicity and low computational effort. This measure also satisfactorily reflects the population diversity, from its maximum level, $1 - 1/n_a$, when the number of each type of allele is the same, to zero, when there is only one type of allele. This diversity measurement method uses only one gene of the genotype, named the reference gene, to describe the gene frequency or population diversity. Gouvêa, Jr., and Araújo [40] showed that it is possible to represent the population diversity with any gene of the genotype.

B. DIVERSITY MAINTENANCE AND CONTROL

In evolutionary algorithm, the control of the population diversity, or minimizing its loss, may benefit the evolutionary process in several ways, such as preventing the premature convergence to a local optimum; spreading the population around distinct Pareto optimal solutions in a multiobjective problem; permitting fast adaptation without reinitialization in dynamic environments; and considering different niches for solutions of multimodal problems [41]–[43].

The diversity control in the adaptive evolutionary algorithm is carried out by Diversity Reference Adaptive Control (DRAC) [10]. Thus, the current population diversity has to track a reference diversity. Figure 1 shows one generation of the adaptive evolutionary algorithm (AEA). There are two loops, the evolutionary algorithm (EA) loop and the control mechanism loop. The EA loop, at generation k, begins when a traditional **selection** mechanism, e.g. tournament, chooses the parent candidates, $\mathbf{Q}(k)$, from the current population, $\mathbf{P}(k)$. Next, **recombination** and **mutation** generate the offspring, $\mathbf{F}'(k)$. In the AEA approach, the new population, $\mathbf{P}(k+1)$, arises from $\mathbf{P}(k) + \mathbf{F}'(k)$ as a result of the **selection** mechanism.

The other control loop aims to calculate the control signal, i.e. the mutation rate, p_m. The control loop starts by calculating the diversity of the population, $\Gamma(k)$, Equation (12). Then, the error, $e(k)$, i.e. the deviation between the desired diversity, Γ_r, and the population diversity, $\Gamma(k)$, is determined. Finally, the control signal is computed by the **controller**, Equation (13). These two cycles are repeated while a stop criterion is not satisfied.

The population diversity, Equation (12), is a function of the allele occurrence rate for a given gene. In binary-coded EA, the number of alleles per gene, n_a, is two. In integer-coded EA, the number of alleles varies with the problem; in this study, the number of alleles is calculated by separating the gene length into defined intervals, i.e. the number of alleles, n_a. Thus, the allele that belongs to a given j interval is regarded as allele g_{ij}, i.e., j-th allele of the i-th gene.

The diversity control is performed by changing the mutation rate, p_m, when there is a deviation between the population, Γ, and reference, Γ_r, diversities. The mutation rate is updated in order to vanish this deviation as follows

$$p_m(k+1) = p_m(k) + \eta\left(\Gamma_r - \Gamma(k)\right) \tag{13}$$

where η is a constants.

C. OBJECTIVE FUNCTIONS

In the context of power systems, this research takes into account three indicators as objective function, presented in Section III, in order to enhance the voltage stability of power systems: (i) the collapse margin by L-index, Equation (2); (ii) the voltage deviation, Equation (1); and (iii) the total reactive

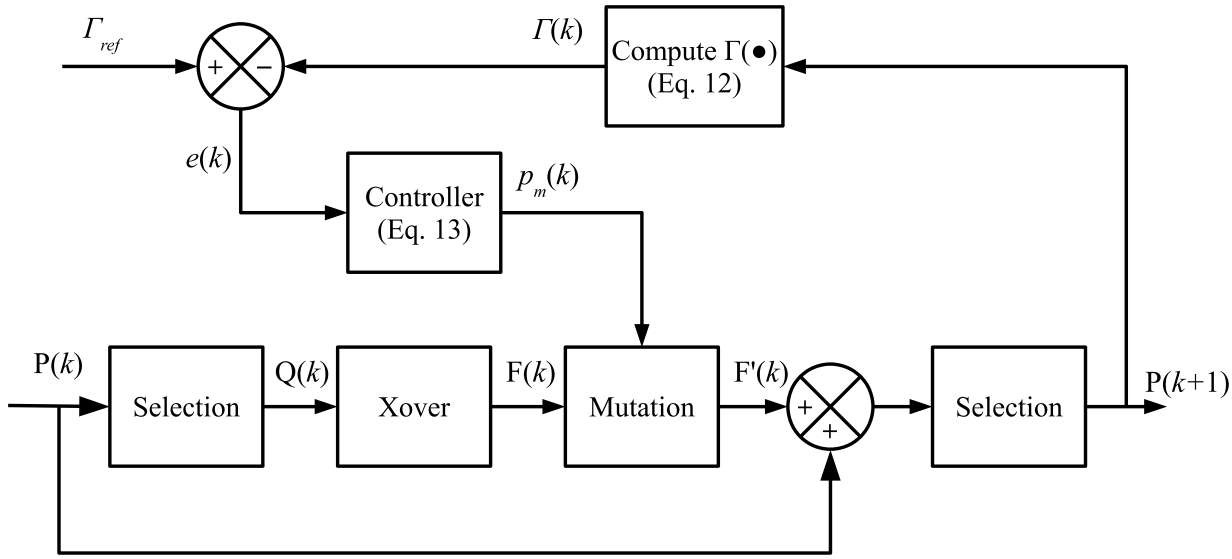


FIGURE 1. **Block diagram of the adaptive evolutionary algorithm.**

power loss. The proposed method minimizes one objective function at a time. In this research study, the multiobjective problem was not considered.

In order to use the first objective function, the proposed method minimizes L, where L is the highest L-index among the load buses, Equation (2), calculated before the optimization process. This approach ensures a global strategy to improve the voltage stability. When the second objective function (ii) is used, the method minimizes the voltage deviation, Equation (1). Finally, the third objective function (iii), i.e. the total reactive power loss calculated by the power flow equations [25], is also minimized.

D. AEA IN THE CONTEXT OF POWER SYSTEMS

In the context of power systems, the proposed method finds the optimum location of FACTS devices and also adjusts the decision variables according to each of the performance indicators, presented in Subsection V-C. These indicators, treated as objective functions, are closely linked to the voltage stability of power systems. Each decision variable represents a gene of the individual.

The reactive power injections, by the generators, are not decision variables. In a busbar in which there is a generator, the decision variable is the voltage magnitude. The reactive power injection, by the generator, is calculated by the power flow equations (PFEs). The power injections in busbars with no generator are made by either capacitor banks or FACTS devices, as decision variables. In these busbars, the voltage magnitudes are calculated by the PFEs.

The individual of the population, which coded the vector of decision variables, $\mathbf{X}$, is formed by the voltage magnitudes of the generator buses, the shunt capacitor banks, the transformer tap settings, and the location and reactive power supply of the TCSC and/or SVC FACTS devices. Figure 2 shows

$V_i^{(m)}$	...	$Q_j^{(m)}$	...	$T_k^{(m)}$	...	$(B, F)_l^{(m)}$

FIGURE 2. **Decision variable coded as an individual.**

the m-th individual of the population. The first genes are the voltage magnitudes of the voltage controlled buses, $V_i^{(m)}$. The next genes are the reactive power injections of the capacitor banks, $Q_j^{(m)}$, and the genes to code the transformer tap settings, $T_k^{(m)}$. The last genes, $(B, F)_l^{(m)}$, are the bus number, B, where the FACTS device is installed, and the reactive power injection, F, from this device.

E. VARIATION OPERATORS

Variation operators are functions which modify the descendents generated from the current population. Descendents are individuals created with genetic material (decision variables) from two individuals of the current population, namely parents. This work uses two typical variation operators of the evolutionary algorithm: crossover and mutation.

In the crossover process, there is a random cut point into the two parents, P_1 and P_2, which defines how the descendents are mixed, as shown in Figure 3. The descendents, D_1 and D_2, are generated from the mixed parts from the two parents according to the cut point. This process provides an local search on the space of solutions.

The mutation, executed after the crossover process, is a random change in the genes of the descendent according to a probability $p_m \in [0, 1]$. In the proposed model, the mutation is performed in the elements of the vector of decision variables, $\mathbf{X}$, according to their respective constraints. Figure 4 shows the mutation process in which the reactive power injection $Q_j^{(1)}$ is changed to $Q_j^{'(1)}$ if $r \leq p_m$, for $Q_j^{'(1)}$, where $r \in [0, 1]$ is an uniform distributed random variable.

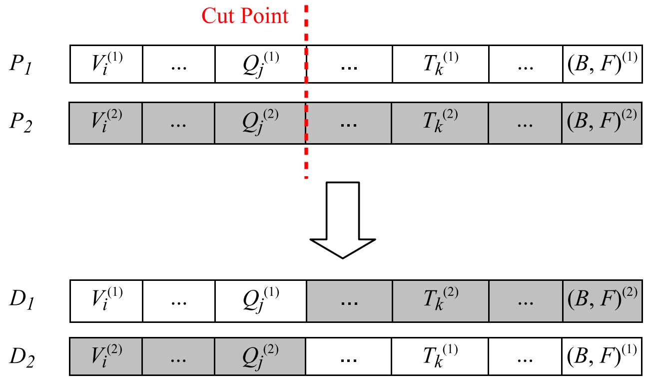


FIGURE 3. One-point crossover.

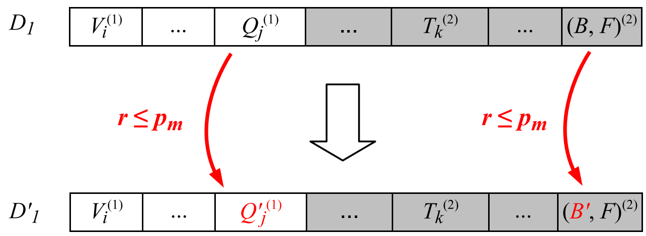


FIGURE 4. Mutation of the descendent after crossover.

TABLE 1. Decision variable parameters.

Variables	Min	Max	Unit
Generation voltage	0.9	1.1	p.u.
Shunt reactive power	0	100	MVAR
TAP	0.9	1.1	pu

The location, B, and the reactive power injection, F, of the FACTS devices are mutated separately, as presented in Figure 4.

VI. EXPERIMENTAL STUDIES

The proposed method is implemented into the Matlab® environment, by using the MATPOWER power flow package [44]. The proposed method is evaluated by using the standard IEEE 14, 57, and 118 busbar systems, and the results are compared with the standard Evolutionary Algorithm (EA) [3], the Particle Swarm Optimization (PSO) [1], and the Simulated Annealing (SA) [45]. All methods are performed after the execution of the MATPOWER optimal active power flow (OAPF) algorithm, which uses the minimal generation cost as objective function. The evaluation of the voltage stability is made by the collapse margin with L-index, voltage deviation, and total reactive power loss, presented in Subsection V-C. For each experiment, 10 runs were performed per algorithm, and the performance analysis was based on the average results of these runs. Table 1 presents the ranges of the decision variables used by all methods.

Table 2 presents the parameters of the SVC and TCSC FACTS devices which adopt the following criteria:

TABLE 2. FACTS device parameters.

FACTS	Where	Min	Max	Unit
SVC	Bus	-100	100	MVAR
TCSC	TL	0	50	%

TABLE 3. Decision variables per system.

Variables	IEEE 14	IEEE 57	IEEE 118
Generation voltage	5	7	54
Shunt reactive	1	3	14
Tap transformer	3	17	9
Serie FACTS	1	2	2
Shunt FACTS	1	2	2
Integer variables	2	4	4
Real variables	11	31	81

TABLE 4. Adaptive evolutionary algorithm parameter.

Parameter	Value
Population size	100
Crossover rate	0.6
Mutation rate	0.05
Selection type	Tournament
Group size	20
Total selected	50
Total individual	100
Number of generations	1000

a)
1) SVC device is not installed either in generation bus or one which has reactive power injection (e.g., synchronous compensator and capacitor)
2) TCSC device is not installed in bus with Tap-Changing Transformers.

Table 3 presents the general parameters of the IEEE systems. The integer variables mean the location of the FACTS devices, and the real ones represent the voltage magnitudes and the reactive power injections of both capacitor banks and FACTS devices.

Table 4 shows the fixed parameters of EA and AEA, which were obtained empirically.

In this work, the population diversity is controlled by the mutation rate, p_m, which is adjusted according to Equation (13). The adjustments are performed as a function of the deviation between population diversity, Γ, and the reference one, Γ_r, as presented in Subsection V-B. Unlike the study by Gouvêa, Jr., and Araújo [10], which used a model reference adaptive control, the desired diversity in this study begins with $\Gamma_{\max} = 0.7$ and declines linearly to $\Gamma_{\min} = 0.3$ along the generations as a strategy in which the search process starts exploratory and then becomes local, thus maintaining a minimal and controlled level of diversity. The following subsections present the results of the experiments with the IEEE busbar systems.

A. EXPERIMENTS WITH THE IEEE 14 BUSBAR SYSTEM

This section presents the experiments with the IEEE 14 busbar system. Table 5 presents the general results with the

TABLE 5. IEEE 14: L-index as objective function.

Algorithm	SVC		TCSC			L-index	Voltage deviation	MVAR loss
	Bus	Power	From	To	%			
OAPF	-	-	-	-	-	0.0785	0.1112	27.5104
AEA	10	20.1554	13	14	48.9468	0.0630	0.3207	16.7652
EA	14	50.7231	13	14	46.8531	0.0628	0.3124	16.2783
PSO	5	-34.7372	13	14	47.6400	0.0638	0.3008	39.4719
SA	5	-20.2154	6	13	35.8917	0.0679	0.2899	11.8787

TABLE 6. IEEE 14: voltage deviation as objective function.

Algorithm	SVC		TCSC			*L-index*	Voltage deviation	MVAR loss
	Bus	Power	From	To	%			
OAPF	-	-	-	-	-	0.0785	0.1112	27.5104
AEA	14	10.7332	6	13	47.7009	0.0793	0.0049	21.6109
AE	14	11.8354	9	10	45.7789	0.0850	0.0043	20.3636
PSO	14	11.7862	4	5	22.2503	0.0850	0.0055	24.0736
SA	7	10.1230	1	5	14.3616	0.0852	0.0213	4.9600

SVC and TCSC FACTS devices (locations and reactive power supplies) for L-index as objective function, Equation (2). Table 5 also shows the results of the other stability indicators. For L-index as objective function, the population based algorithms, AEA, AE, and PSO, reached the best results, thus outperforming SA. For the voltage deviation indicator, OAPF obtained the best result (minimal deviation) at the cost of a high total MVAR loss, i.e., the initial condition provided the best state for this indicator. OAPF increased the reactive power flow, thus becoming greater the total reactive power loss. Other methods provided close voltage deviation with respect to each other. The highest total reactive power loss was obtained by PSO, despite this method reached its results close to those of the other methods. The two evolutionary algorithms, AEA and EA, achieved similar results for the objective function (L-index) and also for the other two indicators. In general, the best results were obtained by the evolutionary algorithms.

All methods found out different points to install SVC and TCSC devices. Almost all methods, AEA, EA and PSO, installed TCSC device in the same transmission line. However, SVC device was installed in three different buses. For AEA and EA methods, SVC device injected reactive power to the bus; on the other hand, for PSO and SA, SVC absorbed reactive power from the bus.

Figures 5a and 5b show the results for the L-index as objective function throughout the iterations – the mean of the best solutions of each run, Figure 5a, and the best solution of all ones, Figure 5b. As can be observed in Figure 5a, the mean result of AEA and EA declined faster than those of the other methods. In the end of the process, AEA and EA provided the best results. In Figure 5b, AEA and EA provided similar performance with respect to their mean results, Figure 5a, thus showing robustness. In the end of the process, AEA, EA, and PSO achieved similar results.

Table 6 shows the results of the experiments with the voltage deviation as objective function and the two other performance indicators – L-index and the total reactive power loss. AEA, AE, and PSO installed the SVC device in the same bus; however, TCSC device was installed in different transmission lines, with emphasis for PSO that adjusted a level of transmission line compensation 50% less than those of AEA and AE methods. In the other indicators, especially the L-index, AEA showed a worsening of 1% versus 8% of the other methods. In the total reactive power loss, SA stood out with a reduction of 81.2%.

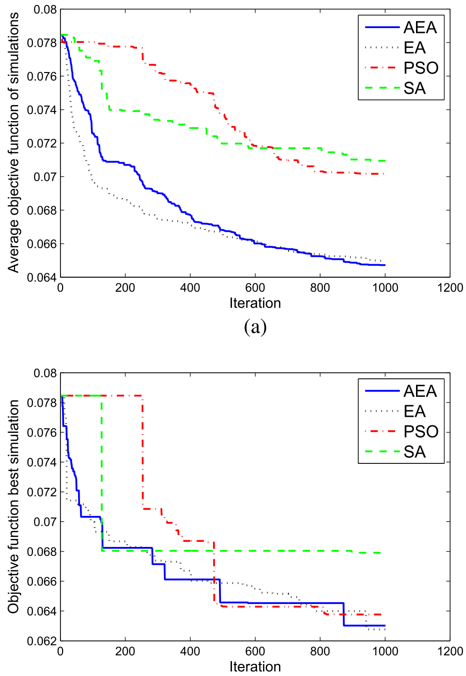


FIGURE 5. IEEE 14: L-index as objective function. (a) Mean. (b) Best solution.

Figures 6a and 6b show the results for the voltage deviation as objective function throughout the iterations. The evolutionary algorithms decreased quickly their fitness in average and maintained the best results at the end, as shown in Figure 6a.

TABLE 7. **IEEE 14: total reactive power loss as objective function.**

Algorithm	SVC		TCSC			*L-index*	Voltage deviation	MVAR loss
	Bus	Power	In	End	%			
OAPF	-	-	-	-	-	0.0785	0.1112	27.5104
AEA	9	23.4951	9	14	22.0962	0.0795	0.1048	0.0121
EA	4	27.3535	1	5	9.4528	0.0888	0.0772	0.0007
PSO	5	-1.5958	1	2	2.6272	0.0843	0.1432	0.0001
SA	5	56.7133	6	13	28.2441	0.0826	0.0717	0.7656

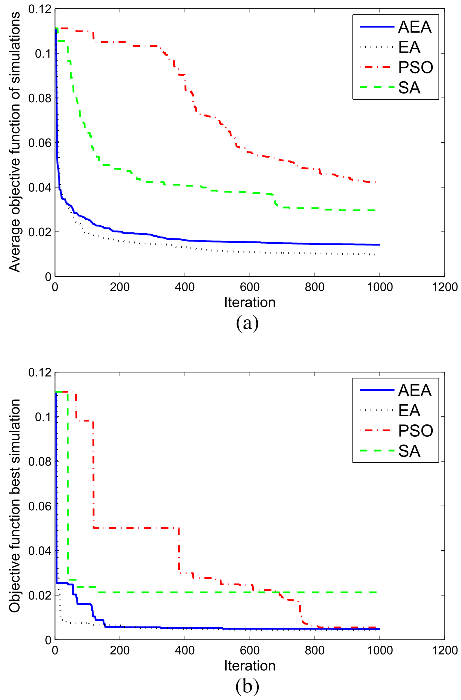


FIGURE 6. **IEEE 14: voltage deviation as objective function. (a) Mean. (b) Best solution.**

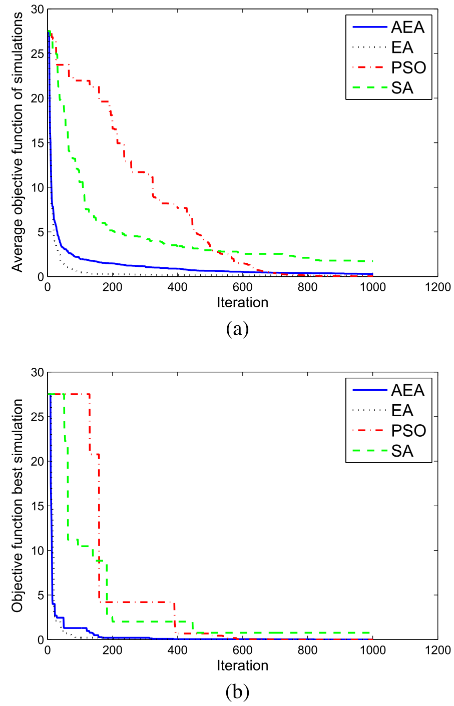


FIGURE 7. **IEEE 14: total reactive power loss as objective function. (a) Mean. (b) Best solution.**

On the best results per algorithms, Figure 6b, the evolutionary algorithms repeated their performances with respect to the mean results. At the end, the population based algorithms, EA, AEA, and PSO, reached the best results.

In the experiments with the total reactive power loss as objective function, AEA and AE presented similar performance – the latter being faster than the former to obtain the best solution, as shown in Figure 7a. At the end, all methods presented similar results, where SA showed the worst performance, as shown in Figure 7b. The results presented in Table 7 showed a large decrease in the total reactive power loss – more than 99% for AEA, AE, and PSO; and 97% for SA. All methods, with exception of PSO, improved the voltage profile. AEA showed less variation in L-index. The methods proposed different locations to install the FACTS devices, where PSO presented the smallest adjustments.

Figures 7a and 7b show the results for the total reactive power loss as objective function throughout the iterations. All methods minimized their objective functions in few iterations and reached similar results at the end for both mean and best results. However, the evolutionary algorithms achieved the best results.

B. EXPERIMENTS WITH THE IEEE 57 BUSBAR SYSTEM

This section presents the experiments with the IEEE 57 busbar system. In the experiments with the L-index as objective function, AEA provided the best mean result, as shown in Figure 8a. However, the best result among the methods was obtained by PSO, as presented in Figure 8b. Table 8 shows that the methods suggested different buses to install the FACTS devices. PSO declined more than 40% in L-index and AEA declined about 35% in the same indicator. In the result of SA, SVC device absorbed reactive power from the bus. In the result of EPO, one SVC device injected reactive power to the bus and the other one absorbed reactive power from the bus.

Figures 9a and 9b show that AEA reached the best performance for the voltage deviation as objective function. As can be seen in these figures, SA failed to minimize the objective function. Table 9 shows that AEA reduced the voltage deviation of 65% with respect to its initial value. AEA provided the smallest voltage deviation by injecting less reactive power than the other methods. On the other indicators, L-index varied less than 2% between all methods, and EA reduced

TABLE 8. IEEE 57: L-index as objective function.

Algorithm	SVC1		SVC2		TCSC1			TCSC2			*L-index*	Voltage deviation	MVAR loss
	Bus	MVAR	Bus	MVAR	In	End	%	In	End	%			
OAPF	-	-	-	-	-	-	-	-	-	-	0.3010	0.1956	92.0447
AEA	35	51.5461	56	87.6345	3	15	41.3139	1	15	50.0000	0.1939	1.5562	46.0117
EA	47	112.1879	20	41.7650	9	10	28.3666	1	17	19.0007	0.2124	1.2002	139.4631
PSO	36	119.1123	18	-109.9928	36	40	0	54	55	48.8321	0.1751	1.8069	62.8345
SA	38	-6.3190	7	-85.7790	9	10	48.2351	56	41	3.6128	0.2084	1.1409	59.6841

TABLE 9. IEEE 57: voltage deviation as objective function.

Algorithm	SVC1		SVC2		TCSC1			TCSC2			L-index	Voltage deviation	MVAR loss
	Bus	MVAR	Bus	MVAR	In	End	%	In	End	%			
OAPF	-	-	-	-	-	-	-	-	-	-	0.3010	0.1956	92.0447
AEA	56	10.2213	36	23.7419	5	6	45.4756	14	15	22.1491	0.3047	0.0677	60.3760
EA	42	24.4921	46	52.6807	1	17	15.5758	46	47	23.3213	0.2947	0.1559	45.3859
PSO	7	14.0604	37	42.3979	28	29	1.8626	38	49	19.5786	0.2989	0.1777	80.3452
SA	-	-	-	-	-	-	-	-	-	-	0.3010	0.1956	92.0447

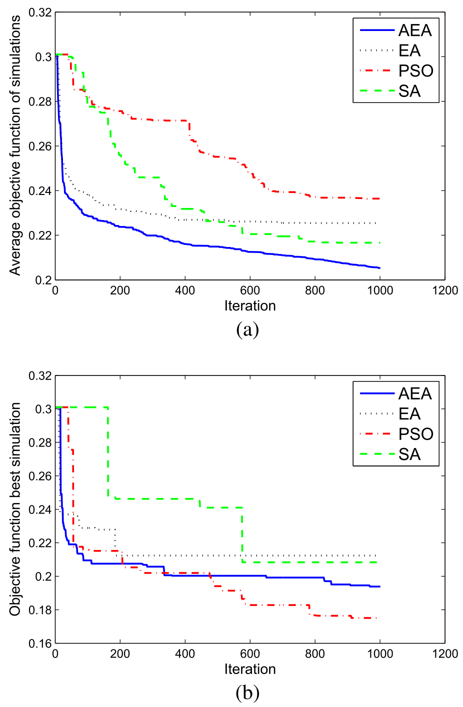


FIGURE 8. IEEE 57: L-index as objective function. (a) Mean. (b) Best solution.

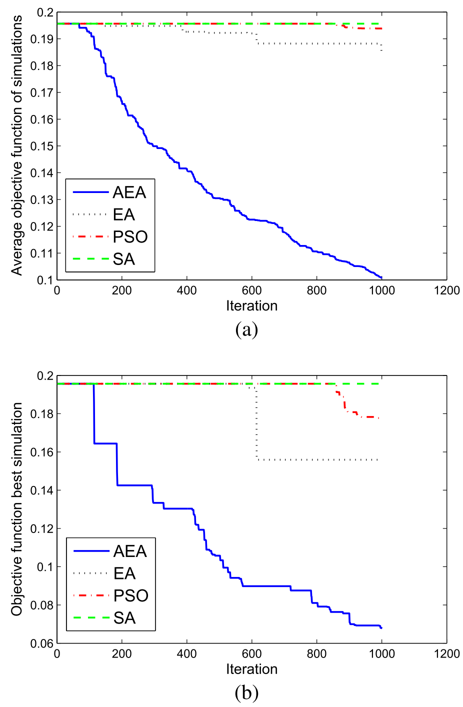


FIGURE 9. IEEE 57: voltage deviation as objective function. (a) Mean. (b) Best solution.

51% of the total reactive power loss versus 34% and 13% reduction by AEA and EPO, respectively.

In experiments for the total reactive power loss as objective function, AE presented the best average performance followed by AEA. PSO and SA achieved similar results, as shown Figure 10a. The best result was obtained by AEA, as shown Figure 10b. The results presented in Table 10 show a reduction larger than 94% of the total reactive power loss, thus highlighting AEA, which minimized 99% of this indicator. The methods suggested different locations to install the FACTS devices. However, the lowest adjustment is obtained by AEA. Despite the good results presented by all methods, only the results presented by AEA and AE are feasible, since the results obtained by PSO and SA led the power system to the voltage collapse, i.e., L-index was equal to 1.

C. EXPERIMENTS WITH THE IEEE 118 BUSBAR SYSTEM

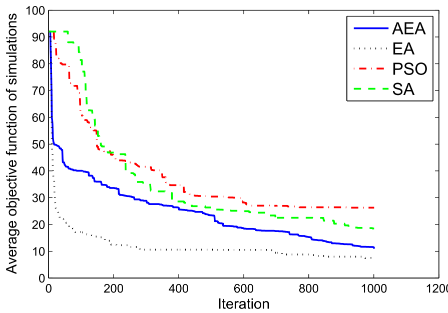
This section presents the experiments with the IEEE 118 busbar system. In these experiments, all methods improved the L-index as objective function, as shown in Table 11. The best result was reached by AEA; however, this method provided the worse voltage deviation and large total reactive power loss – the latter indicator by comparing with EA. This situation probably occurred due to the largest reactive power injection

TABLE 10. IEEE 57: total reactive power loss as objective function.

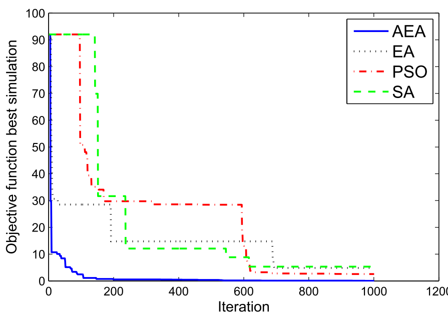
Algorithm	SVC1		SVC2		TCSC1			TCSC2			*L-index*	Voltage deviation	MVAR loss
	Bus	MVAR	Bus	MVAR	In	End	%	In	End	%			
OAPF	-	-	-	-	-	-	-	-	-	-	0.3010	0.1956	92.0447
AEA	34	-3.5757	16	57.7922	41	43	6.6698	7	8	21.9022	0.2467	0.7694	0.0343
EA	17	94.3191	33	19.0892	12	17	10.2896	46	47	37.3275	0.2517	1.0446	4.8458
PSO	40	147.9336	34	159.5246	1	16	8.1435	21	22	0	1.0000	1.4186	2.5529
SA	43	-78.3896	38	4.6959	32	33	4.4890	9	10	5.0637	1.0000	2.0340	5.3299

TABLE 11. IEEE 118: L-index as objective function.

Method	SVC1		SVC2		TCSC1			TCSC2			*L-index*	Voltage deviation	MVAR loss
	Bus	MVAR	Bus	MVAR	From	To	%	From	To	%			
OAPF	-	-	-	-	-	-	-	-	-	-	0.0634	0.3145	473.2
AEA	44	129.1249	95	73.8218	45	46	49.2471	94	100	48.4687	0.0383	0.6627	55507
EA	45	107.7836	67	-7.5829	45	46	45.0476	94	95	46.3582	0.0423	0.4405	15187
PSO	53	118.7873	57	5.2108	45	46	50.0000	83	85	33.0489	0.0424	0.7438	146760
SA	48	-16.5661	43	80.5725	94	95	39.3749	45	46	49.6531	0.0415	0.5422	79525

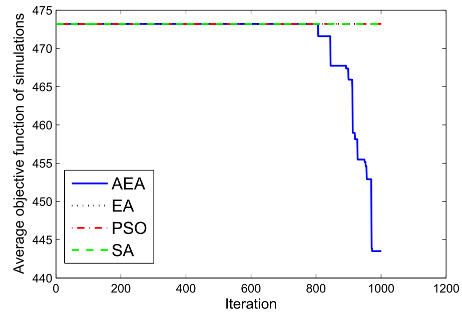


(a)

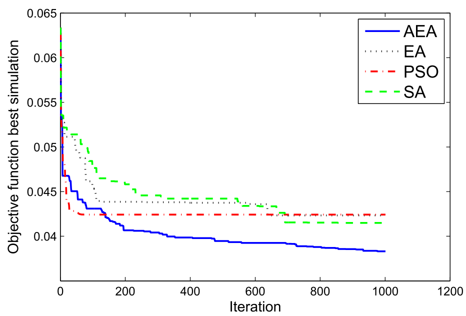


(b)

FIGURE 10. IEEE 57: total reactive power loss as objective function. (a) Mean. (b) Best solution.



(a)



(b)

FIGURE 11. IEEE 118: L-index as objective function. (a) Mean. (b) Best solution.

to the system (SVC1 + SVC2) by AEA. Thus, both the voltage at control buses and the total reactive power loss tended to increase. This argument can be verified by the results of OAPF, which reached the minimum of both voltage deviation and total reactive power loss at cost of the worst L-index. All methods installed the FACTS devices at different buses and transmission lines.

Figures 11a and 11b show the optimization process throughout the iterations for the L-index as objective function. Only AEA minimized the L-index at average, in Figure 11a. The best solution of all method minimized the L-index; however, AEA provided the best result, Figure 11b. AEA reduced 40% of the L-index versus about 34% of the other methods.

For the voltage deviation as objective function, AEA and AE outperformed PSO and SA, and AEA presented the best results, as shown in Figures 12a and 12b. Table 12 also shows that the methods installed the FACTS devices at different buses. AEA improved the voltage deviation more than 85%, followed by EA, which improved 82%. AEA and EA increased the total reactive power loss at the cost of the voltage deviation reduction.

The experiments with the total reactive power loss as objective function were very promising for the method proposed in this paper. Only AEA was able to minimize this indicator,

TABLE 12. IEEE 118: voltage deviation as objective function.

Algorithm	SVC1		SVC2		TCSC1			TCSC2			*L-index*	Voltage deviation	MVAR loss
	Bus	MVAR	Bus	MVAR	In	End	%	In	End	%			
OAPF	-	-	-	-	-	-	-	-	-	-	0.0634	0.3145	473.2
AEA	13	19.2459	102	-16.9070	23	24	50.0000	49	69	4.7175	0.0700	0.0409	13251
EA	97	34.8217	11	-17.9987	70	71	48.9086	17	113	44.0576	0.0695	0.0576	18231
PSO	97	47.2941	83	-9.5501	49	51	8.5806	65	68	0	0.0655	0.0765	46508
SA	3	68.9543	20	-42.6689	27	32	50.0000	51	52	12.4281	0.0675	0.1332	107280

TABLE 13. IEEE 118: total reactive power loss as objective function.

Algorithm	SVC1		SVC2		TCSC1			TCSC2			*L-index*	Voltage deviation	MVAR loss
	Bus	MVAR	Bus	MVAR	In	End	%	In	End	%			
OAPF	-	-	-	-	-	-	-	-	-	-	0.0634	0.3145	473.2
AEA	38	-20.1424	98	20.5834	4.0000	5.0000	31.2535	49.0000	54.0000	17.9257	0.0612	0.2210	345.0

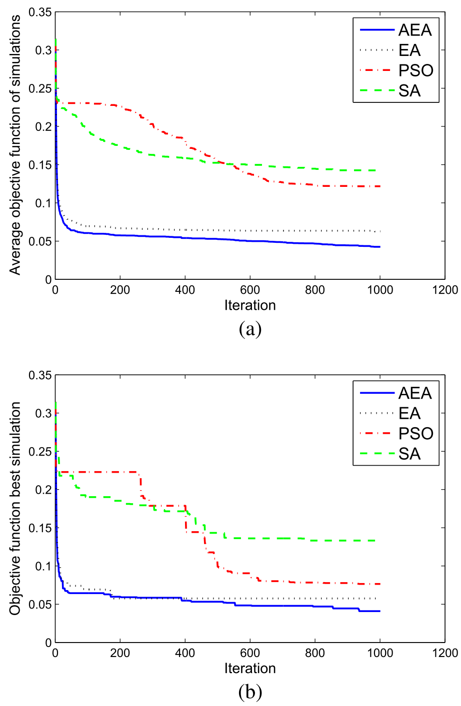


FIGURE 12. IEEE 118: voltage deviation as objective function. (a) Mean. (b) Best solution.

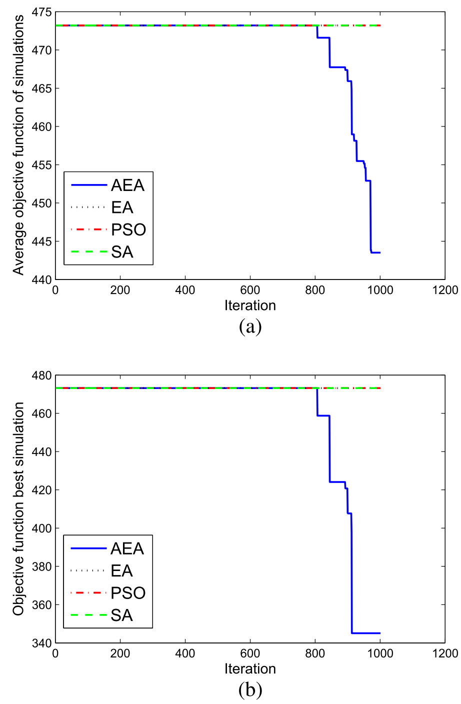


FIGURE 13. IEEE 118: total reactive power loss as objective function. (a) Mean. (b) Best solution.

as shown in Figures 13a and 13b. Although the stability indicator are conflicting, when the total reactive power loss was minimized by AEA, the other indicators, L-index and voltage deviation, were also improved, as shown in Table 13.

D. GENERAL ANALYSIS OF THE RESULTS

AEA presented marginal improvements compared to EA only in the small IEEE 14 busbar system. In IEEE 57, especially in average results, AEA outperformed, significantly, the other methods in two of three objective functions. In the large IEEE 118 busbar system, AEA achieved much better results than those of the other methods, especially in the L-index and total reactive power loss.

For large systems, AEA may present better results since this method does not permit premature convergence. Premature convergence cuts off the feature of the global search of the evolutionary algorithms and that it may lead the evolutionary algorithm to a local optimum.

VII. CONCLUSION

This paper presented a novel method for analysis and enhancement of the voltage stability in power systems. The proposed method uses an adaptive evolutionary algorithm (AEA) in which the population diversity is controlled. The proposed method adjusts the decision variables and automatically allocates two types of FACTS devices: SVC and TCSC. Three voltage stability indicators were used as objective function: L-index, voltage profile, and total reactive power loss. AEA was validated in several experiments by using the standard IEEE 14, 57, and 118 busbar systems in order to compare its performance with probabilistic and heuristic optimization methods.

All methods enhanced the performance of the power systems on the point of view of the proposed objective functions. AEA outperformed the other methods in most of experiments, especially in the IEEE 118 busbar system. The results of the experiments in IEEE 14, 57, and 118 systems showed that the difference of performance among the tested methods increased as the complexity of the systems become greater. In most of them, the proposed AEA reached the best solution.

In several experiments, the methods presented different places to install the FACTS devices. Thus, the results of the proposed method outperformed those of the other ones. As the transmission systems increase, the adjustments of the decision variables provided more influence on the objective functions than the FACTS devices. This is especially observed in the experiments with the IEEE 118. Thus, the relevance to use optimization methods in power systems increases as a complementation of the FACTS devices.

REFERENCES

[1] K. E. Parsopoulos, *Particle Swarm Optimization and Intelligence: Advances and Applications*. Hershey, PA, USA: IGI Global, 2010.

[2] R. Kalaivani and V. Kamaraj, "Enhancement of voltage stability by optimal location of static var compensator using genetic algorithm and particle swarm optimization," *Amer. J. Eng. Appl. Sci.*, vol. 5, no. 1, pp. 70–77, 2012.

[3] D. E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*. Reading, MA, USA: Addison-Wesley, 1989.

[4] M. Gen and R. Cheng, *Genetic Algorithms and Engineering Optimization*, vol. 7. Hoboken, NJ, USA: Wiley, 2000.

[5] A. Gupta and P. R. Sharma, "Application of GA for optimal location of FACTS devices for steady state voltage stability enhancement of power system," *Int. J. Intell. Syst. Appl.*, vol. 6, no. 3, p. 69, 2014.

[6] U. Kılıç, K. Ayan, and U. Arifoğlu, "Optimizing reactive power flow of HVDC systems using genetic algorithm," *Int. J. Elect. Power Energy Syst.*, vol. 55, pp. 1–12, Feb. 2014.

[7] A. E. Eiben and J. E. Smith, *Introduction to Evolutionary Computing*. Berlin, Germany: Springer, 2003.

[8] J. Branke and H. Schmeck, "Designing evolutionary algorithms for dynamic optimization problems," in *Advances in Evolutionary Computing: Theory and Applications*. Berlin, Germany: Springer-Verlag, 2003.

[9] H.-G. Beyer and B. Sendhoff, "Functions with noise-induced multimodality: A test for evolutionary robust optimization-properties and performance analysis," *IEEE Trans. Evol. Comput.*, vol. 10, no. 5, pp. 507–526, Oct. 2006.

[10] M. M. Gouvêa, Jr., and A. F. R. Araújo, "Evolutionary algorithm with diversity-reference adaptive control in dynamic environments," *Int. J. Artif. Intell. Tools*, vol. 24, no. 1, pp. 1450013-1–1450013-36, 2015.

[11] M. Kamel, A. A. Karrar, and A. H. Eltom, "Development and application of a new voltage stability index for on-line monitoring and shedding," *IEEE Trans. Power Syst.*, vol. 33, no. 2, pp. 1231–1241, Mar. 2018.

[12] A. Kapetanaki, V. Levi, M. Buhari, and J. A. Schachter, "Maximization of wind energy utilization through corrective scheduling and FACTS deployment," *IEEE Trans. Power Syst.*, vol. 32, no. 6, pp. 4764–4773, Nov. 2017.

[13] F. Ugranli and E. Karatepe, "Coordinated TCSC allocation and network reinforcements planning with wind power," *IEEE Trans. Sustain. Energy*, vol. 8, no. 4, pp. 1694–1705, Oct. 2017.

[14] M. M. Eladany, A. A. Eldesouky, and A. A. Sallam, "Power system transient stability: An algorithm for assessment and enhancement based on catastrophe theory and FACTS devices," *IEEE Access*, vol. 6, pp. 26424–26437, 2018.

[15] A. Parizad, A. Khazali, and M. Kalantar, "Application of HSA and GA in optimal placement of FACTS devices considering voltage stability and losses," in *Proc. IEEE Int. Conf. Electr. Power Energy Convers. Syst. (EPECS)*, Nov. 2009, pp. 1–7.

[16] A. Esmaeili and S. Esmaeili, "A new multiobjective optimal allocation of multitype facts devices for total transfer capability enhancement and improving line congestion using the harmony search algorithm," *Turkish J. Elect. Eng. Comput. Sci.*, vol. 21, no. 4, pp. 957–979, 2013.

[17] A. A. Mohamed and B. Venkatesh, "Line-wise power flow and voltage collapse," *IEEE Trans. Power Syst.*, vol. 33, no. 4, pp. 3768–3778, Jul. 2018.

[18] X. Xu, Z. Yan, M. Shahidehpour, H. Wang, and S. Chen, "Power system voltage stability evaluation considering renewable energy with correlated variabilities," *IEEE Trans. Power Syst.*, vol. 33, no. 3, pp. 3236–3245, May 2018.

[19] C. Liu, B. Wang, F. Hu, K. Sun, and C. L. Bak, "Online voltage stability assessment for load areas based on the holomorphic embedding method," *IEEE Trans. Power Syst.*, vol. 33, no. 4, pp. 3720–3734, Jul. 2018.

[20] S. M. Mohseni-Bonab and A. Rabiee, "Optimal reactive power dispatch: A review, and a new stochastic voltage stability constrained multi-objective model at the presence of uncertain wind power generation," *IET Gener., Transmiss. Distrib.*, vol. 11, no. 4, pp. 815–829, 2017.

[21] R. S. Wibowo, N. Yorino, M. Eghbal, Y. Zoka, and Y. Sasaki, "FACTS devices allocation with control coordination considering congestion relief and voltage stability," *IEEE Trans. Power Syst.*, vol. 26, no. 4, pp. 2302–2310, Nov. 2011.

[22] T. Nireekshana, G. K. Rao, and S. S. N. Raju, "Enhancement of ATC with FACTS devices using real-code genetic algorithm," *Int. J. Elect. Power Energy Syst.*, vol. 43, no. 1, pp. 1276–1284, 2012.

[23] M. Esmaili, H. A. Shayanfar, and R. Moslemi, "Locating series facts devices for multi-objective congestion management improving voltage and transient stability," *Eur. J. Oper. Res.*, vol. 236, no. 2, pp. 763–773, 2014.

[24] N. G. Hingorani, "High power electronics and flexible AC transmission system," in *Proc. Amer. Power Conf.*, vol. 50, pp. 3–4, 1988.

[25] O. I. Elgerd, *Electric Energy Systems Theory*, 2nd ed. New York, NY, USA: McGraw-Hill, 1982.

[26] P. Kundur, *Power System Stability and Control*. New York, NY, USA: McGraw-Hill, 1993.

[27] M. Kamarposhti and H. Lesani, "Effects of STATCOM, TCSC, SSSC and UPFC on static voltage stability," *Elect. Eng.*, vol. 93, no. 1, pp. 33–42, 2011.

[28] A. Chakrabarti, D. Kothari, A. Mukhopadhyay, and A. De, *An Introduction to Reactive Power Control and Voltage Stability in Power Transmission Systems*. New Delhi, India: PHI Learning Private Limited, 2015.

[29] V. Balamourougan, T. S. Sidhu, and M. S. Sachdev, "Technique for online prediction of voltage collapse," *IEE Proc.-Gener., Transmiss. Distrib.*, vol. 151, no. 4, pp. 453–460, 2004.

[30] Y. Wang, C. Wang, F. Lin, W. Li, L. Y. Wang, and J. Zhao, "Incorporating generator equivalent model into voltage stability analysis," *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 4857–4866, Nov. 2013.

[31] Y.-H. Song and A. Johns, *Flexible AC Transmission Systems (FACTS)*, no. 30. Michael Faraday House, U.K.: IET, 1999.

[32] A. Janke *et al.*, "SVC operation & reliability experiences," in *Proc. IEEE PES Soc. Gen. Meeting*, Jul. 2010, pp. 1–8.

[33] N. G. Hingorani and L. Gyugyi, *Understanding FACTS: Concepts and Technology of Flexible AC Transmission Systems*. Hoboken, NJ, USA: Wiley, 2000.

[34] W. Amos and A. Balmford, "When does conservation genetics matter?" *Heredity*, vol. 87, no. 3, pp. 257–265, 2001.

[35] M. L. Weitzman, "On diversity," *Quart. J. Econ.*, vol. 107, no. 2, pp. 363–405, 1992.

[36] A. Solow, S. Polasky, and J. Broadus, "On the measurement of biological diversity," *J. Environ. Econ. Manage.*, vol. 24, no. 1, pp. 60–68, 1993.

[37] S. Champely and D. Chessel, "Measuring biological diversity using Euclidean metrics," *Environ. Ecol. Statist.*, vol. 9, no. 2, pp. 167–177, 2002.

[38] C. E. Shannon, "A mathematical theory of communication," *Bell Syst. Tech. J.*, vol. 27, no. 3, pp. 379–423, 1948.

[39] A. E. Magurran, *Measuring Biological Diversity*. Oxford, U.K.: Blackwell, 2004.

[40] M. M. Gouvêa, Jr., and A. F. R. Araüjo, "Population dynamics model for gene frequency prediction in evolutionary algorithms," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Hong Kong, Jun. 2008, pp. 1603–1610.

[41] Á. E. Eiben, R. Hinterding, and Z. Michalewicz, "Parameter control in evolutionary algorithms," *IEEE Trans. Evol. Comput.*, vol. 3, no. 2, pp. 124–141, Jul. 1999.

[42] S. Droste, T. Jansen, and I. Wegener, "Dynamic parameter control in simple evolutionary algorithms," in *Foundations of Genetic Algorithms 6*. Amsterdam, The Netherlands: Elsevier, 2001, pp. 275–294.

[43] Y.-Y. Wong, K.-H. Lee, K.-S. Leung, and C.-W. Ho, "A novel approach in parameter adaptation and diversity maintenance for genetic algorithms," *Soft Comput.*, vol. 7, no. 8, pp. 506–515, 2003.

[44] R. D. Zimmerman, C. E. Murillo-Sanchez, and R. J. Thomas, "MATPOWER: Steady-state operations, planning and analysis tools for power systems research and education," *IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 12–19, Feb. 2011.

[45] A. Ajami, G. Aghajani, and M. Pourmahmood, "Optimal location of FACTS devices using adaptive particle swarm optimization hybrid with simulated annealing," *J. Elect. Eng. Technol.*, vol. 5, no. 2, pp. 179–190, 2010.

SIDNEI NASCIMENTO received the B.Sc. and M.S. degrees in electrical engineering from Pontifical Catholic University, Brazil, in 2012 and 2016, respectively. He is currently pursuing the Ph.D. degree with the Federal University of Minas Gerais, Brazil. His areas of interest include power system modeling, optimization, stability, and control.

ROSE M. S. BATALHA received the B.Sc. and M.Sc. degrees in electrical engineering from the Universidade Federal de Minas Gerais, Belo Horizonte, Brazil, in 1984 and 1995, respectively, and the Ph.D. degree in electrical engineering from The University of Akron, Akron, OH, USA, in 2000. Since 1989, she has been with the Pontifícia Universidade Católica de Minas Gerais, where she is currently an Associate Professor with the Electrical Engineering Department. Her research interests include electric power systems, electromagnetic compatibility, numerical methods, and scientific computing applied to computational electromagnetics.

MAURY M. GOUVÊA, Jr. has been teaching and engaging in research with the Pontifical Catholic University of Minas Gerais, Belo Horizonte, since 2009. He takes part in various research projects and activities with a view to sharing the findings with the corresponding research groups in Brazil and in other countries and to seeking opportunities for national and international collaboration with other institutions or networks which have similar interests. His areas of interest include the stability of electrical systems, the dynamics of complex systems, evolutionary computing, and neural networks.