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Voltage stability enhancement in power systems with automatic facts device allocation

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Abstract

The voltage stability problem in modern power systems is an issue related to the system constraints and voltage collapse. Flexible AC Transmission System (FACTS) is an example of modern device able to control the reactive power flow in a more efficient way. This paper proposes an automatic FACTS device allocation process based on evolutionary algorithm. The model aims to enhance the voltage stability of power systems. The results showed that the proposed method enhanced the voltage stability in IEEE system benchmarks, and the method outperformed other probabilistic and heuristic optimization methods.

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Keywords: Voltage Stability; FACTS devices; Reactive Power

1. Introduction

The power system has become the main driver of the world economy. Nowadays, power systems operate near to their constraints due to the continuous demand increase. The voltage instability is the main cause of constraint violations and voltage collapse. The voltage stability is related to the control of the reactive power. The Flexible AC Transmission System (FACTS) becomes the control of the reactive power flow more dynamic, since the acquired flexibility on the transmission system [1]. The optimum location of FACTS devices is a very important issue in power systems, since the weakest busbar and/or transmission lines need to be identified.

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Several works have used FACTS based models in order to control the reactive power flow and to assess the voltage stability [2-6]. In [7,8], a genetic algorithm is used to determine the parameters and location of SVC, TCSC, and UPFC to improve the voltage stability and to reduce active power losses. In the [9,10], the voltage stability is evaluated according to the L-index indicator and the parameters and location of FACTS devices are obtained with a hybrid genetic algorithms and harmony search. In [11], a modified augmented e-constraint method is used to determine the best location and adjustment of a FACTS device to enhance the voltage stability.

The optimum reactive power flow is 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, since this is a probabilistic, population based, and global search method. Classical optimization methods generally are local search based and require a well-defined analytic functions. Evolutionary algorithm only compares the quality of solutions.

This paper presents an automatic FACTS device allocation method with an evolutionary algorithm. The proposed method also adjusts other decision variables in order to enhance the voltage stability. The method used an adaptive evolutionary algorithm to optimize the following stability indicators: the voltage profile, the reactive power flow losses, and the voltage collapse margin. Several experiments were performed, and the results showed that the proposed method enhanced the voltage stability in IEEE 14 and 57 busbar systems, and the method also outperformed other probabilistic and heuristic optimization methods.

2. Voltage stability

Voltage stability is a problem in power systems which are loaded or have a shortage of reactive power. Voltage stability can be analyzed by examining the production, transmission, and demanding of reactive power [12]. The proposed model uses the L-index method for evaluating the voltage stability in power systems through the voltage collapse margin [13,14].

For a power system with n bus, the index that identifies the proximity to the voltage collapse can be defined as

$$L_j = \left| 1 - \sum_{i=1}^{n_C} C_{\mathrm{ji}} \frac{V_i}{V_j} \right| \tag{1}$$

where nG is the number of generation bus, Vi is the voltage in complex form of i-th generation bus, Vj is the voltage in the complex form of j-th load bus, Cji is the element of the matrix C:

$$[C] = -[Y_{LL}]^{-1}[Y_{LG}] \tag{2}$$

The matrix [YLL] and [YLG] are submatrix of Ybus.

$$\begin{bmatrix} I_L \\ I_G \end{bmatrix} = \begin{bmatrix} Y_{LL} & Y_{LG} \\ Y_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} V_L \\ V_G \end{bmatrix} \tag{3}$$

This index Lj ranges from 0, stable system, to 1, voltage collapse.

3. 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 [1]. The following subsections present two FACTS devices used by the proposed method.

3.1. Static var compensator

Static Var Compensator (SVC) is shunt connected to a bus and provides an adjustable reactance [15], [16]. The reactive power supplied by SVC in the j-th bus can be modeled as in Eq. (4)

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

where V_j is the voltage magnitude at j-*th bus and B_{SVC} is the SVC susceptance.*

3.2. Thyristor controlled series compensator

Thyristor Controlled Series Compensator (TCSC) is series connected to a transmission line in order to control its impedance [17]. 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

$$\Delta y_{ij} = y_{ij}^{\mathrm{mod}} - y_{ij} = (g_{ij}^{\mathrm{mod}} + jb_{ij}^{\mathrm{mod}}) - (g_{ij} + jb_{ij}) \tag{5}$$

$$g_{ij} = -\frac{r_{ij}}{\sqrt{\mathrm{r}_{ij}^2 + x_{ij}^2}} \tag{6}$$

$$b_{ij} = -\frac{x_{ij}}{\sqrt{\mathrm{r}_{ij}^2 + x_{ij}^2}} \tag{7}$$

$$g_{ij}^{\mathrm{mod}} = -\frac{r_{ij}}{\sqrt{\mathrm{r}_{ij}^2 + (x_{ij} + x_{TCSC})^2}} \tag{8}$$

and

$$b_{ij}^{\mathrm{mod}} = -\frac{x_{ij+x_{TCSC}}}{\sqrt{\mathrm{r}_{ij}^2 + (x_{ij} + +x_{TCSC})^2}} \tag{9}$$

4. Automatic allocation of facts devices

This research study regards three indicators in order to enhance the voltage stability of power systems: L-index, voltage deviation, and reactive power losses. The proposed optimization method models three objective functions by using these indicators. The first objective function, which uses Lindex, is modeled as in Eq. (12)

$$F_1(X) = \min(\max(L)) \quad (10)$$

where X is the vector of decision variables and L $\in [0;1]$ is the L-index. L equal to 0 means stability and L$\rightarrow$1 suggests proximity to voltage collapse.

The second objective function, which uses the voltage deviation, is modeled as in Eq. (13)

$$F_2(X) = \sqrt{\sum_{i=1}^{N_L} (V_i - 1)^2} \quad (11)$$

where Vi, in pu, is the voltage magnitude of i-th load bus and NL is the number of load buses. The optimization algorithms based on the behavior of living beings has gained prominence in recent years because of the quality of these solutions and the ease of implementation, in addition to these are flexible to change in the objective function. The following subsections present the optimization algorithms used in the experimental study.

4.1. Adaptive Evolutionary Algorithm

Evolutionary algorithm is a powerful mechanism for search and optimization, and one of the best-known evolutionary computation methods [18]. An important issue in an evolutionary algorithm is maintaining its diversity to avoid the premature convergence. The diversity control aims to reduce the difference between the population diversity and a reference value [19]. The proposed method uses an adaptive evolutionary algorithm (AEA) to control the population diversity, avoiding the premature convergence and maintaining the global search.

4.2. Decision Variable Coding

The individual of the population, which coded the vector of decision variable X, is formed by the voltage magnitude of the generator buses, the shunt capacitor bank, transformer tap settings, and the location and reactive power injection of TCSC and SVC devices.

4.3. Variation Operators

This work uses the two typical EA variation operators: crossover and mutation. In the crossover process, there is a random cut point for the two parents, P1 and P2, as shown in Fig. 1. The descendents, D1 and D2 in Figure 1, are generated from the mixed parts of the two parents.

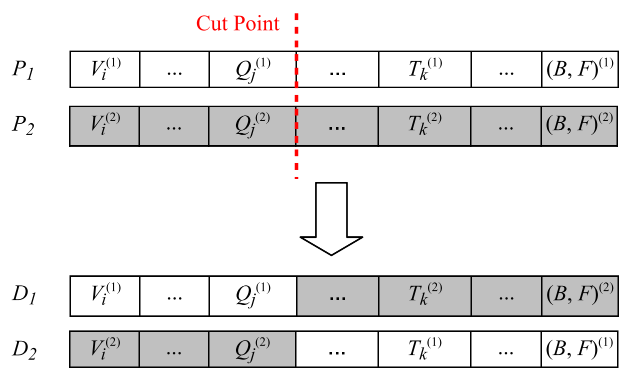

Fig. 1. One-point crossover

The mutation, performed after the crossover, is a random change of the genes (decision variables) according to a probability pm $\in[0;1]$. In the proposed model, the mutation is performed in the elements of the vector of decision variables, X. The location and reactive power injection of the FACTS devices are mutated apart. For example, Fig. 2 shows a descendent before and after mutation, where r $\in[0;1]$ is an uniform distribution random variable. For each gene, if r $\leq$ pm; then, the gene is modified.

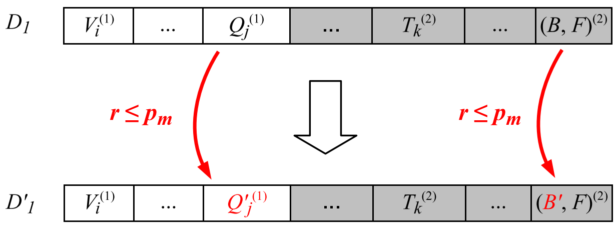

Fig. 2. Mutation of the descendent after crossover

4.4. Diversity Control

The population diversity means how different the individuals are from each other. Control of the population diversity of a EA, or minimizing its loss, may benefit the evolutionary process in several ways, such as, preventing premature convergence to a local optimum and considering different niches for solutions of multimodal problems [20].

In this work, the population diversity is calculated, at k-th generation, as follows

$$\Gamma(k)=1-\sum_{i=1}^{n_s}\rho_i^2 \tag{12}$$

where ns is the number of alleles and pi is the i-th allele occurrence rate. An allele is an interval into the inferior and superior limits of each decision variable.

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

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

where η is a constant.

5. Experimental studies

The proposed method was tested in the standard IEEE 14 and 57 busbar power systems. The algorithms were implemented in Matlab[R] environment and the Matpower package for power system simulations [21].

The SVC devices were not installed at generation buses or where there is some type of compensator, e.g. synchronous or reactive one. The TCSC devices were not installed between processing buses.

In order to validated the proposed method, two other probabilistic optimization methods are used in the experiments: particle swarm optimization (PSO) [22] and simulated annealing (SA) [23]. In a PSO process, a swarm of particles of potential solutions browses the global optimal solution through the search space. During their trip with discrete-time iterations, the speed of each particle in the next iteration is calculated as a function of the best swarm position, the best particle position, and its previous rate. Simulated annealing (SA) emulates the physical annealing process when applied to combinatorial optimization. Simulated annealing aims to find an ideal setting, or state with minimum energy, of a complex problem.

The initial population was randomly created with 100 individuals, the algorithms run 1,000 generations/iterations, and the best parameters of EA, PSO, and SA algorithms were obtained by empirical way. EA used mutation rate equals 5%, crossover rates equals 60%, tournament for selection. PSO used initial and final inertia coefficients equal to 0.9 and 0.4, respectively, and C1 = 3:5 and C2 = 0:5, and initial speed is given for 10% of the initial root position of the particle. SA used τ = 0:2, α = 0:9, the perturbation of each point is made with a probability of 50%, altering the decision variables with a maximum of 10% of their range, the change in temperature occurred only if 50 perturbations did not cause 10 improvements in the objective function. The following subsections present the experiments with standard (non-adaptive) and adaptive evolutionary algorithm.

5.1. Experiments with Standard EA

Table I shows the results for the IEEE 14 busbar system. For the objective functions based on L-index, all methods presented similar results. For the objective functions based on voltage deviation, the proposed method outperformed the other ones. For the objective functions based on MVAR losses, the proposed method and PSO reached similar results and both of them outperformed SA. In general, the proposed EA-based reduced more than 30% in L-index, 20% in reactive power losses, and 90% in voltage deviation.

Table 1. Results for IEEE 14 busbar system

OBJ. FUNCTIONS	INITIAL	EA	PSO	SA
L-index	0.0768	0.0523	0.0523	0.0572
Voltage Deviation	0.1424	0.0067	0.0083	0.0236
MVAR losses	54.54	42.26	42.86	46.93

Table 2 shows the results for IEEE 57 busbar system. The proposed EA-based reduced more than 50% in L-index and voltage deviation. The population based methods, EA and PSO, showed clearly a better performance than SA in IEEE 57 busbar, since its large dimension with respect to the IEEE 14 busbar system.

Table 2. Results for IEEE 57 busbar system

OBJ. FUNCTIONS	INITIAL	EA	PSO	SA
L-index	0.3099	0.1497	0.1561	0.1722
Voltage Deviation	0.2043	0.0906	0.1471	0.1873
MVAR Losses	121.67	75.60	87.23	114.05

5.2. Experiments with Adaptive EA

For case studies by using adaptive evolutionary algorithm (AEA), based on diversity control, pm(0) = 0:05, η = 0:2, ns = 50, Γr = 0:55 for IEEE 14, and Γr = 0:65 for IEEE 57 busbar system.

Figure 3 present the fittest individual for voltage deviation throughout the evolutionary process and at the load buses in IEEE 14 busbar systems, respectively, for EA and AEA. AEA outperformed EA since the beginning of the evolutionary process, and the former reached a final fitness 50% better than the latter.

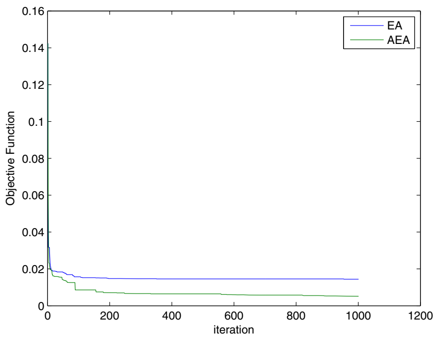

Fig. 3. Voltage deviation in the evolutionary process for EA and AEA in IEEE 14 busbar system

Figure 4 present the fittest individual for voltage deviation throughout the evolutionary process and at the load buses in IEEE 57 busbar systems, respectively, for EA and AEA. Such as in IEEE 14 experiment, Figure 4 shows that AEA also outperformed EA, and the former reached a final fitness 60% better than the latter. Moreover, AEA decreased the fittest individual continuously; on the other hand, EA did that in several generations. Its mean that AEA had an average performance better than EA in the voltage deviations at load buses.

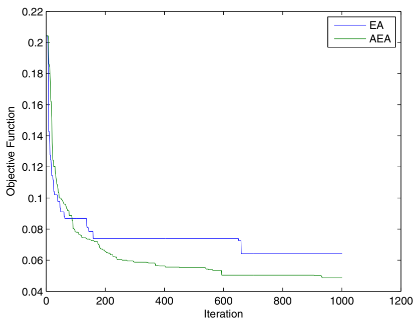

Fig. 4. Evolutionary process with EA and AEA in IEEE 57 busbar system

6. Conclusion

This paper presented a method to enhance the voltage stability through an optimization process. The method proposed an automatic allocation of FACTS devices and adjustments of decision variables by using an adaptive evolutionary algorithm. Three objective functions were modeled by using performance indicator of power systems: L-index for collapse margin, voltage deviation at load buses, and reactive power losses. The method was validated in experimental studies with two standard IEEE power systems by comparing the performance of four different optimization methods: PSO, SA, EA, and the proposed adaptive EA.

The results showed that the EA-based methods outperformed the other ones, especially in IEEE 57 busbar system. In IEEE 14 busbar system, all methods reached similar results in experiments with the objective functions based on L-index and MVAR losses. In experiments with the objective functions based on voltage deviations, EA outperformed the other ones. On the other hand, in experiments with IEEE 57 busbar system, a larger dimension system, EA outperformed the other methods in all experiments. In experiments that EA and adaptive EA were compared, the latter had better performance than the standard EA in all aspects. Several new studies can be started from this work, such as control diversity analysis and a multiobjective approach regarding two or more objective functions used in this work.

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