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Sensitivity analysis by neural networks applied to power systems transient stability

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Abstract

This work presents a procedure for transient stability analysis and preventive control of electric power systems, which is formulated by a multilayer feedforward neural network. The neural network training is realized by using the back-propagation algorithm with fuzzy controller and adaptation of the inclination and translation parameters of the nonlinear function. These procedures provide a faster convergence and more precise results, if compared to the traditional back-propagation algorithm. The adaptation of the training rate is effectuated by using the information of the global error and global error variation. After finishing the training, the neural network is capable of estimating the security margin and the sensitivity analysis. Considering this information, it is possible to develop a method for the realization of the security correction (preventive control) for levels considered appropriate to the system, based on generation reallocation and load shedding. An application for a multimachine power system is presented to illustrate the proposed methodology.

Keywords: Sensitivity analysis; Preventive control; Transient stability; Neural networks; Back-propagation

1. Introduction

Sensitivity analysis [1] is a very important tool to solve several problems present in many areas of human knowledge: engineering, mathematics, physics, economy, medicine, biology, etc., especially when nonlinearities are involved. Therefore, it is possible to infer about the behavior of the system face to parametric variations without the need of solving a problem that involves great complexity, described by a set of nonlinear differential and algebraic equations. The comportamental conclusions are extracted from the calculation of the derivative function under analysis. This is the problem studied in this work, analysis of transient stability for electric energy systems and specifically the preventive control problem [2].

Transient stability analysis is one of the main studies used in electric power systems (EPS). It is a procedure to evaluate the effects caused by perturbations which origin great deviations on the angles of the synchronous machines, e.g., short-circuit, outage/input of electric equipment. In this case, the model of the system is described by a set of nonlinear algebraic and differential equations [3]. Due to unstable cases and/or equipment capability violations, it is necessary to adopt procedures that can lead the system to a secure state, known as security control. The methods for dynamical preventive control have been proposed recently and the publication available in the literature is not abundant, e.g., [2–6].

This work presents a methodology based on neural networks [7–9] to analyze the transient stability – considering short-circuit faults with transmission line outages – and, principally to provide the sensitivity analysis of EPS, that represent the necessary instruments for implementing the preventive control. Neural networks are important resources to deal with the preventive control problem, due to the training be an off-line activity and the analysis be concluded with minimal computational effort (basically the calculus with the input and output of the neural network), being useful for applications in real time. It is important to emphasize that the sensitivity calculus is carried out without computational effort. On the other hand, to obtain the sensitivity model by conventional procedures, require a large quantity of complex matrix calculation, spending much time, principally for applications in huge systems.

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The neural network used is a feedforward multilayer with training by back-propagation (BP) algorithm [10]. The BP algorithm training rate is adjusted by a fuzzy controller [11–14], which monitories the global error and the global error variation during the training as well the adaptive process [15,16]. It is an optimal mechanism that reduces the convergence time and improves the precision of the results, as observed in ref. [15]. The variables used on the training are causal variables of a problem of transient stability analysis (active and reactive nodal electric power which are the input neural network stimulus) and the security margins (output neural network stimulus) generated using the potential energy boundary surface (PEBS) iterative method [17], microcomputer version. The security margin expressed in function of total energy can be interpreted as being a measure of the distance in relation to the condition of the instability of the system. The sensitivity model is referred to the relation with the security margin and the nodal electric power. Thus, the generation reallocation and load shedding necessary for obtaining a secure state of the system can be evaluated, that is, a security level considered adequate for transient stability. It is a tool that can either aid the prevention or, at least, minimize the effects of a blackout [18–20]. An application considering a multimachine system is presented for testing the proposed methodology.

2. System model

Considering an electrical power system composed of *ns* synchronous machines, the dynamical behavior of the *i*th machine, related to Center of Angles (CA), is described by the following differential equation (classical model) [12,21]:

$$M_i\ddot{\theta}_i - P_i(\theta) = 0, \quad i \in N \tag{1}$$

where

$$P_i(\theta) = \mathrm{Pm}_i - \mathrm{Pe}_i - \frac{M_i \mathrm{PCOA}}{MT}; \tag{2}$$

M_i is $2H_i/\omega_s$; $\omega_s \triangleq$ synchronous speed of the rotor, $2\pi f_0$; H_i is the inertia constant (s); f_0 is the nominal frequency of system (Hz); $\theta_i \triangleq$ rotor angle of *i*th synchronous machine related to CA (electrical radians), $\delta_i - \delta_0$; δ_i is the rotor angle of *i*th synchronous machine in relation to synchronously rotating reference frame (in electrical radians); δ_0 is $\sum_{j\in N} M_j\delta_j$; Pm_i is the mechanical power of input (pu); Pe_i is the electrical power of output (pu); PCOA $\triangleq$ accelerating power of CA, $\sum_{j\in N}(\mathrm{Pm}_j - \mathrm{Pe}_j)$; MT is $\sum_{j\in N} M_j$; $N \triangleq$ index set of synchronous machines that comprises the system, $\{1, 2, \ldots, ns\}$; *ns* is the number of electrical synchronous machines.

3. Transient stability analysis

The transient stability analysis of EPS, considering a contingency of index *r*, is effectuated using the security margin criterion [12,17,21]:

$$\mathcal{M}_r = \frac{E_{\mathrm{crit}_r} - E_{\mathrm{e}_r}}{E_{\mathrm{crit}_r}} \tag{3}$$

where E_{crit_r} is the total critical energy of the system; E_{e_r} is the total energy of the system evaluated on the instant of the fault elimination (te).

The critical energy (E_{crit}) and the critical time (t_{crit}), is determined by the iterative PEBS method [4,16], or another procedure that presents a similar result, principally in relation to precision. The total energy related to system (1), is given by [12,17,21]:

$$E(\theta, \omega) = E_{\mathrm{c}}(\omega) + E_{\mathrm{p}}(\theta) \tag{4}$$

where

$$E_{\mathrm{c}}(\omega) = \text{kinetic energy} = \frac{1}{2}\sum_{i\in N} M_i w_i^2; \tag{5}$$

$$E_{\mathrm{p}}(\theta) = \text{potential energy} = -\sum_{i\in N}\int_{\theta_i^p}^{\theta_i} P_i(\theta)\,\mathrm{d}\theta_i. \tag{6}$$

Then, the transient stability for the *r*th contingency is evaluated by the security margin on the following way [17]:

- if $\mathcal{M}_r \geq 0$, the system is considered *stable*, for transient stability;
- if $\mathcal{M}_r < 0$, the system is considered *unstable*, for transient stability.

4. Dynamic preventive control

Considering a list composed of *S* contingencies, the security margin of the system must satisfy the following relation [4]:

$$\mathcal{M} \geq M_{\min} \tag{7}$$

where $M_{\min}$ is the minimum limit of the security margin of the system ($M_{\min} > 0$); $\mathcal{M} \triangleq \min(\mathcal{M}_r, r = 1, 2, \ldots, S)$.

The control actions must cause modifications on the security margins and the following relations must be satisfied [19,4]:

$$\mathcal{M}_r = (\mathcal{M}_r^0 + \Delta\mathcal{M}_r) \geq M_{\min}, \quad r = 1, 2, \ldots, S \tag{8}$$

where $\mathcal{M}_r$ is the security margin referred to the *r*th contingency.

The necessary changing ($\Delta\mathcal{M}_r$) to correct the security margin – in terms of a vector $\boldsymbol{X}$ – is estimated by the sensitivity theory, of first order, according to [19]:

$$\Delta\mathcal{M}_r \cong \left[\frac{\partial\mathcal{M}_r}{\partial\boldsymbol{X}}\right]^{\mathrm{T}} \Delta\boldsymbol{X} \tag{9}$$

or

$$\Delta t_{\mathrm{crit}_r} \cong \left[\frac{\partial t_{\mathrm{crit}_r}}{\partial\boldsymbol{X}}\right]^{\mathrm{T}} \Delta\boldsymbol{X} \tag{10}$$

where $\partial\mathcal{M}_r/\partial\boldsymbol{X}$ is the sensitivity of the security margin in relation to the vector $\boldsymbol{X}$; $\partial t_{\mathrm{crit}}/\partial\boldsymbol{X}$ is the sensitivity of the critical time in relation to the vector $\boldsymbol{X}$; $\Delta\boldsymbol{X}$ is the vector corresponding to the changing on the components of vector $\boldsymbol{X}$.

Equations (9) and (10) represent the sensitivity models considering the interest variables: security margin and critical time, respectively.