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Transient stability analysis of electric energy systems via a fuzzy ART-ARTMAP neural network

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Abstract

This work presents a methodology to analyze transient stability (first oscillation) of electric energy systems, using a neural network based on ART architecture (adaptive resonance theory), named fuzzy ART-ARTMAP neural network for real time applications. The security margin is used as a stability analysis criterion, considering three-phase short circuit faults with a transmission line outage. The neural network operation consists of two fundamental phases: the training and the analysis. The training phase needs a great quantity of processing for the realization, while the analysis phase is effectuated almost without computation effort. This is, therefore the principal purpose to use neural networks for solving complex problems that need fast solutions, as the applications in real time. The ART neural networks have as primordial characteristics the plasticity and the stability, which are essential qualities to the training execution and to an efficient analysis. The fuzzy ART-ARTMAP neural network is proposed seeking a superior performance, in terms of precision and speed, when compared to conventional ARTMAP, and much more when compared to the neural networks that use the training by backpropagation algorithm, which is a benchmark in neural network area.

Keywords: Adaptive resonance theory; ART-ARTMAP

1. Introduction

This work aims to present a methodology to transient stability analysis of electric energy system by artificial neural networks. The stability analysis consists of evaluating the effects proceeding of perturbations that cause great and undesirable oscillations on the angles of synchronous machines. This analysis can be realized by solving non-linear differential equations, that describe the movement of the system – synchronous machine oscillation equation – and, after by the analysis of the evolution of the angular position of each synchronous machine during time (simulation) [1]. The techniques used for the simulation are precise and present no restrictions to the type of the model employed. However, it is necessary to effectuate complex calculus that consists of solving a set of algebraic and non-linear differential equations and examining the oscillation curves that are obtained, increasing the time dispensed to conclude the analysis. An alternative proceeding consists of obtaining the analysis without solving the differential equations. In this way, there is the Lyapunov direct method (LDM) [2], which results are considered satisfactory, principally when it employed the classical method [2–4]. Taking into account the great quantity of the defects to be analyzed, the complexity and the great dimension of the modern electric systems, the simulation, as well as the Lyapunov direct method, are alternatives that, not yet, offer no conditions to applications in real time. New approaches of analysis, based on artificial intelligence, in special the neural networks [5], are presented in the literature aiming to overcome these difficulties, principally concerning to velocity. Therefore, this work investigates the application of artificial neural networks (ANN) on the diagnosis of transient stability analysis of electric energy systems. The transient stability analysis by neural networks, is in general effectuated employing the feedforward networks, with the training based on the backpropagation [6]. This technique is efficient, being considered in the literature, as a benchmark in terms of precision. However, the processing time is relatively high.

This way, in this work it is investigated the use of the fuzzy neural ART-ARTMAP network [7]. The ART-ARTMAP

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network is an architecture based on the supervised training for multi-dimensional mappings (multi-input/multi-output), being composed of three ART modules [8], and an inter-ART module. The ART neural network family has the characteristic of stability (capacity of learning without adjusting the weights) and plasticity (capacity of continue learning with the inclusion of new patterns without loosing the memory in relation to the previous patterns). Considering these characteristics, the expectation is that the network presents a superior performance when compared to the traditional backpropagation [6]. The ARTMAP neural networks, as well as the ART networks, are capable to include innovations that can produce better results [9]. The ART module is used to classify the input vectors (analog data), corresponding to the active and reactive nodal power in different categories and to convert them in binary information $\{\boldsymbol{P}^{\text{bin}}, \boldsymbol{Q}^{\text{bin}}\}$, by a processing module active code/binary code [7]. The fuzzy ARTMAP input module is constituted by the set $\{\boldsymbol{P}^{\text{bin}}, \boldsymbol{Q}^{\text{bin}}\}$, added to the binary information referred to fault conditions and the electric network topology. Thus, the neural ARTMAP network receives only binary data that represent a favorable situation for applications in large systems. This represents a reduction on the computational effort necessary to realize the training and an improvement on the quality of the analysis, when compared to other neural networks.

It is emphasized that, in the specialized literature, there are few references that deal with the stability analysis problem using neural networks [10]. In almost of these references, the transient stability analysis problem is formulated aiming the determination of the critical times for short circuit faults. References [10–12] use neural networks with the training by the backpropagation algorithm. In reference [13], it is used the backpropagation algorithm with a fuzzy controller, which adjusts the training rate, to reduce the number of cycles and the execution time in the training phase. There are other references, in special, that deal with problems associated to the electric power systems by neural networks using the ART concept. In references [14–16], the transient stability analysis problem solved by neural networks is proposed using a fuzzy ARTMAP neural network, considering the variation of the load and generation by proportionality, being this the majority of the solutions adopted in the available references. To illustrate the proposed methodology results are presented considering a multi-machine system.

2. System model

Considering an electric energy system composed of ns synchronous machines, the dynamic behavior of the i-th synchronous machine, related to the center of angles [2] is described by the following differential and non-linear algebraic Eqs. (2)–(4):

$$M_i \frac{\mathrm{d}^2\theta_i}{\mathrm{d}t^2} - P_i(\boldsymbol{\theta}) = 0 \tag{1}$$

$$P_i(\boldsymbol{\theta}) = \frac{\mathrm{Pm}_i - \mathrm{Pe}_i - (M_i\,\mathrm{PCA})}{\mathrm{MT}}, \quad i \in N. \tag{2}$$

where $M_i = 2H_i/\omega_s$; $\omega_s \triangleq$ synchronous velocity ($=2\pi f_0$); H_i = inertial constant (s); f_0 is the nominal frequency of the system (Hz); $\theta_i \triangleq$ rotor angle of the i-th synchronous machine in relation to the center of angles (electrical radians) ($=\delta_i - \delta_0$); δ_i is the rotor angle of the i-th synchronous machine in relation to a machine that rotates in synchronous velocity (electrical radians); $\delta_0 = \sum_{j \in N} M_j\delta_j/\mathrm{MT}$; $\boldsymbol{\theta} = [\theta_1, \theta_2, \ldots, \theta_{\mathrm{ns}}]^{\mathrm{T}}$; $\varpi = [\varpi_1, \varpi_2, \ldots, \varpi_{\mathrm{ns}}]^{\mathrm{T}}$; Pm_i is the input mechanical power (pu); Pe_i is the output mechanical power (pu); PCA $\triangleq$ accelerating power of the center of the angles ($=\sum_{j \in N}(\mathrm{Pm}_j - \mathrm{Pe}_j)$); $\mathrm{MT} = \sum_{j \in N} M_j$; $N \triangleq$ index set of the synchronous machines $=(\{1, 2, \ldots, \mathrm{ns}\})$; ns is the quantity of synchronous machines.

3. Transient stability analysis

The transient stability analysis of electric power systems, considering a contingency of index r, can be realized using the security margin criterion [17]:

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

where E_{crit_r} is the total critical energy of the system; E_{e_r} is the total energy of the system referred to the fault elimination time.

The critical energy (E_{crit}) and the critical time (crit) can be determined using a series of solutions available on the specialized literature, as an example, the method potential energy boundary surface (PEBS) [18,19]. It is observed that for the classical method, the PEBS method gives the same results as the simulation [19]. The total energy, referred to the system defined by Eqs. (1) and (2), is given by [2]:

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

where

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

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

In this work, it is used the iterative PEBS method [19]. Nevertheless, the developed methodology (by fuzzy ART-ARTMAP network) is not dependent of the PEBS method, and another method can be used, since some stability index be provided.

Then, the transient stability of the r-th contingency can be inferred by the security margin on the following way [17]:

- if $\mathcal{M}_r \geq 0$, then, the system is considered stable;
- if $\mathcal{M}_r \leq 0$, then, the system is considered unstable.

4. Transient stability analysis: solution proposed by neural networks

In this section, it is established the input and the output of the neural network. The information are provided by a computational program of transient stability analysis (*Simul*) [17] that, from electrical network data, considering a list of contingencies