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Transient stability evaluation of electrical power system using generalized regression neural networks

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ABSTRACT

Transient stability evaluation (TSE) is part of dynamic security assessment of power systems, which involves the evaluation of the system's ability to remain in equilibrium under credible contingencies. Neural networks (NN) have been applied to the security assessment of power systems and have shown great potential for predicting the security of power systems. This paper proposes a generalized regression neural networks (GRNN) based classification for transient stability evaluation in power systems. In the proposed method, learning data sets have been generated using time domain simulation (TDS). The GRNN input nodes representing the voltage magnitude for all buses, real and reactive powers on transmission lines, the output node representing the transient stability index. The proposed GRNN was implemented and tested on IEEE 9-bus and 39-bus test systems. NN results show that the stability condition of the power system can be predicted with high accuracy and less misclassification rate.

1. Introduction

Power system is getting more complex, has resulted in stress condition and its operating point is close to its stability limit. These leads to instability problem as the transmission lines becoming heavily loaded may cause cascading power interruption, uncontrolled and widespread impact of voltage collapse incident results a great loss to the nation. Therefore, serious attentions have to be focused on appropriate planning and control action to avoid or minimize its occurrences. Thus, TSE is becoming essential requirements for security of power systems in the new utility environment. Recent blackouts in the USA, some European and Asian countries have illustrated the importance and need of more frequent and thorough power system stability assessment. Stability considerations have long been recognized as an essential part of electric power system planning, design, operation, and control. An accurate analysis of the transient stability problems involves a step-by step calculation of the motion of each machine in the system [1,2].

The power system is routinely subjected to a variety of disturbance. Even the act of switching on an appliance in the house can be regarded as a disturbance. However, given the size of the system and scale of the perturbation by the switching of an appliance in comparison to the size and the capability of the interconnected system, the effects are not measurable [3]. Large disturbance do occur on the system. These include severe lightning strikes, loss of transmission lines carrying bulk power due to overloading or weather conditions like a tornado or ice, loss of generation station, or the loss of major load. The ability of power system to survive the transition following a large disturbance and reach an acceptable operating condition is called transient stability [4]. The physical phenomenon following a large disturbance can be described as follows. Any disturbance in the system will cause the balance between the mechanical power input to the generator and the electrical power output of the generator to be affected. As a result, some of the generators will tend to speed up and some will tend to slow down. If, for a particular generator, this tendency is too great, it will no longer remain in synchronism with the rest of the system and will be automatically disconnected from the system. This phenomenon is referred to as a generator going out of step [5].

The transient stability problem is one of the major concerns in studies of planning and operation of power systems. One of the most important roles of transient stability assessment (TSA) is to formulate a transient stability index (TSI), which can be used to assess the stability of power systems and to rank the severity of the contingencies. Fault clearing time (FCT) and critical clearing time (CCT) are very important parameters in order to maintain the stability of power systems. FCT it is the time (seconds) at which fault is cleared after the occurrence of the fault. CCT is the fault clear-

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ing time at which the system is critically stable. If the actual fault clearing time in a system is below CCT then the system is stable [6]. Methods normally employed to formulate TSI are by using time domain simulations, energy function, and hybrid method. Time domain simulation method is implemented by solving the state space differential equations of power networks and to obtain the rotor angles plots, which are then used to determine the transient stability state of a power system [4]. However, the energy function method determines transient stability by calculating the stability margin of power systems and the hybrid method combines both time domain simulation and energy function methods in calculating the TSI. A hybrid method for TSA known as the marginally unstable injection method [7] was developed to provide a more accurate TSI. In [1], a hybrid approach was developed to identify critical machines and to build a TSI, which is able to classify whether a power system is stable or unstable. Online transient stability assessment of a power system is not yet feasible due to the intensive computation involved. Artificial neural networks (ANN) has been proposed as one of the approaches to this problem because of its ability to quickly map nonlinear relationships between the input data and the output [8,9]. Some works have been carried out using the feed forward multilayer perceptron (MLP) with back propagation learning algorithm to determine the CCT of power systems [10,11]. Radial basis function networks proposed to estimate the CCT [12]. Another method to assess power system transient stability using ANN is by means of classifying the system into either stable or unstable states for several contingencies applied to the system [4,12,13]. ANN method based on fuzzy ARTMAP architecture is also used to analyze TSA of a power system [14]. Fuzzy logic controller proposed in for transient stability enhancement considering communication delay [15].

In this paper, transient stability analysis aims to assess the dynamic behaviour of a power system in a fast and accurate way based on NN. A transient stability index is described for the dynamic security of electric power systems by providing a measure for their level of security. GRNN is used for TSE of electrical power system by means of classifying the system into either stable or unstable states for several three-phase faults applied to the system. Time domain simulations were first carried out on the test systems to generate training data for the GRNN and to determine the transient stability state of a power system by visualizing the generator relative rotor angles. The power system analysis and toolbox (PSAT) has been used for time domain simulation based on Matlab, whereas GRNN has been developed using the Matlab neural network toolbox [14]. The paper is organized as such that, mathematical formulations are presented in Section 2. A brief description of GRNN is given in Section 3. Section 4 outlines the approach to transient stability evaluation using GRNN. Simulation results and conclusion are summarized in Sections 5 and 6 respectively.

2. Mathematical model of multimachine power system

The standard analytical formulation of power system dynamics leads to a set of differential equations governing the behaviour of generator frequencies, angles and a set of non-linear algebraic equations modelling the power flow in the network. The dynamic behaviour of an n-generator power system can be described using the following swing equations [4,16]

$$\delta_i = \omega_i \tag{1}$$

$$M_i \omega_i = P_{mi} - P_{ei} \tag{2}$$

where δ_i: rotor angle of machine i, ω_i: rotor speed of machine i, P_{mi}: mechanical power input of machine i, P_{ei}: electrical power output of machine i and M_i: moment of inertia of machine i.

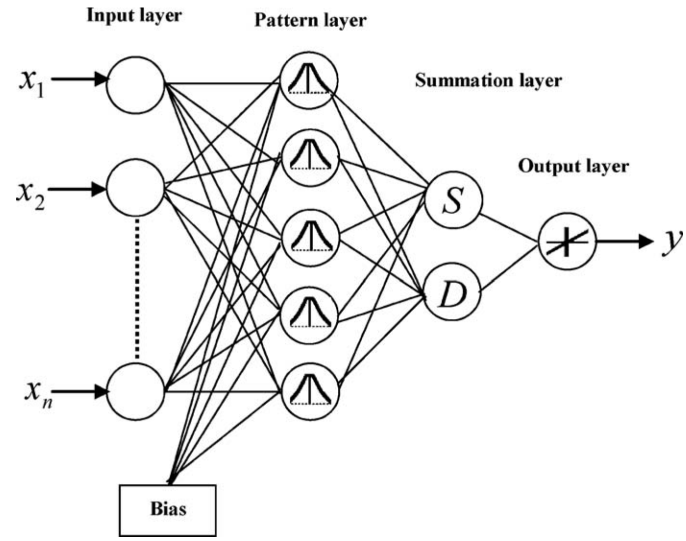

Fig. 1. Structure of GRNN model.

Eqs. (1) and (2) together with other differential and algebraic equation can be represented by general form:

$$F = g(x, y) \tag{3}$$

$$R = h(x, y) \tag{4}$$

where x and y are the state and algebraic variables respectively. Eq. (3) describes the dynamic models while Eq. (4) describes the network and generator interface equations. A conventional time domain simulation program solves these two sets of equations through step-by-step integration in the time domain so as to produce time response of all state variables.

3. Generalized regression neural network

The GRNN implements the Bayesian decision strategy to classify input vectors. A schematic diagram of GRNN is depicted in Fig. 1 in which it consists of four layers, namely, input layer, pattern layer, summation layer and output layer. The number of input units in the first layer is equal to independent factors, x_i. Only the pattern layer (hidden layer) has biases. The first layer is fully connected to the pattern layer, whose output is a measure of the distance of the input from the stored patterns. Each pattern layer unit is connected to the two neurons in the summation layer, known as S summation neuron and D summation neuron. The S summation neuron computes the sum of the weighted outputs of the pattern layer while the D summation neuron calculates the unweighted outputs of the pattern neurons [14]. For D-summation neuron, the connection weight is set to unity. The output layer merely divides the output of each S-summation neuron by that of each D-summation neuron, yielding the predicted value expressed as:

$$y_i = \frac{\sum_{i=1}^{n} y_i \exp[-D(x, x_i)]}{\sum_{i=1}^{n} \exp[-D(x, x_i)]} \tag{5}$$

where n is the number of independent input variables, y_i is the target output value corresponding to the ith input pattern and the