Expert Systems with Applications 38 (2011) 11112–11119

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Fast transient stability assessment of large power system using probabilistic neural network with feature reduction techniques

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A R T I C L E   I N F O

Keywords:
Transient stability assessment
Probabilistic neural network
Correlation analysis
Principle component analysis

A B S T R A C T

This paper presents transient stability assessment of a large 87-bus system using a new method called the probabilistic neural network (PNN) with incorporation of feature selection and extraction methods. The investigated power system is divided into smaller areas depending on the coherency of the areas when subjected to disturbances. This is to reduce the amount of data sets collected for the respective areas. Transient stability of the power system is first determined based on the generator relative rotor angles obtained from time domain simulations carried out by considering three phase faults at different loading conditions. The data collected from the time domain simulations are then used as inputs to the PNN. Feature reduction techniques are then incorporated to reduce the number of features to the PNN which is used as a classifier to determine whether the power system is stable or unstable. It can be concluded that the PNN with the incorporation of feature reduction techniques reduces the time taken to train the PNN without affecting the accuracy of the classification results.

1. Introduction

Power systems currently operate under great economic pressures in the new competitive and deregulated environment. The demand of electricity has escalated in both industrial and service sectors, which causes power system to operate in stressed condition and close to its stability limits. Analysis of recent widespread outages occurring worldwide indicated that blackouts happened when a sequential series of normal events exceeded acceptable security limits and reliability margins. The increasing numbers of blackouts that have occurred have illustrated the importance and need of an established dynamic security assessment (DSA) analysis tool (Pourbeik, Kundur, & Taylor, 2006). DSA is defined as evaluation of the ability of a power system to withstand a defined set of contingencies and to survive the transition to an acceptable steady-state condition (Sauer, Tomsovic, & Vittal, 2007). The evaluation of DSA requires rigorous analysis, including the assessment of rotor angle, voltage and frequency stabilities. Rotor angle stability is divided into two smaller categories which are small signal and transient stabilities (Kundur, 2007). The focus of this paper is on transient stability assessment (TSA) which involves the evaluation of the ability of a power system to maintain synchronism under severe but credible contingencies. The resulting system response due to severe transient disturbance involves large excursions of generator rotor angles. Transient disturbances may include faults, loss of load, loss of generation and loss of system components such as transformers or transmission lines (Morison, 2007). Stability or instability condition of a power system due to transient disturbance can be assessed from the rotor swing angles. Following a transient disturbance, a power system is said to remain stable if the relative generator rotor angles in the system remain in synchronism with each other. On the other hand, a power system is said to be unstable when the relative generator rotor angles go out of step and lost its synchronism. The time frame of interest in transient stability studies is usually from 3 to 5 s for small systems and may extend to 10 s for large systems with dominant inter-area swings (Kundur, 2007).

In general, methods normally employed to assess TSA are by using time domain simulation and direct methods. Time domain simulation method is implemented by solving the state space differential equations of power networks while the direct method involves calculation of the transient energy margins which show the system stability limits. Currently, the TSA method that has been widely used by power utilities is based on time-domain simulations (Selvi & Kamaraj, 2007). However, the use of such a method requires numerical solution of system nonlinear equations which involves time consuming numerical integrations. As for the transient energy function method, the difficulty of designing good energy functions for multi-machine power systems may lead to computational inefficiency and inaccuracy (Pavella, 1998). In addition, due to the expansion and complexity in power system

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doi:10.1016/j.eswa.2011.02.156

structures, TSA of large sized power systems has become a very complex process. The complexities come from the many nonlinear equations that need to be solved for each disturbance which will lead to delayed decisions in providing the necessary control measures for controlling the system. Therefore, there is a pressing need to develop reliable and fast online TSA to analyze the stability status of a power system when exposed to credible disturbances.

Presently, the use of computational intelligence (CI) in TSA has gained a lot of interest among researchers due to its ability to do parallel data processing, high accuracy and fast response (Wang, Wu, Li, & Wang, 2005). Four main paradigms of CI are namely artificial neural networks (ANN), evolutionary computing, swarm intelligence and fuzzy systems. CI techniques are used for TSA of power systems by means of predicting the generators' angle swing behavior after the occurrence of a disturbance so as to assess whether the system is stable or unstable. Earlier ANN method applied in TSA is based on the multi layer perceptron neural network (MLPNN) with back propagation learning algorithm to determine the critical clearing time of power systems (Paucar & Fernandes, 2002). The issues that need to be addressed in the MLPNN are the time taken for training the network which gets worse when large power systems are considered, the arbitrarily manner in choosing the number of hidden neurons and the problem with local minima. Other ANN methods used for estimating the critical clearing time include the use of radial basis function neural network (Bettiol, Souza, Todesco, & Tesch, 2003) and fuzzy ARTMAP architecture (Silveira, Lotufo, & Minussi, 2003). The emergence of support vector machine (SVM) in TSA has overcome some of the drawbacks of using MLPNN for classification (Moulin, da Silva, El-Sharkawi, & Marks, 2004). Various types of SVM have been proposed for TSA, using the v-SVM (Wang et al., 2005), clustering based SVM (Selvi & Kamaraj, 2007) and fuzzy SVM (Selvi & Kamaraj, 2008).

In this research work, the probabilistic neural network (PNN) is used as a classifier for assessing transient stability state of a large sized and practical power system. The purpose of adapting the PNN is to overcome the weaknesses of the MLPNN in terms of its accuracy and time taken for training the ANN. One of the important aspects in achieving good CI performance is by selecting proper sets of system features. For small power system the number of features may be small but when larger systems are considered the number of features increased as the size of the systems increases. In this work, feature selection and extraction methods are incorporated in the TSA intelligent system in order to optimize the performance of the PNN. The feature selection method adopted in this work is based on feature similarity using the correlation analysis method. This method is chosen because some features in power systems tend to correlate with each other after a disturbance. As for the feature extraction method, the principal component analysis is employed due to its simplicity in application and its ability to show the strength of the transformed reduced features in maintaining the accuracy of the CI techniques.

2. Probabilistic neural network (PNN)

PNN is useful for automatic pattern recognition, nonlinear mapping and estimation of probabilities of class membership and likelihood ratios (Specht, 1992). It is a direct continuation of the work on Bayes classifiers (Burrascano, 1991) in which it is interpreted as a function that approximates the probability density of the underlying distribution example. The PNN consists of nodes with four layers, namely input, pattern, summation and output layers as shown in Fig. 1. The input layer consists of merely distribution units that give similar values to the entire pattern layer.

Fig. 2 shows an example of a pattern layer of the PNN with the radial basis function (RBF) used as the activation function in the layer.

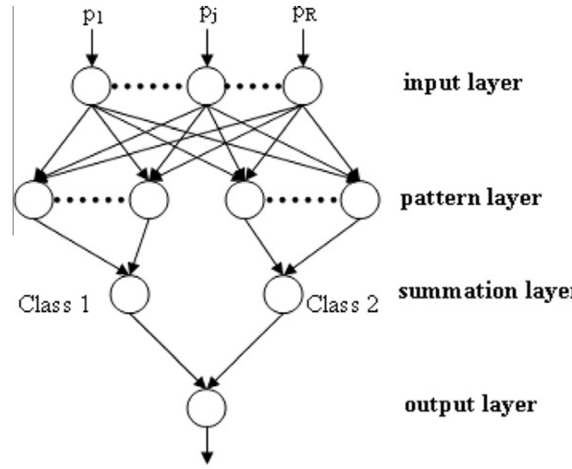

Fig. 1. PNN architecture.

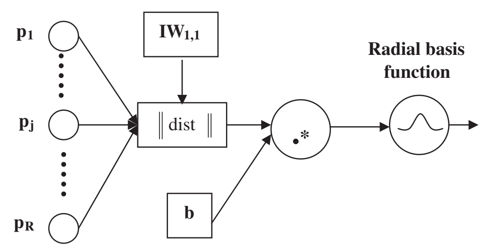

Fig. 2. PNN pattern layer with RBF as activation function.

The ‖ dist ‖ box shown in Fig. 2 subtracts the input weights, $IW_{1,1}$, from the input vector, p, and sums the squares of the differences to find the Euclidean distance. The differences indicate how close the input is to the vectors of the training set. These elements are multiplied element by element, with the bias, b, using the dot product (.*) function and sent to the RBF. The output **a** is given by

$$a = \mathrm{radbas}(\|IW_{1,1} - p\| b) \tag{1}$$

where radbas is the radial basis activation function which can be written in a general form as

$$\mathrm{radbas}(n) = e^{n^2} \tag{2}$$

The training algorithm used for training the RBF is the orthogonal least squares method which provides a systematic approach to the selection of RBF centers (Chen et al., 1991). The summation layer shown in Fig. 1 simply sums the inputs from the pattern layer which correspond to the category from which the training patterns are selected as either class 1 or class 2. Finally, the output layer of the PNN is a binary neuron that produces the classification decision. In this work, the classification is either class 1 for stable cases or class 2 for unstable cases.

The implementation procedures for PNN are given as follows:

(a) The training data are normalized and presented to the input of the PNN.
(b) Pass the training data through the pattern layer and then calculate the Euclidean distances of the training data.
(c) The calculated Euclidean distances are multiplied element by element with the bias and sent to the RBF. Train the RBF using the orthogonal least squares method to provide a systematic approach to the selection of RBF centers.
(d) Train the network in the pattern layer by setting each pattern in the training data equals to the weight vector in one of the pattern neurons and connecting its output to the appropriate summation neurons.