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A new power system transient stability assessment method based on Type-2 fuzzy neural network estimation

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ABSTRACT

Transient stability assessment (TSA) of large power systems by the conventional method is a time consuming task. For each disturbance many nonlinear equations should be solved that makes the problem too complex and will lead to delayed decisions in providing the necessary control signals for controlling the system. Nowadays new methods which are devise artificial intelligence techniques are frequently used for TSA problem instead of traditional methods. Unfortunately these methods are suffering from uncertainty in input measurements. Therefore, there is a necessity to develop a reliable and fast online TSA to analyze the stability status of power systems when exposed to credible disturbances. We propose a direct method based on Type-2 fuzzy neural network for TSA problem. The Type-2 fuzzy logic can properly handle the uncertainty which is exist in the measurement of power system parameters. On the other hand a multilayer perceptron (MLP) neural network (NN) has expert knowledge and learning capability. The proposed hybrid method combines both of these capabilities to achieve an accurate estimation of critical clearing time (CCT). The CCT is an index of TSA in power systems. The Type-2 fuzzy NN is trained by fast resilient back-propagation algorithm. Also, in order to the proposed approach become scalable in a large power system, a NN based sensitivity analysis method is employed to select more effective input data. Moreover, In order to verify the performance of the proposed Type-2 fuzzy NN based method, it has been compared with a MLP NN method. Both of the methods are applied to the IEEE standard New England 10-machine 39-bus test system. The simulation results show the effectiveness of the proposed method in compare to the frequently used MLP NN based method in terms of accuracy and computational cost of CCT estimation for sample fault scenarios.

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Introduction

Nowadays, the continues trend to increase in load demands along with economic and environmental constraints for building new power plants and transmission lines, have lead power systems to operate closer to their limits which increases the occurrence probability of transient stability problem [1,2].

The analysis and methods that are used to determine if a system is safe or unsafe (based on pre-established criteria) is typically referred as power system security assessment. An electric power system might have many changes in the system operating conditions or configuration; therefore, planning phase transient stability studies, would not be reliable for an operational system, so continuous system analysis is necessary for operators to take proper preventative control actions if insecure system conditions occurred.

The primary objective of transient stability analysis (TSA) in a power system is to determine the capability of power system to remain in stable and safe operating condition when a large disturbance such as severe lightning strike, loss of heavily loaded transmission line, loss of generation station, or short circuit on buses [3] influences the system. CCT is a well-known indicator that can be used to measure power system transient stability. The CCT is the maximum time duration by which the disturbance may act on the power system without losing its capability to recover to a steady-state (stable) operation.

We can broadly classify security analysis depending on modeling and used technique into static and dynamic category [3,4]. Static security assessment is related to an equilibrium point of system, where voltage and thermal limits are observed. Generally static security assessment is done using computational tools based on load flow algorithms. The contingencies events must be considered

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to ensure an acceptable steady-state condition, even if one element of the system is lost.

Evaluation of the ability of a power system to withstand a finite set of contingencies and to survive the transition to an acceptable steady-state condition is defined as dynamic security assessment (DSA) [4]. As illustrated in Fig. 1, DSA consists of three main categories: rotor angle stability, voltage stability and frequency stability. Also the rotor angle stability is divided into two sub categories which are small signal stability and transient stability [3,5]. In this paper we focus on TSA which involves the evaluation of the ability of a power system to maintain synchronism under severe but credible contingencies. The DSA studies are usually conducted in a time range between 3 and 5 s for small power systems. For large systems with dominant inter-area swings this time may extend to 10 s [5].

Two main categories of TSA methods are time domain simulation (or numerical integration) method and direct method. Currently, the widely used method by power utilities and most accurate method for TSA is time domain simulation method [5,6]. This method is implemented by solving the differential equations of power network while the direct method involves in calculation of the transient energy margins which shows the system stability limits. This method gives an accurate information about state variables and can be applied to any level of detail of power system models [1,4,7]. In Ref. [37] the concept of lyapunov exponents (LEs) is used to analyze the transient stability of power systems. Also in Ref. [40]; a stochastic-based approach to evaluate the probabilistic transient stability index of the power system incorporating the wind farm is proposed.

However, use of such a method requires numerical solution to nonlinear equations of system which has high online computation cost and involves intensive and time-consuming numerical integration efforts. Also, the difficulty of designing good energy functions for multi-machine power systems may lead to computational inefficiency and inaccuracy [5,6]. So, it does not provide information regarding the degree of stability and the degree of instability in a power system.

In addition, TSA of large sized power systems has become a very complex process due to the exponential expansion of complexity in power system topology. For each disturbance many nonlinear equations should be solved that makes the problem too complex and will lead to delayed decisions in providing the necessary control signals for controlling the system. Therefore, there is a necessity to develop a reliable and fast online TSA to analyze the stability status of a power system when exposed to credible disturbances.

On the other hand, direct method techniques require less online computation efforts and can provide a quantitative measure of the degree of system stability, but it has some challenges and limitations involved in the practical applications for power system TSA [5]. In recent years, machine learning and computational intelligence techniques, such as artificial neural networks (ANNs), have been proposed as promising approaches to solve some complex power system protection and control problems instead of simulating the power system equations for TSA in power systems [5,6,8–17]. These approaches can quickly obtain a nonlinear mapping relationship between the input data and the output and can approximate solutions of power system's differential equations [6]. There are two ways in using ANN for power system TSA, one way is using ANN as a regression function to predict transient stability degree[8–13], such as CCT and system stability margin; another way is using the ANN as a classifier to directly classify the system into either stable or unstable states [14]. There are many different types of NN such as MLP NN and radial basis function (RBF) NN which can be used in different applications.

The feed-forward NN, also best known as MLP NN, was the first and most simple type of NN devised. It was developed in early 1970s and is the most popular topology in use today. This NN consists of an input layer, an output layer, and one or more hidden layers. In this NN the information only moves in forward direction. Data flows into the NN through the input layer, passes through the hidden layer and finally flows out of the NN through the output layer. There are no cycles or loops in the network. These networks can be constructed from different types of units such as binary McCulloch-Pitts neurons. But frequently are devised as continuous neurons, with sigmoidal activation function in the context of back propagation of error. The MLP NN can be considered as simple interpolation of input–output model, with NN weights as free parameters. Such NN configuration can model functions of almost any arbitrary complexity. The function complexity is determined with the number of layers and the number of neurons in each layer.

Another frequently used NN in the literatures is RBF NN [15,16]. RBF NN is powerful method for interpolation in multidimensional space. The RBF can be replaced by the sigmoidal hidden layer in MLP NN. The structure of the RBF NN consists of three layers namely, the input layer, the hidden (or RBF) layer, and the output layer. The nodes within each layer are fully connected to the previous layer. The input nodes are directly connected to the hidden layer neurons. Usually a Gaussian function is used in each node in RBF layer to determine distance of inputs with respect to the mean of the Gaussian function. A linear combination of hidden layer values that represents mean predicted output is generated in the output layer when RBF NN is used in regression problems. When RBF NN is used in the classification problems, the output layer is representing a posterior probability. The output is typically a sigmoid function of a linear combination of RBF layer values.

In RBF NN each input datum is associated with a RBF kernel function such as support vector machine method. In this approach

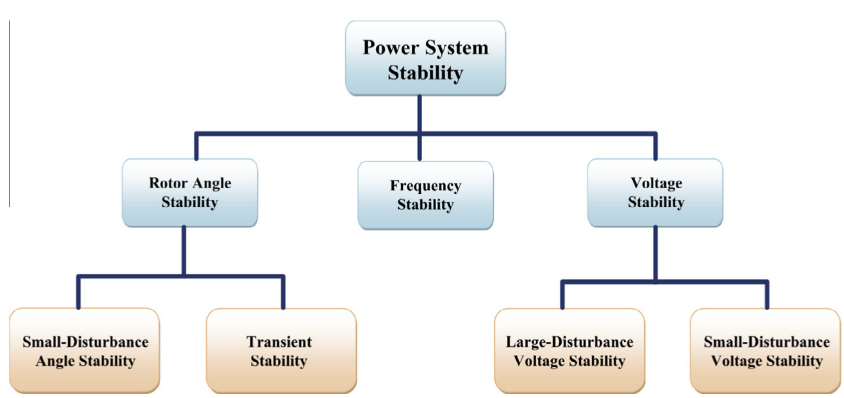

Fig. 1. Taxonomy of power system stability methods.

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