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Current state of neural networks applications in power system monitoring and control

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ABSTRACT

For over two decades Neural Network (NN) has been applied to power system monitoring and control. Conventional controllers suffer from certain limitations which NN as an Artificial Intelligence (AI) technique is able to overcome. Therefore, many researchers prefer to use NN technique in the monitoring and control of power systems. This paper reviews published recently schemes for control and monitoring based on NN. The performance of various NN controllers is compared with one another as well as to the performance of other types of controllers. This review further reveals that the design of a proper NN control can maintain first-swing stability, damp oscillation, ensure voltage stability and the reliable supply of electric power.

1. Introduction

A well-regulated power system is expected to supply consumers with uninterrupted, sufficient and reliable power at least cost. To achieve and maintain this reliability, the power system must be secure. Kundur et al. [1] defined power-system security thus: "Security of a power system refers to the degree of risk in its ability to survive imminent disturbances (contingencies) without interruption of customer service". We may further characterize power system security through the aspects of steady-state security, transient security and dynamic security. The system must be stable and secure against all expected contingencies before its security can be investigated. Security can be achieved through appropriate monitoring, current state estimation and control.

Security can be analyzed by various conventional techniques based on static security assessment [2–7] and dynamic security assessment [8–10]. All possible contingency cases must be estimated quickly and ranked according to their severity. Conventional security assessment involves numerical solution of non-linear load-flow equations and transient stability analysis for all credible contingencies. Because of the combinatorial nature of problem, this approach requires a huge amount of computation time and hence is found infeasible for real time security analysis of large scale power system networks. Therefore, it is difficult to perform security analysis on-line using conventional methods.

Two primary control loops regulate the generating unit: a turbine governor loop controls output power or frequency and an automatic voltage regulator (AVR) loop controls the terminal voltage or reactive power. These two loops do not suffice to protect the power system from the entire variety of events which may occur during operation. Additional control device elements must be inserted into the power system to improve its dynamic response and to avoid losing stability and hence optimize performance. These control elements can be classified as normal (preventive), and emergency controls [11]. Preventive control may be discrete, such as a tap-changer and shunt device, or continuous, such as frequency control. Normal control is usually automatic, as in the operation of tap-changer, reactive shunt device, flexible AC transmission systems (FACTSs), power system stabilizer (PSS) and load frequency control (LFC).

Emergency control complements preventive control and remains continually in readiness to protect the power system with actions such as controlled system separation and load shedding, generator tripping, fast valving, and boosting the exciter on a synchronous generator. When a normal control action cannot prevent or correct instability in the system, emergency control actions come into play. In other words, both normal and emergency controls are necessary to protect the power system from breakdown [11,12].

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Normal control provided by LFC, PSS, FACTS, and emergency control with monitoring can maintain first swing stability, dampen oscillations, and stabilize voltage, and results in improved system security.

Researchers have applied many different techniques to solve significant control problems in power systems. Conventional techniques based on classical control theory and linear optimal control technique have historically been used to control power systems. These methods were developed based on assumptions (i.e. linearization of electric power system) which simplified the parameters. These methods can provide optimal performance for the nominal operating condition and nominal system parameters. However, a modern power system is a large, nonlinear and complex system and it is subject to many kinds of events which lead to many uncertainties. Therefore, these controllers with fixed structure and parameters are not able to provide optimal performance for the contingency operating conditions. Considering their limitations, it is difficult to effectively solve significant power system control problems when one depends only on these conventional and linear optimal control approaches.

To overcome these drawbacks, other modern control techniques like adaptive control and H_∞ control methods have been used to achieve better performance than conventional controllers can provide. In these modern techniques, the control parameters can be adjusted quickly and continuously according to changes in demand [13]. The design of these controllers, however, requires massive mathematical calculations, and high performance computing for on-line parameter identification leads to high implementation costs [14].

Artificial intelligence (AI) techniques have emerged in power systems for over two decades as effective tools to solve many complex problems [15–17]. These can be even more effective when properly coupled with conventional mathematical approaches [18]. Neural network (NN) as an AI technique has efficiently been applied to power system monitoring and control. In this paper, a serious attempt is made to present a comprehensive analysis of the use of NN proposed by researchers recently for monitoring and controlling power systems. The performance of a variety of controllers is demonstrated and compared with each other and other types of controllers.

2. Artificial neural network (ANN)

An artificial neural network is a mathematical model or computational model based on human neural networks. It consists of a number of simple nodes connected together to form either a single layer or multiple layers. The connections between nodes—also termed "neurons"—are called weights that should be adjusted to reach the desired target.

Due to the non-linear mapping properties of the NNs, they have been used for many years as an effective tool for the identification and control of complex systems. The main advantages of utilizing NNs are [19]: (1) it handles stochastic variations of the scheduled operating points via the increase of data, (2) it significantly accelerates both online processing and classifications, and (3) it contains implicit nonlinear modeling and a built in function for system data filtration.

A hybrid intelligent system can be constructed from a NN along with other AI techniques. Such hybrid systems give best results when arranged to interact cooperatively in series or in integration. In the last two decades, engineering applications have benefitted from the application of hybrid systems. These systems involve various combinations of NN, fuzzy logic systems, optimization techniques based AI, and expert systems.

2.1. Models of neural network systems

A NN is said to be a feed-forwarded network if the input and intermediate signals (connections) are always propagated forwards i.e. the information moves from input to output through hidden layers in a forward direction without any loops, while a recurrent neural network (RNN) is a network that has more than one cycle.

2.1.1. Feed-forward neural network

Feed-forward NNs are divided into two categories; which are single and multi-layer networks. In a single layer network, inputs and outputs are directly connected via their respective weights This is due to the fact that for each neuron, the sum of the product of the input and weights are obtained and duly applied to the activation function. The function then produces an output equaling to +1/−1 when its input is either greater than or less than the threshold value (typically 0), respectively [20]. A weighted single layer three-input is shown in Fig. 1.

Meanwhile, a multi-layer network consists of both input and output layers, along with an intermediary layer aptly named hidden layer. This configuration is duly depicted in Fig. 2. The neurons in the hidden layer spots the signal from the input layer, and conducts the intermediate computation prior to directing the signal to the output layer [20]. The following NNs are related to the feed-forward NN.

2.1.1.1. Radial base function neural network. A radial base function neural network (RBFNN) has three layers: input, hidden, and output. In this context of this work, the RBF is usually representative of a Gaussian function. Initially, the hidden layer practices the usage of an unsupervised learning algorithm in order to locate the centers and widths of the radial basis functions for individual pattern units. Locating the weights between the pattern units and the output units, requires training the output layer using a supervised learning algorithm [21].

2.1.1.2. Adaptive critic NN. The basic adaptive critic NN consists of both the critic and action networks. The critic network estimates the system's performance in the absence of a true error measurement. This action is followed by the action network learning the desired performance, based on the information provided by the critic network. The system is trained using the reinforcement learning technique [22].

2.1.1.3. Modular NN. A modular NN consists of a number of expert and gate networks, which combines the outputs of the expert network(s) into one overall output. Each expert network can function as a multi-layer network [22].

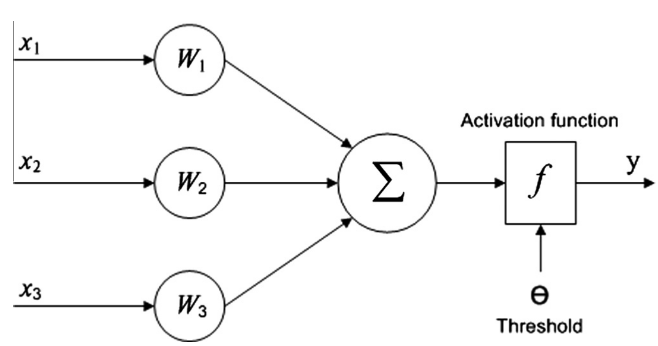

Fig. 1. Single layer three-inputs perceptron.