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Power system voltage stability monitoring using artificial neural networks with a reduced set of inputs

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ABSTRACT

This paper presents an artificial neural network (ANN)-based approach for online monitoring of a voltage stability margin (VSM) in electric power systems. The VSM is calculated by estimating the distance from the current operation state to the maximum voltage stability limit point according to the system loading parameter. Using the Gram–Schmidt orthogonalization process along with an ANN-based sensitivity technique, an efficient feature selection method is proposed to find the fewest input variables required to approximate the VSM with sufficient accuracy and high execution speed. Many algorithms have already been proposed in the literature for voltage stability assessment (VSA) using neural networks; however, the main drawback of the previously published works is that they need to train a new neural network when a change in the power system topology (configuration) occurs. Therefore, the possibility of employing a single ANN for estimating the VSM for several system configurations is investigated in this paper. The effectiveness of the proposed method is tested on the dynamic models of the New England 39-bus and the southern/eastern (SE) Australian power systems. The results obtained indicate that the proposed scheme provides a compact and efficient ANN model that can successfully and accurately estimate the VSM considering different system configurations as well as operating conditions, employing the fewest possible input features.

1. Introduction

Due to the major blackouts caused by voltage collapse [1], the voltage stability problem has become one of the most significant challenges in the planning and operation of the modern electric power systems. Voltage instability is usually characterized by an initial and progressive decrease in voltage magnitudes until a sharp rapid decline occurs; however, in some cases, the voltage magnitudes prior to undergoing the sharp change lie in a permissible range and the operators may observe no advance warning signal until large changes in the system state occurs [2]. Therefore, over the past several years, massive efforts have been devoted to the development of practical measures of the distance from the current operating state to the voltage collapse point, thereby providing an early warning of a critical situation.

Existing methods for voltage stability analysis are usually classified into static methods (such as PV curves and modal analysis), and dynamic methods (such as time domain simulation) [3]. The static approaches are based on the steady state power flow model of the power systems and many aspects of voltage stability problems can effectively be analyzed using these methods; however, such simplified approaches usually lead to unreliable results as shown in [4]. In order to get a much more realistic picture of the voltage stability phenomena, it is necessary to take system dynamics into account. On the other hand, the application of dynamic methods may be too time-consuming for online use.

Using artificial neural networks (ANNs) would be an attractive alternative to overcome the aforementioned problems. ANNs are information processing systems inspired by the way biological neural systems process data. Application of neural networks to power system problems is an area of growing interest [5]. The main reasons are the ability of ANNs to learn complex non-linear relationships and their modular structures, which allows parallel processing [6].

Proposed methods in the past for online voltage stability monitoring using ANNs have led to acceptable results. As summarized in Table 1, the majority of the published works in the literature are based on the multi-layered perceptron (MLP) neural networks [7–14], while the other methods rely on the Radial Basis Function (RBF) networks [15–20].

The previously published approaches often require a large number of input variables [13,14,18]. Having a large number of inputs

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Table 1
Comparison of the proposed methods for voltage stability monitoring using ANNs.

Proposed method	ANN type	ANN inputs	ANN output(s)	Considering different system configurations	Employed method for feature selection
Method of Ref. [7]	MLP	Active and reactive line flows	VSM[a]	Separate ANNs for each configuration	Principal component analysis (PCA), Contingency analysis
Method of Ref. [8]	MLP	Bus net active and reactive powers and generators reactive power	Minimum energy margin	Separate ANNs for each configuration	Sensitivity analysis
Method of Ref. [9]	MLP	Load active and reactive powers	VSM	A separate ANN for each configuration	Regression-based sensitivity analysis
Method of Ref. [10]	MLP	Active and reactive line flows and bus voltages	VSM	A separate ANN for each configuration	Principal component analysis (PCA), K-means clustering
Method of Ref. [11]	MLP	Bus voltage magnitudes and phase angles	VSM	A single ANN for different configurations	Sequential forward selection
Method of Ref. [12]	MLP, Self-organizing map (SOM)	Bus voltage magnitudes, phase angles and injected active and reactive powers	VSM and real part of critical eigenvalues	A single ANN for different configurations or A separate ANN for each configurations	Self-organizing map (SOM) ANN
Method of Ref. [13]	MLP	Load buses voltage magnitude and active and reactive powers	VSM	A separate ANN for each specified bus	–
Method of Ref. [14]	MLP	Voltage magnitudes, active and reactive powers of generator and load buses	L-index	Two separate ANNs one for normal condition and the other for contingency conditions	–
Method of Ref. [15]	RBF	Voltage magnitude of PV buses and total system load	Probability of voltage collapse	–	–
Method of Ref. [16]	RBF	Load active and reactive powers	Voltage performance index	A separate ANN for each cluster of input pattern	Class separability index and Correlation conditions
Method of Ref. [17]	RBF	MVA flows in selected critical lines	VSM	A single ANN for different configurations	–
Method of Ref. [18]	RBF	Load active and reactive powers	VSM	A single ANN for different configurations	–
Method of Ref. [19]	RBF	Dominant features of the voltage profile extracted by wavelet transform	VSM	A single ANN for different configurations	Principal component analysis (PCA)
Method of Ref. [20]	RBF	Active and reactive line flows	L-index	A separate ANN for each configuration	Mutual information

[a] VSM: The MW distance from the base operating point to the critical collapse point.

not only increases the size of the ANN, but also raises the cost as well as the time required for future data collection. In this paper, a fast and efficient method for reducing the number of input variables is proposed. Here, the Gram–Schmidt orthogonalization process is first employed to reduce the number of input variables, and then the neural network-based sensitivity technique proposed in [21] is used to find the minimum number of features required to make a good estimation of a voltage stability margin (VSM). The VSM is defined as the distance from the current operation state to the maximum voltage stability limit point (voltage collapse point) according to the system loading parameter.

In practice, a power system may face with a wide range of contingencies during its actual operating conditions such as unexpected line outages. When a contingency takes place, the system topology (configuration) changes and the trained ANN may fail to provide an accurate estimate of the VSM as it would be unable to capture the input–output relationship properly. Research works presented in [7–9,20], employ a separate ANN to estimate the VSM for each system configuration (contingency). For a large power system, with a huge number of potentially credible contingencies, training a separate ANN for each resulting configuration would be a demanding task. Therefore, in the present study, all single line outages are analyzed and ranked in descending order in terms of their VSMs and then a single MLP ANN is employed to estimate the VSM for the base case operating conditions and for a selected number of the worst case contingencies.

The proposed online voltage stability monitoring scheme is applied to the New England 10-machine, 39-bus test power system and the simplified southern/eastern (SE) Australian power system, considering high order dynamic models for the generators along with their automatic voltage regulators (AVRs). Since the voltage collapse phenomenon is highly affected by reactive power generation limits of the synchronous machines [22], the reactive power generation limits are also imposed in this paper. The MATLAB-based free and open source software tool PSAT (*Power System Analysis Toolbox*) [23] is used in this paper to obtain the required training and/or testing patterns for the ANNs by performing the continuation power flow (CPF) method on both test systems, whereas the proposed neural network models are implemented in MATLAB.

The rest of the paper is organized as follows: the use of VSM for voltage stability monitoring is described in Section 2. Section 3 gives an introduction to the MLP neural networks and presents the methodology of the proposed method. Section 4 describes the employed method for selecting the worst case contingencies. Details of the method used for reducing the number of input features are explained in Section 5. Case studies are given in Section 6, and finally, Section 7 concludes the paper.

2. Voltage stability margin

Voltage instability results from the attempts of loads to draw more power than can be delivered by the transmission and generation systems [24]. Suppose that a sample power system is operating stably at a certain loading level. Fig. 1 shows the variation of the voltage magnitude of a particular load bus in the system against a loading parameter λ, representing an independent system parameter that is slowly varied, such as active and reactive loads and/or active generation dispatch. For the system loading below