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Post-fault prediction of transient instabilities using stacked sparse autoencoder

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A B S T R A C T

Post-fault prediction of transient stability of power systems has a great impact on the performance of wide area monitoring, protection and control systems. Situational awareness capabilities of a power system are improved by fast detection of instabilities after severe fault occurrences. This allows sufficient time to take necessary corrective control actions. In this paper, a novel method based on stacked sparse autoencoder is proposed to predict the post-fault transient stability status of the power system directly after clearing the fault. A dataset is generated off-line to train a stacked sparse autoencoder, and then the trained stacked sparse autoencoder is used in an online application of predicting any transient instability. The stacked sparse autoencoder is fed by the inputs, which are specific points extracted from the fault-on voltage magnitude measurements collected from the phasor measurement units. The effectiveness of the proposed method is demonstrated and compared with the conventional approaches that adopt multilayer perceptrons or post-fault measurements as it is applied to the 127-bus WSCC test system and to the Turkish power system.

1. Introduction

Power systems are exposed to various types of faults that might cause instabilities or even blackouts. To prevent the loss of stability after a severe fault, wide area monitoring, protection and control (WAMPAC) systems are quite effective [1]. WAMPAC systems are designed to increase the reliability and security of the power system by improving its situational awareness capabilities. Phasor measurement units (PMU) are now considered indispensable for achieving the situational awareness in power systems. WAMPAC systems use the PMUs' measurements to counteract the propagation of severe faults [1]. According to the IEEE standard C37.118.1-2011 [2], the synchronized measurements collected from the PMUs help the power system operators to build an accurate view of the entire power system in real-time. PMU measurements are collected at a rate of 30–120 samples per second, which enables WAMPAC system to capture the power system dynamics and oscillations [3], and accordingly to apply a corrective control action, when it is needed. WAMPAC system analyses the collected PMUs' measurements to detect the existence of a disturbance in the system, and to specify its type and location [4,5]. In case of a fault, the measurements can be used for determining whether the system will remain stable or eventually become unstable as the system dynamics evolve. Early prediction of the transient instability is crucial to allow sufficient time for taking corrective control actions. This paper proposes a novel method that utilizes PMU measurements to predict the transient stability after the occurrence of a severe fault.

The problem of post-fault prediction of transient stability using wide area measurements is addressed in many papers [6–23], and the approaches in them can be categorized as (a) time-domain simulations [6,7], (b) Lyapunov exponent based methods [8,9], and (c) machine-learning based classification techniques [10–23]. In the time-domain simulation approach, a large number of differential-algebraic equations (DAEs) are used to model the power system dynamics, and they are to be solved faster than real-time. In Ref. [6], the measurements of PMUs just after clearing the fault are used as the initial condition of the DAEs to predict the future response of the system. In Ref. [7], implicitly decoupled PQ integration technique is used to build a fast DAEs model for the post-fault dynamics. Although time-domain simulations are effective methods for stability prediction, they may suffer from impracticability, since all the system parameters and information must be updated periodically in real-time, which is a requirement that is hard to accomplish. The method of maximal Lyapunov exponent (MLE) is another way for predicting the transient instabilities in the power system after the occurrence of a disturbance [8,9]. In these studies, a relationship between transient stability and MLE is established. MLE is calculated using the rotor angles over a time window of 1 s in Ref. [8],

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and up to 5 s in Ref. [9]. This approach assumes that the rotor angles are available from the PMU measurements. Moreover, the time window needed for calculating the MLE may not be short enough for triggering fast corrective controls. Post-fault transient instability can also be predicted using machine learning based classification methods, e.g., artificial neural networks (ANN) [10–12], long short-term memory (LSTM) [13,14], support vector machines (SVM) [15–18], core vector machines (CVM) [19], decision trees (DT) [20,21], and extreme learning machines (ELM) [22,23]. Machine learning methods in these methods attempt to capture the mapping relationship between the PMUs' measurements (input) and the corresponding transient stability status (output). For enhancing the performance of the machine learning algorithms, feature selection algorithms can be used, e.g., as in Ref. [18]. Feature selection algorithms are time consuming tasks and lack generalizability under certain circumstances [24]. As a novel approach in this paper, a sparse autoencoder (SAE) is adopted for prediction. The SAE can automatically extract features from a dataset and overcome the shortcomings of the conventional machine learning tools.

The classification techniques above use the post-fault measurements of PMUs to predict the power system stability after the occurrence of a fault. However, the stability of the system not only depends on the post-fault operating point, but also on the pre-fault operating point, the fault location, and its duration [25]. Therefore, in this paper, a methodology based on a stacked sparse autoencoder (SSAE) and softmax classifier is proposed to achieve the classification task, as the measurements from the whole fault-on time period are exploited. The fault-on time period starts from the fault occurrence and lasts up to its clearance. A preliminary study of utilizing the fault-on trajectory is carried out in Ref. [26], where a multilayer perceptron is used to predict the post-fault transient instabilities. This approach of utilizing the fault-on measurements contrasts to the existing approaches in Refs. [10–23], in which only the post-fault measurements are used. Using this method, the accuracy of the SSAE in labelling the power system transient stability status is greatly enhanced, as some specific points on the trajectories of voltage magnitudes measured by PMUs are adopted as inputs to the SSAE. The SSAE is trained off-line using the extracted voltage magnitude measurements, and then is used online for predicting the post-fault stability directly after clearing the fault. The proposed method is able to correctly predict the post-fault stability directly at the moment when the fault is cleared, without waiting for further post-fault measurements as in the existing approaches in literature [10–23]. The proposed method is tested on two different power systems, the 127-bus, 37-generator Western System Coordinating Council (WSCC) test system, and the Turkish power system. The method's efficiency is examined through the assessment of its prediction accuracy in the training and the test sets, which are obtained under different operating conditions of the power system.

2. Stacked sparse autoencoder based classification

2.1. Deep learning

Deep learning is a breakthrough in the study of neural networks. Deep learning networks are typically deeper than three layers to further learn the essential high-level features of the low-level input data [27]. In each layer in a deep learning network, a different set of features is extracted from the previous layer, resulting in extraction of more complex features from the inputs. These discriminative high-level features make the deep learning achieve more satisfying performance as compared to the performance of the conventional neural networks. The deep learning network is pre-trained via unsupervised learning, and then fine-tuned in a supervised manner at the last layer for different purposes, e.g. classification [27].

Deep learning networks have various types of architectures, e.g. deep belief network (DBN), deep Boltzmann machine (DBM), convolutional neural network (CNN), and sparse autoencoder (SAE). In this paper, a stacked SAE is adopted for classifying the transient stability status of the power system after a fault.

2.2. Sparse autoencoder

Sparse autoencoder (SAE) is a feed-forward neural network that attempts to learn an approximation to the identity function that is used to reconstruct the given input $\boldsymbol{x}$ into a compressed representation in the output $\boldsymbol{y}$, by means of unsupervised learning [28]. SAE consists of two parts: encoder and decoder. The encoder transforms the input vector $\boldsymbol{x} = (x_1, x_2, ..., x_d)$, $\boldsymbol{x} \in \boldsymbol{R}^d$, into a more abstract feature vector $\boldsymbol{a} \in \boldsymbol{R}^h$, where d is the number of inputs and h is the number of hidden units. Then, the decoder maps $\boldsymbol{a}$ to the output $\boldsymbol{y} \in \boldsymbol{R}^d$. The encoding and decoding stages can be represented as follows:

$$\boldsymbol{a} = f(\boldsymbol{W}_1\boldsymbol{x} + \boldsymbol{b}_1) \tag{1}$$

$$\boldsymbol{y} = f(\boldsymbol{W}_2\boldsymbol{a} + \boldsymbol{b}_2) \tag{2}$$

where $f(\cdot)$ is the activation function of the neurons, which is a non-linear function, e.g. sigmoid function. $\boldsymbol{W}_1 \in \boldsymbol{R}^{h\times d}$ is the matrix of weights for the connections between the input layer (encoder) and the hidden layer. $\boldsymbol{W}_2 \in \boldsymbol{R}^{d\times h}$ is the matrix of weights for the connections between the hidden layer and the output layer (decoder). $\boldsymbol{b}_1 \in \boldsymbol{R}^{h\times 1}$ and $\boldsymbol{b}_2 \in \boldsymbol{R}^{d\times 1}$ are the bias vectors of the hidden and the output layers, respectively.

The power of SAE lies in its reconstruction-oriented learning, which enables it to recover the input $\boldsymbol{x}$ perfectly from $\boldsymbol{a}$. This learning process aims to bring the SAE's output $\boldsymbol{y}$ as close as possible to the input $\boldsymbol{x}$, by means of optimizing the cost function [28] defined as

$$J = \frac{1}{d}\sum_{i=1}^{d}\left(\frac{1}{2}\|y_i - x_i\|^2\right) + \frac{\lambda}{2}\sum_{i=1}^{d}\ \|W_i\|^2 + \beta\sum_{i=1}^{h}\ KL(\rho\|\hat{\rho}_i) \tag{3}$$

The first term is the average sum-of-squares error, which is used to describe the distinction between the input $\boldsymbol{x}$ and the output $\boldsymbol{y}$. The second term is the regularization term, or the weight decay term, which is used to control the value of the weights to prevent the overfitting. The last term is the sparsity penalty term, which is used to induce the SAE to learn more features from the input by enforcing the constraint $\hat{\rho}_i = \rho$ during the training, where ρ is the sparsity parameter, which is typically close to 0, and $\hat{\rho}_i$ is the average activation of the hidden neuron i. λ and β are the weighting factors that are used to control the impact of the weight decay and the sparsity penalty terms, respectively [25]. $KL(\rho\|\hat{\rho}_i)$ is the Kullback–Leibler divergence, which is used to measure the difference between ρ and $\hat{\rho}_i$ [28]. $KL(\rho\ \|\hat{\rho}_i)$ is equal to zero when the constraint $\hat{\rho}_i = \rho$ is satisfied. $KL(\rho\|\hat{\rho}_i)$ is defined as

$$KL(\rho\|\hat{\rho}_i) = \rho\log\frac{\rho}{\hat{\rho}_i} + (1-\rho)\log\frac{1-\rho}{1-\hat{\rho}_i} \tag{4}$$

SAE is trained using the back-propagation algorithm to minimize the cost function J, which depends on the weights ($\boldsymbol{W}_1$ and $\boldsymbol{W}_2$) and the biases ($\boldsymbol{b}_1$ and $\boldsymbol{b}_2$) [28]. First, the weights and biases are initialized as small random values, and then an optimization algorithm is used to minimize J. In this paper, the scaled conjugate gradient descent algorithm is used to optimize the cost function J.

A stacked sparse autoencoder (SSAE) is a deep neural network that is composed of an array of basic SAEs, where the decoder of each SAE is connected to the encoder of the successive SAE, as shown in Fig. 1(a). The structure of the SSAE enables it to extract extra features from the inputs since each hidden layer can learn different features than the previous layer does. The SSAE uses the same learning process as in SAE, where back-propagation algorithm is used to update the weights and biases of each layer by minimizing the cost function of the overall network.

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