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A novel radial basis function neural network principal component analysis scheme for PMU-based wide-area power system monitoring

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ABSTRACT

A novel model-based principal component analysis (PCA) method is proposed in this paper for wide-area power system monitoring, aiming to tackle one of the critical drawbacks of the conventional PCA, i.e. the incapability to handle non-Gaussian distributed variables. It is a significant extension of the original PCA method which has already shown to outperform traditional methods like rate-of-change-of-frequency (ROCOF). The ROCOF method is quick for processing local information, but its threshold is difficult to determine and nuisance tripping may easily occur. The proposed model-based PCA method uses a radial basis function neural network (RBFNN) model to handle the nonlinearity in the data set to solve the no-Gaussian issue, before the PCA method is used for islanding detection. To build an effective RBFNN model, this paper first uses a fast input selection method to remove insignificant neural inputs. Next, a heuristic optimization technique namely Teaching-Learning-Based-Optimization (TLBO) is adopted to tune the nonlinear parameters in the RBF neurons to build the optimized model. The novel RBFNN based PCA monitoring scheme is then employed for wide-area monitoring using the residuals between the model outputs and the real PMU measurements. Experimental results confirm the efficiency and effectiveness of the proposed method in monitoring a suite of process variables with different distribution characteristics, showing that the proposed RBFNN PCA method is a reliable scheme as an effective extension to the linear PCA method.

1. Introduction

With the increasingly high penetration of renewable generating units such as wind farms and solar power generation systems, their considerable impact on the power system operation and control, in particular on the system monitoring and protection, has drawn a lot of attention in recent years [1–3]. The loss-of-mains problem, which is also referred to as islanding detection and monitoring, has become a critical issue to be tackled in power systems.

Traditional islanding detection techniques are based on the measurements of system parameters at distributed generation sites. Among these, the rate of change of frequency (ROCOF) [4] method is widely used. However, the thresholds are difficult to determine as they are mainly dependent on the strength of the actual power systems. Synchrophasors, generated by the Phasor Measurement Unit (PMU) technology, have been widely adopted in the applications of power system mode monitoring [5], stability margin prediction [6], islanding detection [7] and many other areas [8]. Yet, utilizing PMU measurements for wide-area monitoring still faces significant challenges, especially on how to effectively extract useful information from the huge amount of PMU data in a statistical way.

To address this issue, Principal Component Analysis (PCA) methods have been used to process redundant and high dimensional data [9]. Inspired by the statistical way of analysing power system data, PCA was successfully introduced into wide-area power system monitoring recently [10–12]. In our previous work [13], a distributed real-time learning framework has been proposed to support wide-area monitoring using synchrophasors, aiming to integrate the PCA techniques into an hierarchical incremental learning scheme for decision making. The PCA method offers a means for fault detection under nearly all load and generation conditions using the wide-area information sampled by the synchrophasors.

However, linear PCA is unable to handle all process variables due to the normal Gaussian distribution assumption imposed on them,

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and many extensions using neural networks have been developed [14,15]. Main challenges exist for integrating PCA with neural networks, such as reducing the redundant input variables, obtaining higher model accuracy and utilizing non-Gaussian distributed variables. To address these challenges, this paper proposes an improved radial basis function neural network (RBFNN) model-based PCA method for loss-of-main monitoring. The neural input selection is based on a fast forward input selection algorithm [16], and a recently proposed meta-heuristic algorithm named Teaching-Learning Based Optimization (TLBO) [17] is integrated to tune the nonlinear parameters in the RBF network. Then, the model residuals are used to construct a PCA model for fast and accurate islanding detection.

This paper presents a novel statistical approach for islanding detection for power systems, which is distinctively different from existing methods, and it also integrates some of the recent methods presented in our earlier work. In our early work [16], a fast recursive algorithm (FRA) was proposed for the identification of nonlinear dynamic systems using linear-in-the-parameters models. This paper adopts the FRA to select neural inputs in the proposed RBFNN based PCA method, and this is achieved by considering the neural input selection as variable selection problem in nonlinear system modelling. An extended two-stage method was developed in [18] to build RBFNN model for nonlinear systems, which combines a two-stage model structure selection and parameter optimization by calculus-based continuous optimization. In contrast, this paper focuses on the development of a wide-area power system monitoring scheme using RBFNN based PCA method, and the RBFNN model is built to solve the non-Gaussian problem associated with the PMU data, while the conventional PCA method is incapable of handling this problem. It also should be noted that the method to build RBFNN model in [18] is an analytic approach, while this paper uses a hybrid approach for RBFNN model construction which combines both FRA based neural input selection and training of the RBFNN model using a latest meta-heuristic approach, namely teaching-learning-based-optimization (TLBO). In summary, the new contributions of this paper are: (1) FRA is adopted in the proposed monitoring scheme for neural input selection to reduce the neural inputs; (2) TLBO is applied to effectively and efficiently tune the parameters in the RBFNN based PCA model, rather than using the conventional optimization approaches; (3) an advanced statistical approaches presented in this paper, namely RBFNN based PCA method is for the first time applied to wide-area power system monitoring, and the experimental results confirm its effectiveness.

This paper is organized as follows. After an introduction of the wide-area monitoring system in Section 2, detailed preliminaries of the PCA method, RBF neural networks, fast input selection and TLBO are given in Section 3. Then, the complete RBFNN PCA monitoring scheme is detailed in Section 4. Section 5 analyses the events, and demonstrates the effectiveness of the proposed method using experimental results in comparison with existing approaches. Finally, Section 6 concludes the paper.

2. Synchrophasor based wide-area monitoring framework

As described in [13], the wide-area monitoring and detection framework is illustrated in Fig. 1. The framework comprises distributed agents (PMUs) for autonomous local condition monitoring and fault detection, and a central unit for generating global view for situation awareness and decision making. The local agent PMUs, which have been deployed by Laverty et al. [19] in the system of British/Irish utility networks, were developed and manufactured in conjunction with the OpenPMU project at Queen's University of Belfast (QUB) and Scottish & Southern Energy. A dependable utility site is needed so that a reference signal could be acquired. At the generator site, the reference signal is compared to the synchrophasors acquired at the generator terminals. The synchronized measurements with a sampling rate of 10 Hz are then transmitted to a QUB server and stored for further analysis. Only the frequency variable was utilized in [10] due to non-Gaussian distribution assumption. This paper will focus on establishing a novel PCA model using the optimized RBF neural network with selected network inputs to tackle the non-Gaussian issue for other variables.

3. Preliminaries

3.1. Principal component analysis

Suppose that the number of PMUs is a, each PMU measurement consists of m variables, here $m = 3$ and variables include the voltage magnitude, the phase angle and the frequency in a real power system. The raw data before normalization containing n samples is stacked into a matrix $\mathbf{X}^0 \in \mathbb{R}^{n\times m_a}$, $m_a = m \times a$. It is first normalized to a matrix $\mathbf{X}$ with zero mean and unit variance. PCA can then decompose the normalized data matrix into scores and loadings, as shown below [20]:

$$\mathbf{X} = \mathbf{t}_1\mathbf{p}_1^T + \mathbf{t}_2\mathbf{p}_2^T + \cdots + \mathbf{t}_l\mathbf{p}_l^T + \mathbf{E} = \mathrm{TP}^T + \mathbf{E} \tag{1}$$

where $\mathbf{T} \in \mathbb{R}^{n\times l}$ is the score matrix, $\mathbf{P} \in \mathbb{R}^{m\times l}$ ($l \le m_a$ is the number of retained principal components (PCs)) is the loading matrix, $\mathbf{t}_i$ and $\mathbf{p}_i$ are corresponding score and loading vectors. The important statistic for PCA monitoring is given by the Hotelling's T^2, which is the sum of normalized squared scores defined as [21],

$$T_i^2 = \mathbf{t}_i\boldsymbol{\lambda}^{-1}\mathbf{t}_i^T = \mathbf{x}_i\mathbf{p}_i\boldsymbol{\lambda}^{-1}\mathbf{p}_i^T\mathbf{x}_i^T \tag{2}$$

where $\boldsymbol{\lambda}$ is a diagonal matrix containing the l eigenvalues, and $\mathbf{x}_i$ is the row vector of $\mathbf{X}$. The squared prediction errors (SPE) or Q is defined by:

$$Q_i = \sum_{j=1}^{m_a}(x_{ij} - \hat{x}_{ij})^2 \tag{3}$$

where x_{ij} is the ith measurement value of the jth variable, while $\hat{x}_{ij}$ is the prediction value. To statistically assess the fault detection ability of a method, two impact factors can be used, namely the fault detection ability (FDA) and false alarm rate (FAR) which are defined below:

$$FDA = \frac{N_{f_{\det-fault}}}{N_{f_{actual}}} * 100\% \tag{4}$$

$$FAR = \frac{N_{f_{\det-normal}}}{N_{total}} * 100\% \tag{5}$$

where $N_{f_{\det-fault}}$ is the number of true faults that are correctly detected, and $N_{f_{actual}}$ is the total number of the actual faulty points for FDA. $N_{f_{\det-normal}}$ is the number of false faults that are detected, and N_{total} is the total number of normal samples.

3.2. Radial basis function neural networks

RBF neural networks use radial basis functions as the activate functions in the hidden layer nodes, each of them has two key parameters that describe the location of the function's centre and its width respectively. In this paper, Gaussian function is used, thus a general multiple-inputs-single-output (MISO) RBFNN can be formulated below [22,18]:

$$y(t) = \sum_{i=1}^{n_n} w_i \cdot \phi_i(\mathbf{x}(t), c_i, \sigma_i) + \mathbf{e}(t) \tag{6}$$