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Voltage stability assessment using multi-objective biogeography-based subset selection

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ABSTRACT

We propose a method for voltage stability assessment of power systems using a support vector machine (SVM). We input the information from measurement signals to the SVM. The objectives of this paper are twofold: (1) to select the minimum number of features for training an SVM using multi-objective optimization (MOO); (2) to find the minimum misclassification rate for the SVM. To address these objectives, the training data size is decreased in two stages. First, a mutual information (MI) criterion is used to remove the less significant measurements from the data set. Second, the most relevant features are selected using multi-objective biogeography-based optimization (MOBBO). The minimization objectives are the measurement data size and the misclassification rate of the SVM. The BBO-based MO methods are vector evaluated BBO (VEBBO), nondominated sorting BBO (NSBBO), niched Pareto BBO (NPBBO), and strength Pareto BBO (SPBBO). These four MOO methods are compared using Pareto front normalized hypervolume, relative coverage, and statistical analysis. The methods are applied to a 39-bus benchmark system and a 66-bus real power grid. The results verify that the reduced measurement data using MOO lead to efficient and accurate SVMs. For the real power grid, the trained SVM accurately predicts the voltage stability of the system by using only 8% of the measurement data. The misclassification rates of the SVMs are as low as 2% for the real power grid. Normalized hypervolume, relative coverage, and statistical tests indicate that NSBBO performs better than the other methods.

1. Introduction

Power system voltage stability is the power system's capability to maintain steady voltages after being subjected to various contingencies [1]. System conditions are associated with power system stability in voltage stability analysis [2]. A power system can face voltage problems and large scale blackouts if the voltage stability is assessed inaccurately and in an untimely manner [3]. Thus, it is essential to use monitoring devices like supervisory control and data acquisition (SCADA) and phasor measurement units (PMUs) in power systems for timely decision making. SCADA has been widely used in real-world power systems but it does not provide the time synchronization of the measured data and suffers from slow sampling time [3]. PMUs overcome the drawbacks of SCADA by providing accurate and fast data acquisition where the sequence of measurements of current and voltage waveforms are synchronized using the global positioning system (GPS). PMUs have been developed over the past few decades for various power system applications, such as transient stability and voltage stability [3–7]. In this paper, we can use either SCADA or PMU measurements since voltage stability assessment can be observed from either type of signal. We use PMU measurements in this research because of its suitability for our intended follow-on research, but the proposed method can be applied with either SCADA or PMU measurements.

Power system voltage stability has been assessed using several methods. Different voltage stability indices have been defined to identify the weak buses and lines such as P-V curve, energy function, maximum power that can be transferred through a line and so on [8]. There are some other methods which use the computational intelligence (CI) methods such as decision trees (DTs) [2,3], neural networks (NNs) [9–12], fuzzy neural networks [13], and support vector machines (SVMs) [14,15] to evaluate the voltage stability in power systems. In order to obtain a suitable knowledge of power systems, different operating conditions (OCs) are considered and in each operating condition possible contingencies are applied to the system. Several parameters such as pre-contingency power flow quantities and topological data or post-contingency data are collected to evaluate the stability status of the system [2,3,7,16]. It has been shown that categorical data provide rich information for classification and improve the

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classification accuracy [3,4].

The large amount of collected data from power systems is of concern since training a CI method with all gathered information is not practical and it may lead to a time-consuming procedure with inadequate prediction accuracy. Since there is a highly nonlinear relationship among the attributes of power grids, reducing the number of features must be performed in a systematic way while considering their dependencies [17]. Therefore, different data reduction and feature selection approaches have been utilized [18]. For instance, feature selection methods such as mutual information (MI) and Fisher discrimination techniques and feature extraction methods like principal component analysis (PCA) are implemented in [9–11,17,19] to extract the significant data from the input features.

In our previous work [7], a method was proposed for online power system voltage security assessment based on PCA, correlation analysis, and DTs. We used fault location to improve prediction accuracy, while we reduced the number of training cases to achieve fast prediction. Various types of reduced information can be obtained from the original data depending on the feature selection and dimension reduction techniques and the accuracy that is required from the reduced data. A compromise exists between the simplicity and prediction accuracy of a trained CI method. Thus, multi-objective optimization (MOO) is viewed here as an important step for finding the optimal accuracy of reduced training data while considering both simplicity and prediction accuracy as objective functions. Therefore our research [7] continued to [16], where we minimized the number of principal components and the number of training cases while keeping the error rate as low as possible using several multi-objective methods. We suggested some possible directions to continue our research in [16], which leads us to this paper.

This paper proposes a new SVM-based scheme for power system voltage stability assessment. The original data is reduced to a much lower dimension using MI and MOO. The paper's main contribution is to develop and implement multi-objective BBO for optimum subset selection of the measurement data. There are two objective functions that need to be minimized: the misclassification rate of the SVM, and the number of features input to the SVM. To address this, vector evaluated BBO (VEBBO), nondominated sorting BBO (NSBBO), niched Pareto BBO (NPBBO), and strength Pareto BBO (SPBBO) are utilized to obtain the best Pareto set.

Although other MOO methods could be implemented on our problem [20,21] we select the aforementioned methods as representative EA/ MOO combinations [22,23]. Note that the combination of BBO and the MOO methods (VE, NS, NP, and SP) have not been used for feature selection in voltage stability assessment before now although the individual components are well-known and widely used in different areas [22,24,25].

The rest of this paper is organized as follows. Section 2 discusses the basic theory of SVM, MI, and MOO. Section 3 explains the proposed voltage stability assessment method using MI and MOBBO for subset selection of SVM input data. SVM is used to classify the data into stable cases and unstable cases. MI is used as a feature selection method for removing irrelevant features from the measurement data. After elimination of irrelevant features, MOO is used as an optimum feature selection method to select the best subset from the relevant features. Section 4 discusses simulation results for both the 39–bus benchmark system and a 66-bus real power grid. The results verify that the MOBBO methods select the most significant features from the measurement data and lead to a remarkable reduction of data size. The best selected set of features with minimum classification error are systematically compared using relative coverage, normalized hypervolume, and statistical tests. These comparisons show that NSBBO performs better than other MOO methods for both the test case and the real-world case in this paper. Section 5 presents the conclusion and suggests future work.

2. Background

In this section, SVM equations are reviewed. This classifier will be used for voltage stability assessment in Section 3. Then, the MI method is presented. MI is used for pre-selection of the measurement data. Finally, MOBBO is briefly discussed. This MOO method will be used for subset selection of the data while keeping the classification error rate as low as possible.

2.1. Support vector machines

Support vector machines (SVMs) are effective and well-known learning algorithms used for binary and multi-class classification [26–29]. In our research, SVM is used for binary classification. In binary SVM, the two class labels are $Y_j \in \{-1, +1\}$. The training data is defined as follows.

$$\mathbf{X}_{\mathbf{m}\times\mathbf{n}} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \ddots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} = \begin{bmatrix} X_1^T \\ X_2^T \\ \vdots \\ X_m^T \end{bmatrix}, \quad \mathbf{Y}_{\mathbf{m}\times\mathbf{1}} = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_m \end{bmatrix} \tag{1}$$

where m is the number of training cases and n is the number of features.

As illustrated in Fig. 1(a), the objective of SVM is to find an optimal linear hyperplane with maximum margin and bounded error that divides the training data into two separate classes. The linear hyperplane is defined as

$$\omega^T\phi(X_j) + b = 0 \quad \omega \ and \ X_j \in R^{n\times 1}, \ \ b \in R \tag{2}$$

where $\phi(.)$ maps the input pattern into the feature space. ω^T is the weight vector and b is the bias. The optimal hyperplane with maximum margin is expressed as the following convex quadratic optimization problem.

$$\min_{\omega,b} \frac{1}{2}\|\omega\|^2 + C\sum_{j=1}^{m} \xi_j$$
$$Y_j(\omega^T\phi(X_j) + b) \geqslant 1-\xi_j \quad \xi_j \geqslant 0, \ \ j = 1,\cdots,m \tag{3}$$

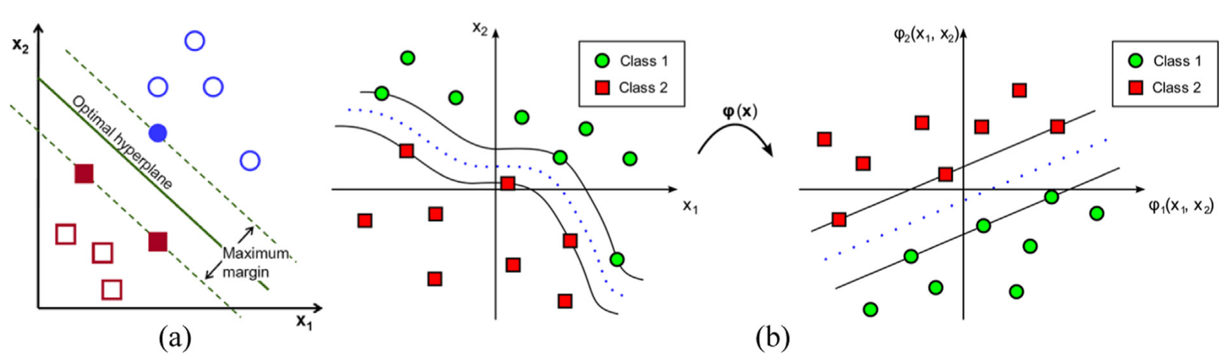

Fig. 1. (a) Simple linear SVM classifier, (b) SVM classifier with kernel.