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Genetic algorithm based support vector machine for on-line voltage stability monitoring

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ABSTRACT

A Genetic Algorithm based Support Vector Machine (GA-SVM) approach for online monitoring of long-term voltage instability has been proposed in this paper. The conventional methods for voltage stability monitoring are highly time consuming hence infeasible for online application. Support vector machine is a powerful and promising function estimation tool. To improve the accuracy and minimize the training time of SVM, the optimal values of SVM parameters are obtained using genetic algorithm. The proposed approach uses the voltage magnitude and phase angle obtained from Phasor Measurement Units (PMUs) as the input vectors to SVM and the output vector is the Voltage Stability Margin Index (VSMI). The effectiveness of the proposed approach is tested using the New England 39-bus test system and the Indian Northern Region Power Grid (NRPG) 246-bus real system. The results of the proposed GA-SVM approach for voltage stability monitoring are compared with grid search SVM (GS-SVM) and artificial neural networks (ANN) approach with same data set to prove its superiority.

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Introduction

Earlier, the electric power systems were limited to relatively small geographical regions but today the connection of regional power network forms a highly interconnected large system. Such large power system leads to complexity in the monitoring and operation, as disturbance in one part of the system may adversely affect the entire system. The power system observability is a necessary condition for real-time power system monitoring, protection and control for effective implementation of Wide Area Monitoring Protection and Control Systems (WAMPC). The Phasor Measurement Unit (PMU) is the main technology enabler of WAMPC. PMU measures voltage phasor at the installed bus and current phasors to all connected buses [1]. PMU provides synchronized voltage phasors, current phasors, frequency and rate of change of frequency. Synchronization in PMU is achieved through a common referenced clock of Global Positioning System (GPS) [2].

In recent years, voltage collapse is a major cause for many power system blackouts [3] around the globe. The traditional method for voltage stability analysis relied on static analysis using the conventional power flow method such as Gauss–Seidel or Newton–Raphson method. In reference [4–8], numerous voltage stability indexes based upon conventional power flow have been proposed. The main drawback of these techniques is the singularity of the Jacobian matrix at the maximum loading point. To overcome this problem, Continuation Power Flow (CPF) method is used to compute voltage stability margin [9]. In reference [10], *P–Q–V* curve technique is proposed for voltage stability margin assessment with demonstrates the maximum limits of power demands and its corresponding voltage magnitude. The aforementioned techniques require comparatively large computations and are not efficient for on-line applications.

In recent years, the machine learning techniques such as artificial neural network (ANN), fuzzy logic, pattern recognition, support vector machine etc. have been used for power system analysis. Zhou et al. [11], proposed a new online monitoring technique for voltage stability margin using synchrophasor measurement. Ref. [12] introduces a method of using ANN model based approach for on-line voltage security assessment. The proposed approach uses radial basis function (RBF) networks to estimate the voltage stability level of the system under contingency state. Hashemi et al. uses wavelet transform for feature extraction of voltage profile along with RBF network to estimate voltage stability margin [13]. Usually, ANNs are considered more powerful, flexible method known for performing nonlinear regression. However, ANNs suffer from the amount of training time and the scores of the learning parameters. Support Vector Machine (SVM) is a powerful new machine learning technique. It is based on the Vapnik–Chervonenkis (VC) dimension theory of Statistical Learning Theory (SLT) and structural risk minimization principle [14].

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Using this principle, SVM built optimized network structure with the right balance between the empirical error and VC-confidence interval. This balance gives a better generalization performance than other neural network models. For the past several years, SVM has been successfully applied in solving a large range of practical problems in different areas [15–23].

Even though with these superior features, SVM is still limited in industrial application and academic research. It is because the user has to define various parameters known as hyper-parameters appropriately. Inappropriate selection of these parameters leads to overfitting or underfitting of SVM model. Therefor selection of these parameters is an important step in SVM modeling. At present, no general guidelines are available to select these parameters. The grid search (GS) method [24] is commonly used as parameter selection method in SVM. However, this method is prone to trap at local optimal points because GS is limited to the parameter value set initially [25]. It outperforms both in terms of accuracy and time efficiency. Particularly, when the optimized parameters are many or with great ranges, the time consumption is huge using grid algorithm method [26,27].

In the present work, Genetic Algorithm, based Support Vector Machine (GA-SVM) approach is proposed for online monitoring of long-term voltage instability. Genetic Algorithm is used to optimize the SVM parameter such as RBF kernel (γ), regularization parameter (C) and insensitive loss function (ε) to improve the performance of SVM. GA-SVM is applied to emulate the continuation power flow for estimation of Voltage Stability Margin Index (VSMI) for steady state voltage stability analysis. The input features of GA-SVM are formed by voltage magnitude and voltage phase angle, which is assumed to be obtained from PMU. Although the PMUs have high precision level, still there are possibilities that the signal processing may introduce some errors in phasor calculation. Thus, the impact of these uncertainties in synchrophasor measurements is also analyzed to detect the deviation of VSMI at the operating point. The effectiveness of the proposed approach is tested using the New England 39-bus test system and the Indian Northern Region Power Grid (NRPG) 246-bus real system. Three other models, GS-SVM model and two models of Multilayer Perceptron-back propagation neural network (MLP-BPNN) i.e. MLP-BP1 and MLP-BP2 are considered in this study with same data set to compare the result of the proposed GA-SVM approach for voltage stability monitoring. The performance indices values along with Regression Receiver Operating Characteristic (RROC) curves and Area Over the RROC Curve (AOC) demonstrate that the GA-SVM outperforms the GS-SVM and MLP-BPNN models.

Problem formulation

Voltage Stability Assessment (VSA)

The main objective of voltage stability analysis is to determine whether the current operating point of power system is stable, meeting various operational criteria. The voltage vs real power curve (*P–V* curve) [4] as shown in Fig. 1 can be used directly to obtain voltage stability margin. Considering if at the current operating point the total active power delivered to the load is P_{current} and the maximum active power transfer is $P_{\max}$, then the Voltage Stability Margin (VSM) for the load bus i, can be calculated as

$$\text{VSM}_i = P_{\max,i} - P_{\text{current},i}, \quad \text{where } i = 1, 2 \ldots l \tag{1}$$

where, l is the total number of load buses in the power system. The Voltage Stability Margin Index (VSMI) for the network is given by:

$$\text{VSMI} = \min\left(\frac{\text{VSM}_i}{P_{\max,i}}\right) \tag{2}$$

VSMI is an indicator that determines the voltage collapse point. The VSMI varies in a range between 1 (no load) and 0 (maximum loadability). Fig. 1 shows that as the operation point moves to voltage collapse point the VSMI defined in (2) approaches zero. Therefore, VSMI is a suitable indicator for voltage stability monitoring. To determine the collapse point, *PV* curve is drawn using the continuous Power Flow (CPF) technique [7,28]. CPF is used because the conventional power flow (Gauss–Seidel or Newton–Raphson) method fails to converge as the operating point reaches the nose point (voltage collapse point) of *PV* curve.

The CPF program calculates the voltage stability limit starting from a specified initial operating point. The flow of the procedure involved in the determination of VSMI is shown in Fig. 2. Every power network has different types of nodes. For *PV*-node, real power and voltage magnitude are known and for *PQ*-nodes, real and reactive power is specified. So these known parameters are fed to conventional power flow to calculate the values of voltage

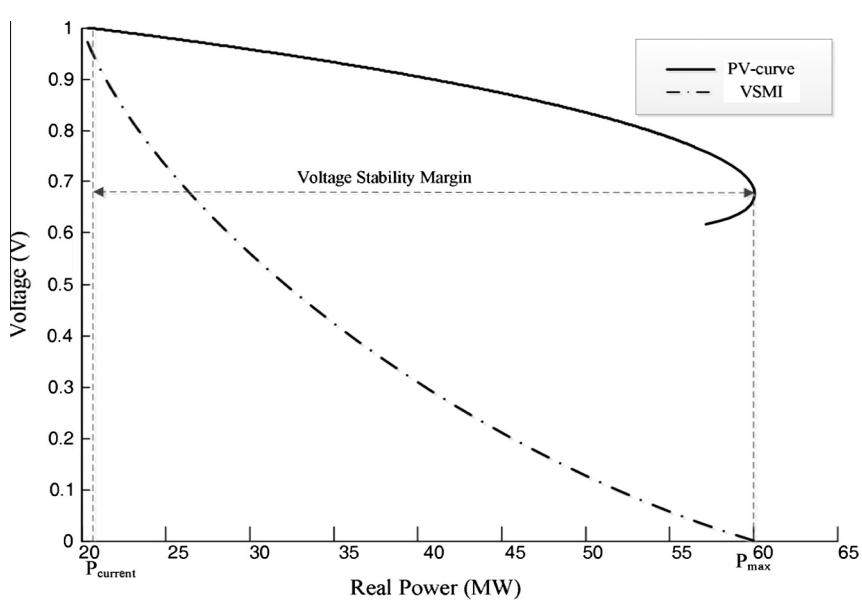

Fig. 1. *P–V* curve.

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