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Support Vector Regression Model for the prediction of Loadability Margin of a Power System

M.V. Suganyadevi*, C.K. Babulal

Department of Electrical and Electronics Engineering, Thiagarajar College of Engineering, Madurai 625015, Tamilnadu, India

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ABSTRACT

Loadability limits are critical points of particular interest in voltage stability assessment, indicating how much a system can be stressed from a given state before reaching instability. Thus estimating the loadability margin of a power system is essential in the real time voltage stability assessment. A new methodology is developed based on Support Vector Regression (SVR) which is the most common application form of Support Vector Machines (SVM). The proposed SVR methodology can successfully estimate the loadability margin under normal operating conditions and different loading directions. SVR has the feature of minimizing the generalization error in achieving the generalized network over the other mapping methods. In this paper, the SVR input vector is in the form of real and reactive power load, while the target vector is lambda (loading margin). To reduce both mean square error and prediction time in SVR, the kernel type and SVR parameters are chosen determined by using grid search based on 10-fold cross-validation method for the best SVR network. The results of SVRs (nu-SVR and epsilon-SVR) are compared with RBF neural networks and validated in the IEEE 30 bus system and IEEE 118 bus system at different operating scenarios. The results demonstrate the effectiveness of the proposed method for on-line prediction of loadability margins of a power system.

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Introduction

In recent years, the analysis of voltage stability has become a major concern in many power system planning and operation since it has been the cause for many power system blackouts [1] around the world. The lack of new generation and transmission facilities, over exploitation of the existing facilities geared by increase in load demand especially in a deregulated environment where systems operate closer to their security boundaries makes this type of problem more likely to happen in the present power systems.

Generally, loading margin determination can be achieved by two techniques namely direct method and Homotopy method. In direct methodology, the loadability margin is calculated using set of nonlinear equations includes power flow equations and constraints aimed to impose the conditions of either the saddle-node bifurcation (SNB) or the limit-induced bifurcation (LIB). The major drawbacks of direct methods are requirement of a good initial guess for determining SNB points and formulation of different set of equation for each bifurcation point. The solution does not provide whether maximum loading condition is due to LIB or a SNB and taking into account all possible bifurcations which leads to lengthy process.

Another direct method is using nonlinear programming techniques as in optimal power flow method. The computational burden of an optimal power flow problem of a real power system cannot be neglected [2]. The homotopy method consist of a continuation equation whose Jacobian matrix is not singular at bifurcation points, hence they are numerically robust. The continuation power flow (CPF) approach is one of the homotopy methods and consists of predictor–corrector scheme in order to forecast the bifurcation point of *PV* or *QV* curves [3,4]. But it fails to give the accurate result if the step length is more. The loadability margin evaluation considering operating system limits, which can be associated with Hopf bifurcations [5].

The comparative study of various voltage stability indices for the estimation of loadability margin is presented in ref. [6], which gives some other useful information such as identification of critical bus/line in a power system. In order to obtain a set of optimal loading parameters that maximizes system loadability an interior-point nonlinear optimization method is proposed in ref. [7]. In [8] multiple load flow solutions are proposed to obtain the "minimum" loadability margins. In [9], an energy-function-based approach is proposed to evaluate the loadability margins on a given loading direction. The authors in [10] maximize the loadability margin in a given loading direction through minimizing the reactive power losses near the critical loading point by means of linear programming.

Thus various optimization techniques are used for estimating the loadability margin of power systems have been proposed related to voltage stability limits [11–13] but these are depend on size and non linearity of the problem. In [14], the fuzzy logic has been used to find the loadability limit, but this algorithm does not give global optima.

ANN is a highly efficient computational tool that could be used for on-line loadability evaluation. Some research work has been devoted to NN applications to voltage security assessment and monitoring. Multilayered feed forward neural network has been used for power margin estimation associated with static voltage stability limits by means of different training criteria and algorithms. In [15–18], the active and reactive powers on load and generation buses, bus voltage magnitude and angles are used as the inputs. In [19], the authors had proposed a new methodology for loading margin estimation based on subtractive clustering and ANFIS, where various voltage stability indices are selected as inputs. This method gives good results to deal with uncertain load behaviour and can be used in a real time environment.

* Corresponding author. Tel.: +91 452 2562011.
E-mail addresses: mvsuganyadevi@yahoo.com (M.V. Suganyadevi), ckbeee@tce.edu (C.K. Babulal).

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Mostly artificial intelligence methods have failed to predict the voltage stability margin correctly because they cannot find the global minima accurately.

In [20] ant colony optimization technique and [21] uses evolutionary programming for estimation of maximum loadability. Paper [22] compares the multilayer perceptron obtained using hybrid particle swarm optimization technique with the results from CPF technique.

In [23] a new DEPSO algorithm which combines the advantages of DE and PSO to determine the maximum loading point has been proposed which gives more accurate results compared to other evolutionary algorithms. In general any evolutionary based technique requires large time per iteration and hence it cannot be applicable for practical large power system.

From the previous observation, the problem of loadability prediction still needs further investigation for real time applications. In the operation of practical power systems, different loading scenarios may result in very different loadability margins for the same operating point, hence loadability margins should be predicted for any loading direction.

Support vector machine is a powerful machine learning approach based on statistical learning theory, which has been first developed by Vapnik [24]. It has become a very interested topic of intensive study due to its successful application in classification tasks [25] and regression tasks [26], specially on time series prediction [27] and function estimation [28]. The SVM is one of the approaches to supervised learning that takes an annotated training data set as input and output a generalized model, which can then be used to accurately predict the outcomes of future events. The merits of SVM over multilayer neural network classifiers are global optimum solution and robustness to outliers [28]. Support vector regression (SVR) is the most common application form of SVMs. An overview of the basic ideas underlying support vector (SV) machines for regression and function estimation has been given in [29]. Recently, the SVR has been applied to various fields such as foreign exchange rate forecasting [30], fault diagnosis [31], particle swarm optimization [32], thunderstorm prediction [33], breast cancer diagnosis [34], aero-engine model reconstruction [35]. In [36] dynamic voltage collapse prediction on an actual power system using support vector regression is presented. The paper [37] proposed a novel transmission line fault location scheme, combining wavelet packet decomposition (WPD) and support vector regression (SVR). The hybrid load forecasting model combining differential evolution (DE) algorithm and support vector regression are used to solve the annual load forecasting problem [38], short term load forecasting problem [39]. The SVR has been widely used to solve nonlinear predicting problems such as software reliability prediction problem [40], prediction of the next day solar insolation for effective use of *PV* systems [41]. SVR and ANNs are both AI techniques and they are used widely in many areas of science and engineering. The paper [42] deals with ν-support vector regression based prediction model of critical heat flux for water flow in vertical round tubes and the results are compared with ANN. In paper [43] a method is used for local prediction of maximum post-contingency deviation of power system frequency using ANN and SVR learning machines. The on-line loadability margin under different loading conditions are estimated by spider-SVM and the results are compared with ANN in [44].

This paper presents a new methodology for the estimation of voltage stability margin of a power system based on SVM. In this paper, we use the ν-SVR and ε-SVR models to predict the loadability margin under different loading scenarios. The datasets are collected from CPF results. Two different kernel functions have been used, the RBF kernel and the polynomial kernel and various SVR parameters are selected by 10-fold cross-validation method are used for SVR model. The proposed method is successfully tested on IEEE 30 bus and IEEE 118 bus systems. The predicted results of SVR models are compared with those of ANN and CPF results. The performance of SVR is compared with ANN on statistical measures like best, mean, standard deviation of results and average computation time. Results show the superiority of SVR over CPF and ANN algorithms on accuracy and consistency.

The structure of the paper is as follows: In "Estimation of loadability margin" section, a summarized description of estimation of loadability margin methodology such as CPF, ANN and SVR are sketched. "SVR model design" section presents the algorithm for the design of SVR and its data generation. The simulation results of the proposed approach and the comparison of SVR result with ANN are also carried out in "Simulation results and discussions" section. Finally, conclusions are drawn in "Conclusion" section.

Estimation of loadability margin

Loadability margin is the distance with respect to the loading parameter, from the current operating point to voltage collapse point [5].

Continuation power flow methodology

Continuation power flow (CPF) is a powerful algorithm to trace the power flow solution, starting at a base load leading up to the steady state voltage stability limit, for determining the loadability margin. It employs a predictor–corrector scheme to find a solution path of a set of power flow equations that have been reformulated to include a load parameter. It starts from a known solution and uses a tangent predictor to estimate subsequent solution corresponding to a different value of the load parameter. This estimate is then corrected using Newton–Raphson method employed by a conventional power flow. The local parameterization mentioned earlier provides a mean of identifying each point along the solution path and plays an integral part in avoiding singularity in Jacobian. The purpose of continuation load-flow is to find a continuum of load-flow solutions for a given load/generation change scenario, i.e. computation direction. It is capable of producing the whole *PV* curve illustrated in Fig. 1. The singularity of continuation load-flow equations is not a problem; therefore, the voltage collapse point can be determined.

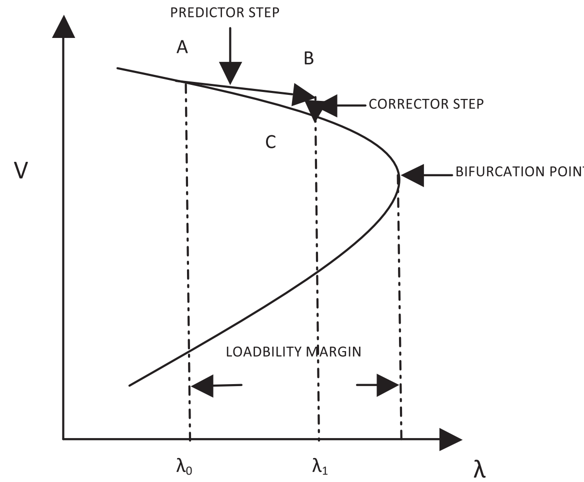

Fig. 1. *PV* curve and loadability margin.

The intermediate results of the continuation process also provide valuable insight into the voltage stability of the system and the areas prone to voltage collapse.

Artificial Neural Network methodology

The Artificial Neural Network (ANN) has been emerged as a powerful tool for function approximation and dynamic system control [45], because of the merits of high computational rate and unique learning capability. In order to determine the capability of the proposed technique to predict the voltage stability margin of a power system, a comparative study was conducted by developing an ANN system and used it to perform the similar task. A multilayer feedforward ANN with error backpropagation learning was developed [46]. The typical back propagation neural network consists of a three layer structure namely: input layer, hidden layer and output layer nodes as shown in Fig. 2. The hidden layer may consist of one or more nonlinear neurons and it performs continuous, nonlinear transformations of the weighted input. Nonlinear activation function transforms the weighted input of a neuron nonlinearly to an output. Popularly used activation function is sigmoidal and widely used sigmoid functions are logistic and hyperbolic tangent function, where $[P_{di,1}, P_{di,2}, \ldots P_{di,n}]$ is the real power load vector of *i*th bus for '*n*' number of patterns, $[Q_{di,1}, Q_{di,2}, \ldots Q_{di,n}]$ is the reactive load vector of *i*th bus for '*n*' patterns.

The ANN methodology has two phases namely training and testing. During the training phase, a set of real and reactive power demands at all load buses of a system is given as inputs and the model is trained to determine the loading margin of the system as shown in Fig. 3. From the trained model, the testing of the network is done which represents the relationship between the load direction and loading margin. From the predicted values of the output,

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