Prediction of Voltage Stability Margin using SVR for the Real Time Environment

Dr. M. V. Suganya Devi [1,]
Assosciate Professor,
Saranathan College of Engineering,
Panjappur, Trichy-12,

P. Pavithraa[2], A. Yuvarani[2],
K. G. PavithraDevi[2],
UG Scholar,
Saranathan College of Engineering,
Panjappur, Trichy-12

Abstract: **This paper investigates the use of reactive power re-serves (RPR) as an indicator to estimate voltage stability margin (VSM) in an online environment. The methodology relies upon the relationship between system-wide RPRs and VSM. Support vector regression model(SVM) are utilized in order to express how variations in RPRs can be transformed into direct information about VSM. Data regarding RPRs and system VSM are obtained through an offline voltage stability assessment (VSA) and stored in a database for further SVR development. Different load in- crease directions and a comprehensive list of contingencies are considered to account for uncertainty present in real-time operations. Once properly designed and validated, the SVRs are ready to be used in the online environment. The methodology is tested on the IEEE 30-bus system and a real Indian bus system containing 181 buses. Preliminary results show that SVRs can be successfully employed in online VSM estimation.**

Keywords: Support vector regression, Voltage stability margin, Regression, Reactive power, CPF

NOMENCLATURE:

Y - dependent variable (or response).

X - independent variable (or regressor) in the SVR.

β - regression coefficient.

$\varepsilon - i$th residual.

n - Number of samples.

λ –Load Increase Parameter.

I INTRODUCTION

In the world, number of times condition of blackout occurs, by which a lot of consumers gets affected. Some of major blackouts from all over the world in the last few decades include a massive breakdown in India on 30-31/July/2012,by which 7 states and approx.620 millions peoples affected. This is called biggest ever power failure in the world. Another one is fault in transmission line occurs at Uttar Pradesh state in India on 2/Jan/2001,by which 230 millions peoples affected. On 1/Nov/2014 Bangladesh suffered nationwide power outage for almost 10hrs and almost 150 million peoples affected. On 26/Jan/2015 over 80% of Pakistan went power off due some technical fault at power station in sindh, by which 140 million peoples affected. A transmission system failure occurs in java-Bali, Indonesia on 18/Aug/2005,approx.100 million peoples get affected [1].

At any point of time, a power system operating condition should be stable, meeting various operational criteria, and it should also be protected in the event of any realistic emergency. Power system stability may be defined as that property of a power system that enable it to remain in a state of operating equilibrium under normal operating conditions and to regain an acceptable state of equilibrium after being subjected to disturbances. Present day power systems are being operated closer to their stability limits due to economic and environmental constraints[2]. Maintaining a stable and secure operation of a power system is therefore a very important and challenging issue. In order to improve reactive power management, the North American Electric Reliability Corporation (NERC) has issued several reliability standards related to real-time reactive power reserve monitoring and voltage control [3]–[4]. Real-time reactive power reserve monitoring has also been identified as one of the recommended actions to reduce the likelihood of future system blackouts [5]. The inherent relationship between reactive power support and voltage stability is the general argument used to support these practices.

Despite the development of new standards and practices, re- active power monitoring systems are not a novelty for some North American and European utilities. Bonneville Power Administration (BPA) developed an online reactive power monitoring system that monitors the available RPRs at some generators and SVCs for different areas of their system [6]. At low levels of RPR, an alarming system will indicate that corrective actions should be taken in order to move the system to a safer operating condition. Other utilities rely on the monitored amounts of RPRs to implement special protection schemes against voltage collapse [7]–[8].Real-time reactive power reserve monitoring has also been identified as one of the recommended actions to reduce the likelihood of future system blackouts. The relationship between reactive power support and voltage stability is used to support these practices. However, monitoring RPR alone cannot provide quantitative information of , how far a system might be from a voltage collapse. Therefore, the development of alternative tools to process monitored RPRs into quantitative information regarding VSM would be extremely valuable .

Machine learning is a field of computer science that gives computers the ability to learn without being explicitly programmed[9].It is related to computational statistics ,which also focuses on prediction-making through the use of computers. In machine learning support vector machines (SVM) is also known as support vector networks [10] are supervised learning models with associated learning algorithms that analyze the data used. SVM are learning machines implementing the structural risk minimization inductive principle to obtain good generalization on a limited number of learning patterns.

The VSA is performed and data related to RPRs and VSM are obtained for all considered LIDs(Load increase directions) and network topologies. SVR(Support Vector Regression) are then designed using the offline database and they are further used to estimate VSM in online operations. And this project contribute to the smart grid initiative (SGI). The SGI is expected to increase the use of digital information and faster the development of new applications to maintain a reliable and secure operation of the power grid.

II VOLTAGE STABILITY MARGIN

voltage stability refers to the capability of the system to maintain a steady frequency, following a system drastic change resulting in a remarkable imbalance between generated and demand power. voltage collapse generally occurs on power system which is heavily loaded or faulted or has shortage of reactive power voltage collapse is usually associated with reactive power demand of load not being met due to shortage in reactive power production and transmission[11]. Generally, it is related with the ability of power system to maintain the steady acceptable voltages at all system buses under normal conditions as well as when the system is being subjected to contingency conditions[12].

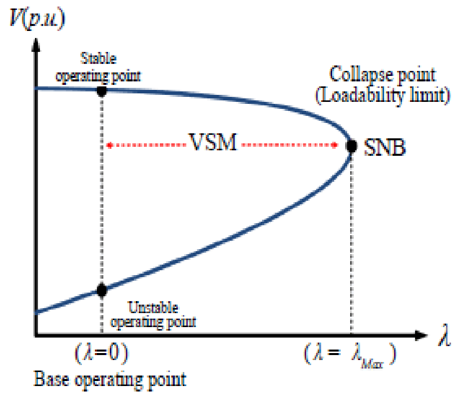
Loadability margin is defined as the interval with respect to the loading parameter, from the current operating point to the voltage collapse point [13]. At this point any unexpected ascend in the load level can cause voltage collapse Phenomena, this phenomenon has made the voltage stability condition as a crucial point in the power system operation and planning. For evaluating the security level, Voltage stability margin(VSM) of the weakest bus as well as of the forthcoming weakest bus is calculated. If VSM is large then the bus is more secured.

At the voltage collapse point(saddle point) of the PV curve, voltage drops rapidly with an increase in real power transfer. Refer Figure (1). In order to calculate the available power transfer capacity, net power transfer capacity or total power transfer capacity, VSM of a power system is measured. The voltage stability monitoring is expressed by load power margin which is defined to be distance between the current operating point λo and system maximum loading point λ_{max} .Thus, the voltage stability margin (VSM)of the system is defined by the percentage of the load power margin as,

$$VSM = \frac{\lambda_{\max} - \lambda_0}{\lambda_0} * 100$$

Know the proximity →Instability point →Margin for the safety operation of the Power system volta ge stability is also called as load stability refers to the ability of the system to maintain load bus voltages within acceptable limit, following some disturbance or change in power demand. The only way to prevent the system from voltage collapse is to reduce the reactive power load or additional reactive power prior to attaining the point of voltage or maximum loading point[14]. VSM can be expanded by reactive power support and this can be provided by introducing shunt capacitors and /or flexible AC transmission system (FACTS)controllers at the appropriate location[15].

Figure 1: voltage stability margin with saddle point



III CONTINUATION OF POWER FLOW

Continuation Power Flow (CPF) remains well conditioned around critical pint not affected by consequence like divergence like contingency conditions[16] . Intermediate results of the process are being used to develop a voltage stability index and identify areas of the system most prone to voltage collapse[17].The main motive of CPF is about finding a continuation of power flow solutions starting at some of base load and leading to the steady state voltage stability limit (critical point) of the system[18]. Refer figure (2). A salient feature of the continuation power flow is that it remains well-conditioned at and around the critical point[19]. As a consequence, contingency due to any fault or blast is not encountered at the critical point, even when single method of computation is used. Intermediate results of the process are used to develop a voltage stability index and identify areas of the system most prone to voltage collapse[20].

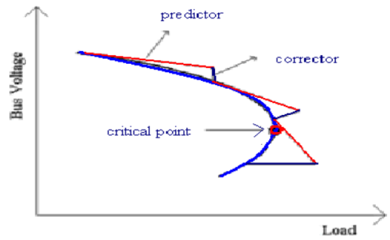


Figure 2: CPF with predictor , corrector and critical points.

The method demonstrates how singularity in the Jacobian can be avoided by slightly reformulating the power flow equations and applying a locally parameterized continuation technique. The divergence and error due to a singular Jacobian are not encountered. As a result, single precision computations can be used to obtain power flow solutions at and near the critical point .The continuation algorithm used in this work is from a well documented class of techniques used to find a path of equilibrium solutions of a set of nonlinear equations[21].

IV SUPPORT VECTOR REGRESSION

Regression are often stated as processes of deriving a function f(x) that has least deviation between predicted and experimentally observed responses of all training examples. The characteristics of Support Vector Regression (SVR) is that instead of minimizing the observed training error, SVR attempts to minimize the generalized error bound so as to achieve generalized performance[22].

V TESTS AND RESULTS

The proposed method is applied to the sample-30 bus. These are standard systems used by most researchers to validate their results. The numerical data for sample-30 bus system are taken [23].

A Prediction of loading margin for without contingency case:

i) *Generation of data*

The required data is generated using CPF method available in PSAT. In sample- 30 bus system, using 400 patterns (400x12), 4800 data samples are generated by varying the real and reactive loads randomly from its base case value to 150% of its base case value. Power factor at all load buses are maintained constant.

ii) *Training and Testing Data: Out of total 4800* generated data in the sample-30 bus system, 80% of 400 patterns (320) were used for training the SVM model and the remaining 20% (80) patterns are used for testing. Out of 35820 data samples in IEEE 30 bus system, 80% of total samples (28656) were selected arbitrarily for training, while 20% (7184) were used for testing. The data samples used for testing the SVM model are unseen values that are not used in training.

iii) Algorithm:

The SVM implementation procedure is described as follows:

1. Input load, generator and line data of the test system. Run the CPF using PSAT.
2. Generate training and testing data for the SVM, by carrying out simulations considering a) increase (real and reactive)loads at all load buses b) increase (real and reactive)loads at individual load buses c) increase of real load alone and d) increase of reactive load alone.
3. Create a data base for the input vector in the form of real and reactive power load. The target or output vector is in the form of lambda (loading margin).
4. For the training data sets, select 80% of the total patterns of real and reactive load powers.
5. Train the SVM using the selected training data sets.
6. Compare the results of SVM and convectional CPF in terms of accuracy and mean square error (MSE) as given in equation (4)

$$MSE = \sum_{i=1}^{n} \frac{(X_i - Y_i)}{n} \qquad (4)$$

Where X_i is the output value and Y_i is target value.

SVM parameter:

In the SVM training, initially the Kernel function type, Kernel parameter and sigma were determined by trial and error. The various Kernel types considered for SVM were the RBF, linear, poly and Gaussian .For the accurate SVM model the MSE value was chosen to be very less.

Therefore in the training model of SVM, the RBF Kernel and sigma 1.0 value are chosen for the lowest MSE value is used to determine the loadability margin. The training data is used to train the SVM model. The trained model is then tested with different testing patterns for its performance evaluation.

In cases where there is no contingency, the voltage stability margin by L index ,the target value (loadability margin value calculated using conventional CPF method from PSAT) and output value (loadability margin value obtained using SVM model) are compared in Table II and Table III respectively for few testing patterns due to limited spaceThe tables show clearly that the proposed SVM model estimate the same loadability margin as obtained by the conventional techniques with greater accuracy. Without outage occurrence in the power system the prediction of loading margin using SVM model with best MSE is shown in the below table.

TABLE I: COMPARISON OF TARGET AND COMPUTED OUTPUT TESTING PATTERNS FOR WITHOUT CONTINGENCY CASES OF SAMPLE-30 BUS SYSTEM (BASE MVA = 100)

No	Target (CPF)	Output (SVM)	Error
1	0.6931	0.693075	2.45277E-05
2	1.0166	1.01667	-7.0263E-05
3	1.3228	1.322824	-2.3701E-05
4	1.6100	1.610003	-3.157E-06
5	1.8770	1.877077	-7.6593E-05
6	2.1225	2.12252	-2.0139E-05
7	2.3452	2.345237	-3.7069E-05
8	2.5437	2.543652	4.7998E-05
9	2.7156	2.71562	-2.0337E-05
10	2.8557	2.855631	6.91565E-05

The results show that the network is able to produce the output with good accuracy in both the cases (10^{-3}). The MSE and the computational time for the system obtained are also very less in the order of 10^{-007} and in few seconds respectively. It is shown in table I.

TABLE II :MEAN SQUARE ERROR VALUE FOR TEST SYSTEM

Test System	Mean Square Error	Training Time(sec)	Testing Time(sec)
Sample-30 bus	$5.007e^{-007}$	15.295 sec	0.0127

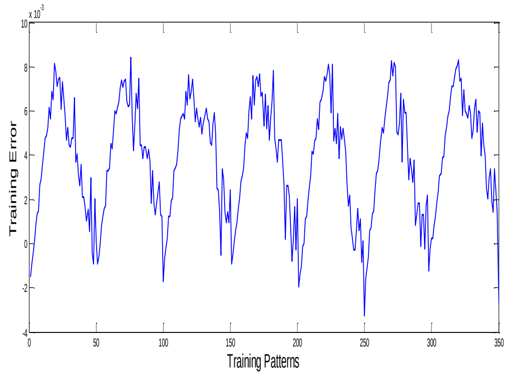


Figure 3:Comparison of training error and training pattern for without-Contingency of sample- 30 bus system.

The Fig. 3 and Fig. 4 show the comparison of training and testing patterns for without-contingency of sample- 30 bus system with respect to its error

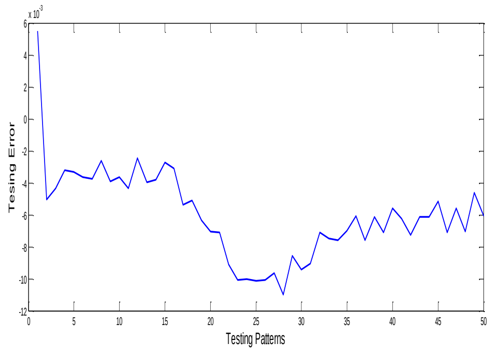


Figure 4: Comparison of testing error and testing pattern for without-Contingency of sample- 30 bus system.

B Prediction of loading margin for contingency cases

For loading margin estimation in the contingency cases, a large number of load patterns are generated by single line outages and multi line outages in the power system randomly to screen all possible scenarios. In sample- 6 bus system, the study has considered all possible single line outages and few double line outages. Totally (235x12), 2850 samples are generated by line outages. Among that 80% of patterns (188) are selected for training and remaining 20% (47) patterns are used for testing the model. Similarly for IEEE 30 bus system 19840 samples are generated by all single line and few double line outages. Among that 15840 samples are used for training and the remaining 3960 samples are selected for test the model. The same SVM model developed for pre-contingency is used to estimate the loading margin for post-contingency.

TABLE III:COMPARISON OF TARGET AND COMPUTED OUTPUT OF POST-CONTINGENCY TESTING PATTERNS OF SAMPLE-30 BUS SYSTEM (BASE MVA = 100)

No	Post-Contingency Loading Margin		
	Target (CPF)	Output (SVM)	Error
1	2.3059	2.305	9E-05
2	2.1768	2.1725	4.3E-03
3	2.0061	2.0062	-1E-04
4	1.7787	1.7892	-0.0105
5	1.5051	1.6008	-0.0957
6	1.1907	1.1829	7.8E-03
7	1.0308	1.0230	7.8E-03
8	0.9731	0.9889	-0.0158
9	0.9704	0.9763	-5.9E-03
10	0.9637	0.9687	-5E-03

The table II and III shows the comparison of L index, CPF and SVM loading margin values. The prediction of loadability margin of power system by SVM model is very accurate and speedy when compared to L index and CPF method. The value of voltage stability margin for many contingencies are lesser or far away from the actual loading margin (without-contingency cases).

TABLE IV: MEAN SQUARE ERROR VALUE FOR TEST SYSTEM

Test System	Mean Square Error	Training Time(sec)	Testing Time(sec)
Sample-30 bus	$1.105e^{-005}$	5.878	0.0299

The MSE and the computational time for the system obtained are also very less in the order of 10^{-006} and in few seconds respectively. It is shown in table IV.

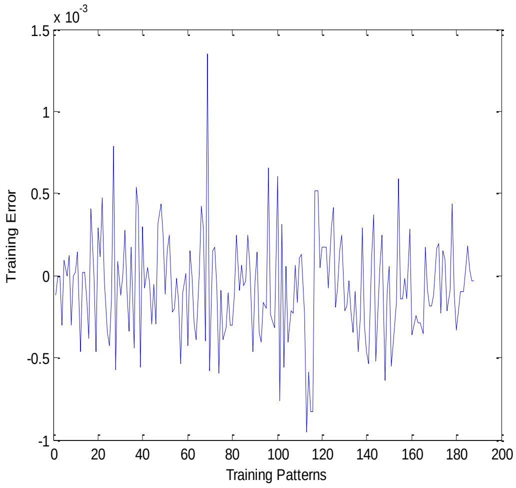


Figure 5:Comparison of training error and training pattern for Post-Contingency of sample-30 bus system.

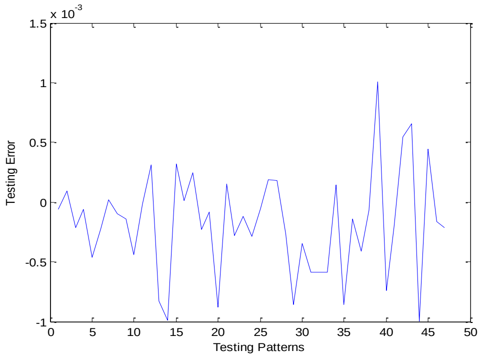


Figure 6:Comparison of testing error and testing pattern for Post-Contingency of sample-30 bus system.

The Fig. 5 and Fig. 6 show the comparison of training and testing patterns for post-contingency of sample- 30 bus systems with respect to its error. The MSE of post-contingencies are smaller and lesser than the pre-contingency cases.

VI CONCLUSION

Estimation of loadability margin for a power system is important so that fast corrective action can be taken to mitigate voltage collapse. In this paper, it is determined using SVM by testing on a IEEE 30 bus system. The proposed method is simple and proves to produce good results for small as well large power systems. The trained network is able to calculate loadability margin for normal loading conditions and also under contingency cases for a given system instantaneously with greater accuracy. This method can also be used for on-line calculation of loadability margin.

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