In today’s world of rapid growth there is an increase of demand for a reliable and stable power supply. Power utilities are pressured to cater the rising demand with the existing system. Thus, monitoring the voltage stability of the system has become crucial. Conventional methods of performing continuous load flow and stability studies are highly time consuming and infeasible for online application. It necessitates a requirement of an online tool to calculate the loadability margin under normal condition as well as under contingency cases. In this paper the voltage stability margin of a power system with and without the FACTS devices under different loading conditions using Support Vector Machine (SVM) are determined. SVM is a powerful and promising data classification and function estimation tool. In SVM the input vector in the form of real, reactive power load, voltage magnitude, phase angle and the target/output vector is in the form of lambda (loading margin) are considered. New England 39 bus test system has been used to verify the effectiveness of the proposed SVM method and the performance are compared with Artificial Neural Network (ANN) and Adaptive Neural Fuzzy Inference System (ANFIS).

Keywords: Loadability Margin, Support Vector Machines, Contingency, Voltage Stability, FACTS.

1. Introduction

Severe and increasing strain has been observed in the power system in recent years due to incongruent between the generation and transmission infrastructure. Environmental issues, change in energy portfolio and deregulated energy markets are some of the prime factors. The kind of stress developed in the system has caused concerns for voltage instability. Voltage stability refers to the ability of a power system to maintain steady voltages at all buses in the system after being subjected to a disturbance from a given initial operating condition [1]. It is very closely related to load dynamics [2]. There are several studies [3] focused on measures to accurately predict system conditions with respect to voltage stability and optimal control actions to avoid collapse in the online paradigm. As most of these problems are highly nonlinear and computationally intensive, there is a need of research to help in reducing computation and using direct measurements for estimation of stability margin.

Load margin analysis has been profoundly identified as one of the fundamental measurement in voltage collapse or voltage stability studies. In load margin assessment, the voltage collapse condition is predicted to occur when the load is increased exceeding the maximum loading point and subsequently the system starts to lose its equilibriums [4,5].

Traditional methods of voltage stability investigations have relied on static analysis using the conventional power flow method. Computed P–V/V–Q curves are the most widely used method for evaluating the voltage stability of a power system. The CPF
method was used to compute the voltage stability margin, but the loading level is increased until there is no feasible solution for the power flow equation or the solution does not satisfy required ranges of voltages. Though Interior Point method (IP) is efficient to solve the maximum loading problem, this method has the limitation of starting and terminating conditions [6]. The Sequential Quadratic Programming (SQP) algorithm includes the differentiation of the constraints. This method is very slow as it involves many matrices during the iteration process. Tiranuchit [7] proposed the minimum singular value of the Jacobian of the load flow equation as a voltage stability index. Gao et al. [8] used the modal analysis technique to compute the voltage stability level of the system. The aforementioned techniques require large computations and are not efficient for on-line applications. With the development of artificial intelligence based techniques such as ANN, fuzzy logic etc. in recent years, there is growing trend in applying these approaches for the analyses of power system [9]. ANN systems gained popularity over the conventional methods as they are efficient in discovering similarities among large data and synthesizing fault tolerant model for nonlinear system. Usually, artificial neural networks (ANNs) are used and considered to be good nonlinear regression methods for the treatment of spectral data. However, ANNs suffer from the amount of training time and the scores of the learning parameters. Fuzzy logic has been used to find the loadability limit in [10], this algorithm doesn’t give the global optima. Evolutionary algorithms have been applied to solve this problem. In [11], the authors have proposed a new methodology for loading margin estimation based on subtractive clustering and Adaptive neuro-fuzzy inference system, wherein various voltage stability indices has been selected as inputs. This method has proven to give good results to deal with uncertain load behavior and hence, can be implemented in a real time environment. However, most of the Artificial Intelligence (AI) based methods have failed to predict the voltage stability margin correctly, because they cannot find the global minima accurately.

PSO is a computational intelligence-based technique that is not affected largely by the size and nonlinearity of the problem and can converge to the optimal solution in many problems [12]. PSO performance is improved by incorporating breeding technique of genetic algorithm into PSO [14]. Maximum loadability limit can be identified by using DE. DE sometimes results in instability of performance. DEPSO eliminates the disadvantages of the DE [13].

In recent years, support vector regression (SVR) as a powerful new tool for data regression has rapidly gained widespread acceptance in many fields. SVR is a new type of machine learning theory based on the statistical learning theory [14].

In this paper, a new method for estimation of loadability margin is proposed by using SVM for fast and accurate prediction of voltage collapse. SVM’s have been successfully applied to a number of applications ranging from bioinformatics to text categorization and face or fingerprint identification. By using Feature Selection techniques, the investigation of stability analysis can be found in [15]. SVM based pattern recognition (SMV-PR) approach for security assessment problem has been found out in [16] for a power system. By using Fuzzy-SVM the credit risk for a power system has been evaluated in [17]. The ANN and SVM techniques are compared for the location of fault in radial distribution systems are discussed in [18]. Thus SVM based techniques are used for various power system problems. For estimation of loadability margin using SVM model is a new work for
a power system. Introducing FACTS devices is the most effective way for utilities to improve the voltage profile and voltage stability margin of the system [19]. However, to obtain good performance from these controllers, proper placement of these devices in the grid is important. It is important for operators and planners to find out the limit point of voltage stability and the distance from present operating point to voltage instability point.

The procedure to determine the loadability margin using SVM is explained and the performance of the SVM is compared with the ANN and ANFIS so as to verify the effectiveness of the proposed method. Load increase at all the load buses was considered for generating the training and testing data sets. The performance of the proposed SVM technique developed was evaluated by implementing it on the New England 39 test bus systems.

The organization of the paper is as follows. Section 2 presents an overview of Voltage Stability Assessment for a power system and its methodology is explained and in Section 3 its simulation results are discussed. In Section 4 concludes the paper.

2. Voltage Stability Assessment

Many methods are available to determine the voltage stability limit. One of them is PV curve. The solutions of load voltages are often presented as a PV-curve; Fig.1 presents the PV curve, the load voltage as a function of real power demand or sum of load demand. It presents both solutions of power system. The power system has low current-high voltage and high current low voltage solutions. Power systems are operated in the upper part of the PV-curve. This part of PV-curve is statically and dynamically stable. The head of the curve is called the maximum loading point. The critical point where the solutions become unit is the voltage collapse point. Recently, various studies for detecting loadability limits of power systems have been proposed in relation to voltage stability and security monitoring.

![Fig. 1 PV Curve and Voltage Stability Limit](image)

The maximum loadability limit is the margin between the operating point of the system and the maximum loading point. In general the maximum loading point is more iterating from the practical point of view then the true voltage collapse point, because the maximum
of power system loading is achieved at this point. The load increase beyond the voltage collapse point results in loss of equilibrium and power system can no longer operate. The voltage dependence of loads affects the point of voltage collapse. The power system becomes voltage unstable at the voltage collapse point. Various methods have been proposed to determine the maximum loadability limit [20]. Among these methods, the continuation power flow (CPF) technique has been widely used. This method fails to give the accurate result if the step length is more.

2.1 ANN

Artificial neural networks are highly parallel, adaptive learning system that can learn a task by generalizing from case studies of the tasks. Among the various ANN architectures available in the literature, the multilayer feed forward network with back propagation learning algorithm has been used for the present study because of its simple approach and good generalization capability [21,22]. The network consists of an input layer, an output layer and at least one hidden layer. Each layer includes a set of neurons. The neurons are interconnected by weight. There is no coupled relation between neurons in the same layer. The structure of the artificial neural network is shown in Fig.2. The designed networks are trained by the back-propagation algorithm using Lavenberg-Marquardt optimization. Early stopping regime is also applied to improve ANN generalization by preventing the training from over fitting problem. In the context of neural network, over fitting is also known as overtraining where further training will not result in better generalization. The error of validation set is periodically monitored during the training process. The training error usually decreases as the iteration grows, so does the validation error. When the overtraining starts to occur, the validation error typically tends to increase. Therefore, it would be useful and time saving to stop the training after the validation has increased for some specified number of iteration. The important factors influencing the performance of the neural network are the number of processing elements in the hidden layer and the number of iterations. As the number of hidden layer neurons increases, the neural network takes more time to learn.

![Fig.2 Architecture of backpropogation neural network](image-url)
2.2 ANFIS

A unique approach in neuro fuzzy system is the adaptive neuro fuzzy inference system (ANFIS), which has been proven better performance in modelling nonlinear function [23]. The ANFIS models possess human-like expertise within a particular domain which adapts itself and learns to do better in changing environment condition [24]. An ANFIS aims at automatically generating unknown fuzzy rules from a given input and output data sets [25]. Fig. 3 shows a typical architecture of ANFIS and each circle shows a fixed node, whereas every square indicates an adaptive node, where the parameter of each adaptive node is updated according to given training data and to a gradient-based learning procedure.

ANFIS uses a hybrid learning rule which combines the gradient method and the least square estimate. This approach is much faster and reliable than the simple gradient descent.

![Architecture of ANFIS](image)

Fig. 3 Architecture of ANFIS

2.3 SVM

Support vector machines (SVMs), a recently introduced learning paradigm, have very interesting theoretical and practical characteristics [26-28]. They rely on so called support vectors (SVs) to identify the decision boundaries between different classes. The SVs are located near the separation surfaces, which are critical to achieve correct classifications. In this method the input vectors are mapped into a higher dimensional feature space and an optimal separating hyper plane in this space is constructed. Fig. 4 shows the architecture of SVM model.

![Architecture of SVM model](image)

Fig. 4 Architecture of SVM model
Support Vector Machine can be applied not only to classification problems but also to the case of regression. Still it contains all the main features that characterize maximum margin algorithm: a non-linear function is leaned by linear learning machine mapping into high dimensional kernel induced feature space [29]. The capacity of the system is controlled by parameters that do not depend on the dimensionality of feature space.

It seeks to optimize the generalization bounds given for regression. They relied on defining the loss function (epsilon intensive – loss function) that ignores errors, which are situated within the certain distance of the true value.

The most important ideas in Support Vector Regression cases is that presenting the solution by means of small subset of training points gives enormous computational advantages. Using the epsilon intensive loss function we ensure existence of the global minimum and at the same time optimization of reliable generalization bound.

A large number of loading patterns are generated by changing real power load, reactive power load and both real and reactive power load at different load buses randomly. The data samples in train and test set needs to be scaled properly before applying SVM. This is important as kernel values depend on the inner products of feature vector. Fig.5 shows the overall block diagram for estimation of loadability margin using SVM.

where \[
\begin{bmatrix}
P_{d1} , P_{d2}, ..., P_{dn}
\end{bmatrix}
\] is the real power load vector of \(i\)th bus for ‘n’ number of patterns, \[
\begin{bmatrix}
Q_{d1} , Q_{d2}, ..., Q_{dn}
\end{bmatrix}
\] is the reactive load vector of \(i\)th bus for ‘n’ patterns, \[
\begin{bmatrix}
V_{1} , V_{2}, ..., V_{n}
\end{bmatrix}
\] is the voltage magnitude of load buses for ‘n’ number of patterns and \[
\begin{bmatrix}
\phi_{1} , \phi_{2}, ..., \phi_{n}
\end{bmatrix}
\] is the voltage phase angle of load buses for ‘n’ number of patterns

Fig. 5 Block diagram for estimation of loadability margin using Support Vector Machine model

3. Simulation Results and discussions

The NE 39bus system consist of 1 slack bus, 9 generator buses, 29 load buses and it consist of 46 branches [30]. The SVM implementation procedure is described as follows:

Input load, generator and line data of the test system. Run the CPF using PSAT[31]. Generate training and testing data for the SVM, by carrying out simulations for the following three different loading scenarios:

CASE 1: Reactive load power alone increased at many load buses.
CASE 2: Both active and reactive load power increased at many load buses at constant power factor.

CASE 3: Both active and reactive load power increased at many load buses at 0.8 lagging power factor.

Create a data base for the input vector in the form of real, reactive power load, voltage magnitude and voltage phase angle of all load buses. The target or output vector is in the form of lambda (loading margin). For the training data sets, select 80% of the total patterns of real and reactive load powers. Select the parameter values of Kernel type and Kernel parameter used for training the Spider SVM [32]. Train the SVM using the selected training data sets. The results are compared with ANN and ANFIS network for accuracy.

3.1 Estimation of Voltage Stability Margin without FACTS Devices

The required data is generated using CPF method available in PSAT. In NE 39 bus system, using 635 patterns (600x156), 93,000 data samples are generated by varying the real and reactive loads randomly from its base case value to 150% of its base case value. Out of total generated data in the NE 39 bus system, 80% of 635 patterns (510) were used for training the SVM model and the remaining 20% (125) patterns are used for testing. The data samples used for testing the SVM model are unseen values that are not used in training. The base loads are increased gradually and the load flow is performed for every increment of the load. The increment of the load continues until line flow and bus voltage violation occurs. Table I shows the maximum system loadability that can be achieved without any FACTS device.

Table 1: Maximum System Loadability without FACTS devices for all cases

<table>
<thead>
<tr>
<th>No</th>
<th>Loading Margin without FACTS device</th>
<th>Target (CPF)</th>
<th>ANN $\lambda$</th>
<th>ANFIS $\lambda$</th>
<th>SVM $\lambda$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.6931</td>
<td>0.98730</td>
<td>1.01484</td>
<td>0.693075</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>1.0166</td>
<td>1.47323</td>
<td>1.32049</td>
<td>1.01667</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>1.3228</td>
<td>1.87949</td>
<td>1.60731</td>
<td>1.322824</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>1.6100</td>
<td>1.97001</td>
<td>1.87386</td>
<td>1.610003</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>1.8770</td>
<td>1.89904</td>
<td>2.11875</td>
<td>1.877077</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>2.1225</td>
<td>2.34514</td>
<td>2.34065</td>
<td>2.12252</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>2.3452</td>
<td>2.82107</td>
<td>2.537659</td>
<td>2.345237</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>2.5437</td>
<td>2.87788</td>
<td>2.706636</td>
<td>2.543652</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>2.7156</td>
<td>3.39864</td>
<td>2.839433</td>
<td>2.71562</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>2.8557</td>
<td>3.48260</td>
<td>2.880869</td>
<td>2.855631</td>
<td></td>
</tr>
</tbody>
</table>

In this case where there is no FACTS device, the voltage stability margin by ANN, ANFIS, 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 for few testing patterns due to limited space in table 1. But ANN and ANFIS are unable to detect the loading margin exactly, because it gives a greater value.
when compared to CPF and ANFIS take much computational time. Table 2 shows the loadability margin value of CPF and SVM with minimum MSE and percentage. The tables show clearly that the proposed SVM model estimate the same loadability margin as obtained by the conventional techniques with greater accuracy.

Table 2: Comparison of target and computed output of some testing patterns

<table>
<thead>
<tr>
<th>No</th>
<th>Loadability Margin for all loading scenarios</th>
<th>Error</th>
<th>Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.642259</td>
<td>-2.9E-06</td>
<td>-0.000177223</td>
</tr>
<tr>
<td>2</td>
<td>0.841744</td>
<td>8.99E-06</td>
<td>0.001068269</td>
</tr>
<tr>
<td>3</td>
<td>3.109866</td>
<td>-9.4E-06</td>
<td>-0.000302372</td>
</tr>
<tr>
<td>4</td>
<td>3.227254</td>
<td>-7.3E-06</td>
<td>-0.000225268</td>
</tr>
<tr>
<td>5</td>
<td>2.718372</td>
<td>-6.3E-06</td>
<td>-0.000230389</td>
</tr>
<tr>
<td>6</td>
<td>3.441657</td>
<td>-7.9E-06</td>
<td>-0.000229249</td>
</tr>
<tr>
<td>7</td>
<td>2.313002</td>
<td>-3.5E-07</td>
<td>-1.30071E-05</td>
</tr>
<tr>
<td>8</td>
<td>2.561065</td>
<td>7.1E-07</td>
<td>2.77168E-05</td>
</tr>
<tr>
<td>9</td>
<td>3.478932</td>
<td>-7E-06</td>
<td>-0.0002025</td>
</tr>
<tr>
<td>10</td>
<td>1.374591</td>
<td>-8.6E-06</td>
<td>-0.000177223</td>
</tr>
</tbody>
</table>

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 by SVM are also very less in the order of 10⁻⁰⁰⁷ and in few seconds respectively when compared to ANN and ANFIS network and it is shown in table 3.

Table 3: Mean Square Error And Computation Time Value For All Network

<table>
<thead>
<tr>
<th>Test System</th>
<th>Mean Square Error</th>
<th>Training Time(sec)</th>
<th>Testing Time(sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>5.007e⁻⁰²</td>
<td>7.256</td>
<td>0.0671</td>
</tr>
<tr>
<td>ANFIS</td>
<td>8.271e⁻⁰³</td>
<td>1586.22</td>
<td>672.34</td>
</tr>
<tr>
<td>SVM</td>
<td>4.335e⁻⁰⁰⁷</td>
<td>4.418</td>
<td>0.0378</td>
</tr>
</tbody>
</table>

3.2 Estimation of Voltage Stability Margin after placing FACTS device

The behaviour of the test system with and without FACTS device under different loading conditions is studied. FACTS devices can be connected to a transmission line in various ways, such as in series, shunt, or a combination of series and shunt. For example, the static VAR compensator (SVC) and static synchronous compensator (STATCOM) are connected in shunt; static synchronous series compensator (SSSC) and thyristor controlled series capacitor (TCSC) are connected in series; thyristor controlled phase shifting transformer (TCPST) and unified power flow controller (UPFC) are connected in a series and shunt combination.

TCSC is one of the important FACTS devices which come under series compensation technique in the line intended to decrease the line reactance thereby maintain flat voltage profile and increase the power transfer capacity of the line. TCSC is extremely simple circuit in which a capacitor is inserted directly in series with the transmission line and the
A thyristor-controlled inductor is mounted directly in parallel with the capacitor. 20% line reactance compensation is inserted in the 36th transmission line. The location of the SVC device is determined through CPF technique, 20% susceptance compensation is inserted and 25th bus is chosen for the SVC placement. The loadability margin are re-estimated after the insertion of FACTS devices and the changes in the system behaviour are given below.

The voltage stability margin with FACTS devices using ANN, ANFIS and SVM model are compared in Table 4 respectively for few testing patterns due to limited space. The table shows clearly that the proposed SVM model estimate the same loadability margin as obtained by the conventional techniques with greater accuracy. After installing TCSC in 36th line, the loadability margin is increased for all loading scenarios. The quantitative analysis shows that 20% reactance compensation in the line, increased the loadability margin of the system by 3.26% because the voltage profiles became flatter and the loadability margin of the system is increased when compared to loadability margin without FACTS devices as in table 1.

Table 4: Maximum System Loadability with TCSC

<table>
<thead>
<tr>
<th>No</th>
<th>Target (CPF)</th>
<th>Loading Margin with TCSC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ANN (\lambda)</td>
<td>ANFIS (\lambda)</td>
</tr>
<tr>
<td>1</td>
<td>2.0288</td>
<td>2.2281</td>
</tr>
<tr>
<td>2</td>
<td>2.1494</td>
<td>2.2671</td>
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<td>3</td>
<td>2.2664</td>
<td>2.2709</td>
</tr>
<tr>
<td>4</td>
<td>2.3223</td>
<td>2.2483</td>
</tr>
<tr>
<td>5</td>
<td>2.3316</td>
<td>2.2056</td>
</tr>
<tr>
<td>6</td>
<td>1.8969</td>
<td>2.147</td>
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<tr>
<td>7</td>
<td>1.8223</td>
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</tr>
<tr>
<td>9</td>
<td>1.6379</td>
<td>1.8997</td>
</tr>
<tr>
<td>10</td>
<td>1.5212</td>
<td>1.7965</td>
</tr>
</tbody>
</table>

Table 5 shows the loadability margin value after installed SVC at 25th bus. The 20% compensation of susceptance (SVC) is increased the loadability margin by 2.78%. As expected, the bifurcation for the system with the SVC placed at bus 25 occurs at a higher load value, i.e., \(\lambda = 2.81\) (with SVC). The loadability margin of the system is increased when compared to loadability margin without FACTS device \(\lambda = 2.79\).

The MSE values and computational time are simulated for all networks are tabulated in table 6. The training computational time of ANFIS network is slightly higher than the SVM and ANN. The SVM training and testing time are faster and accurate when compared to ANN model. However the results show that the SVM type predicts the result quickly when compared to other models and the computational time also less for the estimation of loadability margin of a power system. The results show that the SVM network is able to produce the output with good accuracy \((10^{-3})\). The MSE and the computational time for the system obtained are also very less in the order of \(10^{-4}\) and in few seconds respectively.
Table 5: Maximum System Loadability with SVC.

<table>
<thead>
<tr>
<th>No</th>
<th>Target (CPF)</th>
<th>Loading Margin with SVC</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>ANN</td>
<td>ANFIS</td>
<td>SVM</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>2.3059</td>
<td>2.3239</td>
<td>2.393</td>
<td>2.305</td>
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</tr>
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<td>2</td>
<td>2.1768</td>
<td>2.27</td>
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</tr>
<tr>
<td>3</td>
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<td>2.1989</td>
<td>2.0062</td>
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</tr>
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</tr>
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</tr>
<tr>
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</tr>
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</tr>
<tr>
<td>10</td>
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<td>1.1102</td>
<td>1.1093</td>
<td>0.9687</td>
<td></td>
</tr>
</tbody>
</table>

Table 6: Comparison of SVM, ANN and ANFIS after placing FACTS devices

<table>
<thead>
<tr>
<th>FACTS Devices</th>
<th>Training data samples</th>
<th>Testing data samples</th>
<th>Networks</th>
<th>Training Time (sec)</th>
<th>Testing Time (sec)</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>TCSC</td>
<td>37440</td>
<td>9360</td>
<td>ANN</td>
<td>9.812</td>
<td>0.0928</td>
<td>3.89e-03</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ANFIS</td>
<td>1447.42</td>
<td>518.63</td>
<td>1.481e-05</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>SVM</td>
<td>5.878</td>
<td>0.0299</td>
<td>1.105e-05</td>
</tr>
<tr>
<td>SVC</td>
<td>31200</td>
<td>7800</td>
<td>ANN</td>
<td>7.165</td>
<td>0.134</td>
<td>3.234e-03</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>ANFIS</td>
<td>1827.95</td>
<td>611.62</td>
<td>2.784e-05</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>SVM</td>
<td>3.436</td>
<td>0.129</td>
<td>1.925e-05</td>
</tr>
</tbody>
</table>

Fig.6 Testing error for all loading scenarios patterns of SVM model

The fig. 6 show the comparison of all testing patterns for SVM networks with respect to its error after TCSC and SVC placement. It shows that with FACTS devices the prediction of loading margin using SVM model gives best MSE when compared to other networks.
The SVM predicts the loadability margin more quickly and accurately when compared to ANN and ANFIS network.

5. 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 New England 39 bus system. The proposed method is simple and proves to produce good results for three different loading scenarios. The trained network is able to calculate loadability margin for normal loading conditions and also under contingency cases with and without FACTS devices 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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