ONLINE VOLTAGE STABILITY MARGIN ASSESSMENT AND ENHANCEMENT IN DEREGULATED ENVIRONMENT USING SUPPORT VECTOR REGRESSION

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Abstract: *Recently the operation of power system strategies has changed significantly due to the introduction of deregulation in electricity markets. The power systems are being operated with high stress, hence sufficient voltage stability margin and reactive power support are necessary to be managed to ensure secure operation of the power system. This paper proposes a Support Vector Regression (SVR) along with Fuzzy Logic Controller (FLC) based tool for online voltage stability monitoring and estimation of VAR support requirement at the critical load buses of power system for improving voltage stability margin at different operating conditions. The SVR input vector is in the form of bus voltage angle and reactive power load. The voltage stability margin index (VSMI) and voltage stability factor (VSF) of the most vulnerable bus is used as target for SVR. The proposed tool successfully estimates the voltage stability margin and VAR support for various transactions in deregulation environment and also under N-1 contingency. This method has been successfully applied to the IEEE 14 bus and IEEE 30 bus test systems and the results of SVR are compared with Artificial Neural Networks (ANN) based methods.The results obtained using SVR is better than that of ANN in terms of mean squared error and execution time.Which are chosen as performance indices.*

Keywords:*Support vector regression, Artificial neural networks, Fuzzy logic controller, Voltage stability margin Index,Voltage stability factor and VAR support*.

1. Introduction

The electrical power system is continuously expanding in size and growing in complexity all over the world with the increase of population and modernization. Therefore the governments have been changing their rules and regulations by allowing the private sectors into the power generation, transmission and distribution (Deregulated Power System) [1]. Because of less regulation in power flow patterns and more intensive use of available transmission facilities through bilateral and multilateral transactions in deregulated power systems, the systems are operated closer to the voltage stability boundaries [2].Voltage stability refers to the ability of a power system to maintain acceptable voltages at all buses both under normal operating conditions and after being subject to a disturbances [3]. A power system enters a state of voltage instability when disturbingit, which results in a progressive and an uncontrollable voltage decline leading to voltage collapse[4,5]. Many utilities around the world have experienced major blackouts caused by voltage instabilities and insufficient reactive power supports [4].In order to prevent the occurrence of voltage collapse, it is essential to accurately predict the operating condition of a power system. So, Independent System Operator (ISO) needs a fast and accurate voltage stability index to help them for monitoring the system condition. Many authors have proposed the voltage stability indices based on repeated power flow analysis [6-8]. The main difficulty in these methods is that Jacobian matrix of power flow equation becomes singular at voltage the stability limit. Singularity in the Jacobian matrix can be avoided by slightly reformulating the power flow equations using continuation power flow (CPF) technique [9-10].

CPF technique isfairly accurate for voltage stability analysis, but hampered by the fact of taking longer computational time for large-scale power systems. For online applications, there is a need for quick detection of the potentially dangerous situations of voltage instability so that necessary actions may be taken to avoid the occurrence of voltage collapse in a power system. In recent years, the machine learning techniques such as ANN, fuzzy logic controller (FLC), support vector machine (SVM), etc. have been used for power system voltage stability analysis. The ANN has been emerged as a powerful tool due to its ability to map complex nonlinear problem offline with selective training, which can lead to a sufficiently accurate online response.

In reference [11], the authors have investigated voltage magnitudes and the phase angles are the best predictors of online voltage stability margin (VSM) assessment. The phase angles and load reactive power are used as the best predictors of online VSM assessment in [12]. A comparative study of various voltage stability indices for the estimation of loadability margin is presented in reference [13]. Usually, ANN is a powerful, flexible method known for performing nonlinear regression. But, ANN suffers from larger training time and cannot find the global minima parameters.

Nowadays, SVM is a powerful new machine learning technique and widely used in power system to predict the VSM. A new SVM model for online prediction of loadability margin for power system leading to fast voltage stability assessment and analysis of various regression models is presented in [14]. A new SVR methodology is trained to predict the VSM in a short period of time even for a large power system and proved that ε -SVR gives less mean square error compared to ν -SVR in[`15]. A Genetic Algorithm based SVM approach for online monitoring of long-term voltage stability using voltage stability margin index has been proposed in [16].

In power system, voltage and reactive power support are linked to each other. The main reason of voltage instability tends to occur from lack of reactive power supports. In the deregulated power markets, reactive power management is under the responsibility of ISO. So ISO should take appropriate actions to provide VAR support for ensuringvoltage stability. A multi-objective genetic algorithm is used for voltage stability enhancement using rescheduling of the generator and optimal placement of FACTS devices briefed in [17]. A reactive power control approach based on fuzzy sets theory, for voltage stability enhancement by monitoring L-index has been presented in [18].The ANN and fuzzy based online tool to determine the minimum VAR support required for the projected load demand with a view to ensure voltage stability in a power system based on VAR support injected in the critical bus and remaining load buses of the system had been developed in [19].

From the observation of vast literature shows that the researchers have considered assessment of voltage stability or VSM estimation or VAR support estimation separately in the monopoly power system. This paper employs bus voltage angle (θ_L) and load reactive power (Q_L) as input attributes and two output voltage stability indices $VSMI^{CB}$ and VSF^{CB} to predict the VSM and determine the minimum VAR support required for enhancing voltage stability margin in restructured power system. It also presents the development of Support vector regression and fuzzy logic controller based tool for online voltage stability monitoring as well as estimation of adequate VAR support provided in the critical buses for enhancing VSM at different loading and system configurations in restructured power system.

The rest of this paper is organized as follows. Section 2 describes the voltage stability indices and calculation of $VSMI^{CB}$ and VSF^{CB} using CPF. The design of the proposed tool by using ANN or SVR along with the FLC is presented in section 3. Section 4 describes the algorithm of the proposed approach. The simulation results and the effect of VAR support are discussed in section 5 and section 6 provides the conclusion about the proposed work.

2. Voltage Stability Indices

The following two indices are used to predict the condition of VSM.

2.1 Voltage Stability Factor

The differential change in voltage magnitude at each bus for a given differential change in total active power demand is defined as Voltage stability factor (VSF).

$$\mathrm{VSF}_i = \frac{dV_i}{dP_{Total}} \quad (1)$$

Where, dP_{Total} and dV_i are respectively total active demand change and per unit voltage magnitude change at i^{th} bus in the system. The bus with the highest VSF can be treated as the most critical bus in the system, hence the VSF at the most critical bus is given in Eq. (2).

$$\mathrm{VSF}^{CB} = Maximum\left(\frac{dV_i}{dP_{Total}}\right) \quad (2)$$

The index value of the most critical load bus is adequate for voltage stability margin assessment, because the most critical bus is the one that is nearest to experiencing voltage collapse. So it is a recognized fact that the voltage stability assessment at the most critical bus is treated as an assessment for the entire power system[19].

2.2 Voltage Stability Margin Index

The VSM is defined as a megawatt distance between the current operating point(λ_i) and maximum loading condition ($\lambda_{\max}$) according to the system loading parameter (λ) as illustrated graphically in Fig.1. The $\lambda_{\max}$ is correlated to the voltage collapse point of the mostcritical load bus.The VSM of the most critical bus, can be calculated as

$$\text{VSM}=\lambda_{\max}-\lambda_i \quad (3)$$

The VSM Index for the most critical load bus(VSMI^{CB}) is given by

$$\text{VSMI}^{CB}=\frac{\lambda_{\max}-\lambda_i}{\lambda_{\max}} \quad (4)$$

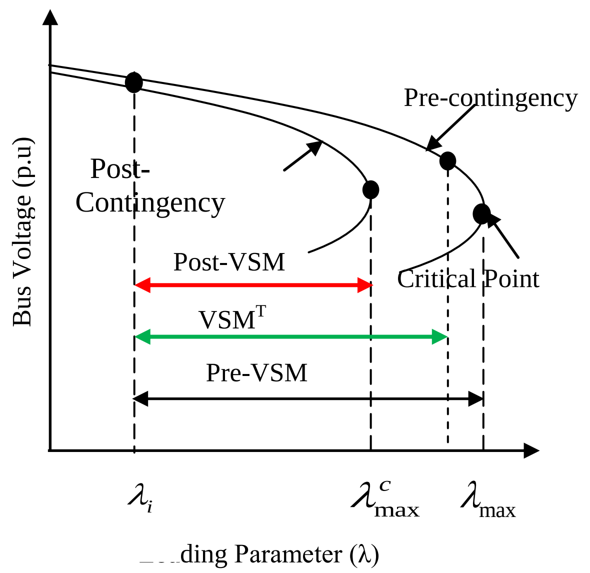

Fig.1.Definition of VSM^T, Pre-VSM and Post-VSM.

VSMI^{CB} is an indicator that determines the voltage collapse point. The VSMI^{CB} varies in a range between 1 (no load) and 0 (maximum loadability). The VSF^{CB} and VSMI^{CB} are computed by using CPF method. CPF is a powerful algorithm to trace the power flow solutions, starting from a base case load level and leading up to the steady state voltage stability limit. The λ –V curve obtained from the CPF of the most critical load bus is shown in Fig.1. Pre-VSM is VSM with no contingency in the system. Post-VSM is VSM after N-1 contingency in the system. VSM for the post-contingency ($\lambda^c_{\max}$) is less than that of pre-contingency ($\lambda_{\max}$) due to N-1 contingency. Threshold Value of VSM (VSM^T)to be kept in the system for voltage stability.

3. Proposed system

The block diagram representation of the proposed system is shown in Fig. 2. Which conceptually provides the structure and process involved in the proposed online system. It is developed by using a SVR, FLC and VAR limit controller. ANN can also be used in the place of SVR for comparative analysis. A multi-output SVR model evaluate the voltage stability of the power system from the values of VSMI^{CB} and VSF^{CB} under the different system configurations by monitoring the system θ_L and Q_L . When the power system operating conditions are closer to voltage instability, a FLC along with VAR limit controller computes the required VAR support to be provided to enhance the voltage stability of the system. The design of ANN, SVR and FLC are described in the next sections.

3.1. Support vector regression

SVM is a machine learning method that is widely used for data analyzing and pattern recognizing first developed by Vapnik [20] in 1995. The merits of SVM over ANN are global optimum solution and robustness [21].SVM works on the principle of structural risk minimization seeking to minimize an upper bound of the generalization error, rather than minimize the training error. With the introduction of Vapnik's e-insensitive loss function, SVM has been extended to solve nonlinear regression estimation problems [22].

Recently, the studies of SVR mainly focus on the single output regression. However, the multi-output SVR problems often meet in our real life. The basic idea of Multi-output SVR is to map the data of multivariate input space into a multivariate output space via a nonlinear mapping and to do linear regression in this space [23]. Consider a training set for regression as follows.

$$D=\{(x_1,y_1),(x_2,y_2).......(x_l,y_l)\} \quad (5)$$

with $x_i \in \mathbf{R}^n, y_i \in \mathbf{R}^m$

Where, x_i input attribute vector is consist of θ_L and Q_L fori^{th}operating point of the *n* samples. y_i are associated target values of VSMI^{CB} and VSF^{CB} corresponds to the *m* size of the training data. Multi-output SVRdesigns at predicting an output vector $y_i \in \mathbf{R}^m$ from a given input vector $x_i \in \mathbf{R}^n$ and takes the form.

$$f(x)=\langle w,x\rangle+b \quad (6)$$

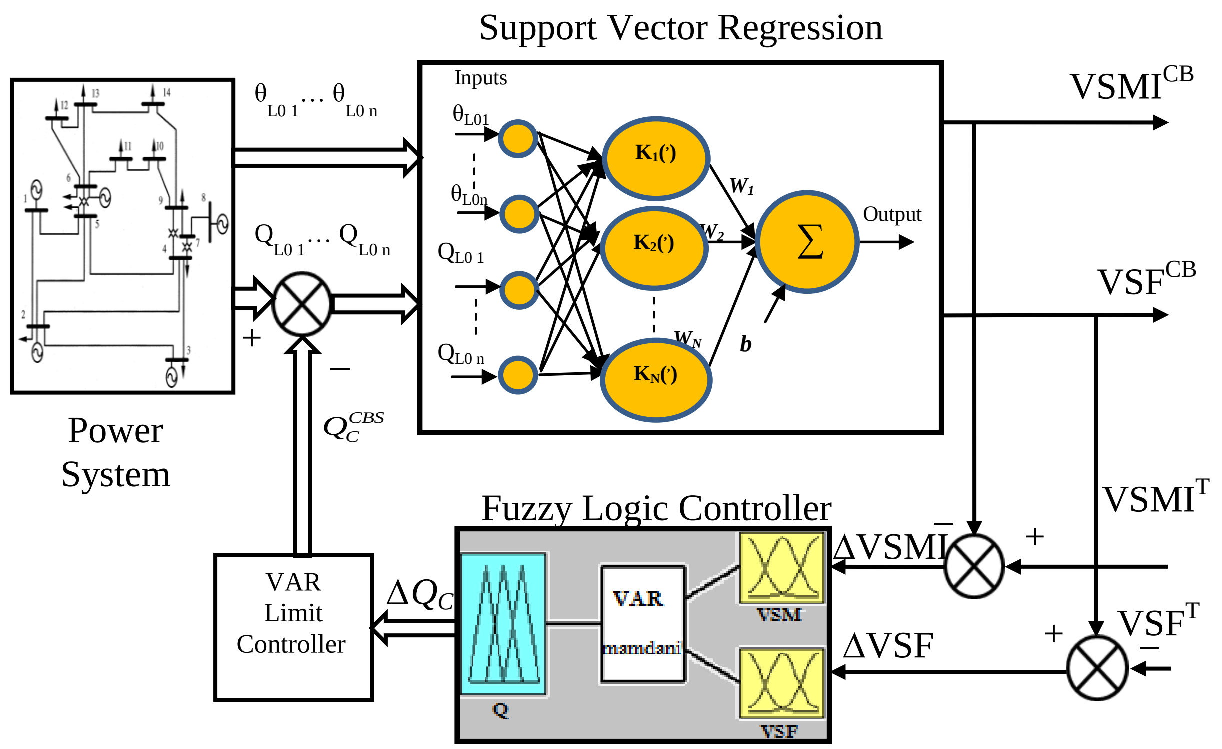

Fig.2.The block diagram representation of the proposed system.

Where

$f(x)$: Output function

w : Weight vector

x : Input

b : Bias threshold

< . , . >: Dot products in the feature space.

The objective is to find the values of the weight vector (w), bias (b) such that the values of x can be determined by minimizing the following objective function with constraints:

Minimize

$$L(w,\xi_{ij}^-,\xi_{ij}^+) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}\sum_{j=1}^{m}(\xi_{ij}^- + \xi_{ij}^+) \quad (7)$$

Where, C is a pre-specified value, and ξ^-,ξ^+ are slack variables that measure the error of the up and down sides, respectively and ϵ is the insensitive loss function

Subjected to

$$y_i - w*\phi(x_i) - b \le \varepsilon + \xi_i^-, \quad i = 1,.....,l$$
$$w*\phi(x_i) + b - y_i \le \varepsilon + \xi_i^+, \quad i = 1,.....,l$$
$$\xi_i^-,\xi_i^+ \ge 0, \quad i = 1,.....,l$$

The slack variables $\xi^- and \xi^+$ deal with infeasible constraints of the optimization problem by imposing the penalty to the excess deviations which are larger than ε.To solve the optimization problem Eq. (7), we can construct a Lagrange function from the objective function with Lagrange multipliers as follows:

$$L = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}\sum_{j=1}^{m}(\xi_{ij}^- + \xi_{ij}^+) - \sum_{i=1}^{l}\sum_{j=1}^{m}\alpha_{ij}^-(\varepsilon + \xi_{ij}^- - y_{ij} + \langle w_i, x_j\rangle + b_i)$$
$$-\sum_{i=1}^{l}\sum_{j=1}^{m}\alpha_{ij}^-(\varepsilon + \xi_{ij}^+ + y_{ij} - \langle w_i, x_j\rangle - b_i) - \sum_{i=1}^{l}\sum_{j=1}^{m}(\eta_{ij}^-\xi_{ij}^- + \eta_{ij}^+\xi_{ij}^+) \quad (8)$$

Where,

$\alpha_{ij}^-,\alpha_{ij}^+,\ \eta_{ij}^-\eta_{ij}^+ \ge 0, (i = 1,....,l,$ j=1,....,m)

Differentiating the Lagrangian function with respect to w,b, $\xi^- and \xi^+$,we can derive the dual problem of the Eq. (7) as follows:

$$\max_{\alpha^-\alpha^+} -\frac{1}{2}\sum_{k=1}^{l}\sum_{i,j=1}^{m}(\alpha_{ik}^- - \alpha_{ik}^+)(\alpha_{jk}^- - \alpha_{jk}^+)(x_i.x_j)$$
$$+\sum_{k=1}^{l}\sum_{i,j=1}^{m}(\alpha_{ik}^- - \alpha_{ik}^+)y_{ik} - \sum_{k=1}^{l}\sum_{i,j=1}^{m}(\alpha_{ik}^- - \alpha_{ik}^+)\varepsilon \quad (9)$$

Subjected to

$$\sum_{i=1}^{l}(\alpha_i^- - \alpha_i^+) = 0,$$
$$0 \le \alpha_i^-, \alpha_i^+ \le C, \quad i = 1,....,l \qquad (10)$$

Once the solutions of α^- and α^+ in the Eq. (9) are determined, we can obtain the linear regression function

$$f(x) = \sum_{i=1}^{l}(\alpha_i^- - \alpha_j^+)(x_i.x) + b \quad (11)$$

Eq. (11) can map the training vectors to target values allowing some errors, but it cannot handle the nonlinear SVR case. In order to extend linear to the nonlinear case, we applied the following kernel trick.

$$f(x) = \langle w, k(x_i, x)\rangle + b \quad (12)$$

Here, $k(x_i, x)$ is a kernel function which gives the dot product ($\phi(x_i)$. $\phi(x_j)$) in the higherdimensional space. The nonlinear multi-output SVR can be obtained by resolving the Eq.(8)

$$\max_{\alpha^-\alpha^+} -\frac{1}{2}\sum_{k=1}^{l}\sum_{i,j=1}^{m}(\alpha_{ik}^- - \alpha_{ik}^+)(\alpha_{jk}^- - \alpha_{jk}^+)k(x_i.x_j)$$
$$+\sum_{k=1}^{l}\sum_{i,j=1}^{m}(\alpha_{ik}^- - \alpha_{ik}^+)y_{ik} - \sum_{k=1}^{l}\sum_{i,j=1}^{m}(\alpha_{ik}^- - \alpha_{ik}^+)\varepsilon \qquad (13)$$

Subjected to

$$\sum_{i=1}^{l}(\alpha_i^- - \alpha_i^+) = 0, \qquad (14)$$
$$0 \le \alpha_i^-, \alpha_i^+ \le C, \quad i = 1,....,l, \quad j = 1,....,m$$

Finally,we can obtain the SVR function $f(x)$ using the kernel function.

$$f(x) = \sum_{i=1}^{l}(\alpha_i^- - \alpha_j^+)k(x_i.x) + b \quad (15)$$

3.2. Performance Measure

To evaluate the performance of SVR or ANN for the testing data, Mean Square Error (MSE) is used. The expression for calculating MSE is given in Eq. (16).

$$\text{MSE} = \sum_{i=1}^{n}\frac{|y_i - y_0|}{n} \qquad (16)$$

Where, y_0 is the target VSM/VSF obtained from the CPF program and y_i is the VSM/VSF estimated by the SVR or ANN and n is the number of unseen cases.

3.3 Design of fuzzy logic controller

3.3.1 Fuzzy modeling

Fuzzy Logic is a methodology used to solve the problems which are too complex to be understood quantitatively. It is based on fuzzy set theory, introduced by Prof. Zadeh [24]. Use of fuzzy sets in logical expression is known as fuzzy logic.In this paper, fuzzy logic is used to compute the reactive power support required to be provided in the system. The proposed system takes change in VSMI (ΔVSMI) and change in VSF (ΔVSF) as inputs and gives the required reactive power at a load bus (ΔQ_C) taken as output. The fuzzy inputs ΔVSMI and ΔVSF are determined from Eq. (17).

$$\Delta\text{VSMI}=\text{VSMI}^{T}-\text{VSMI}^{CB};\ \Delta\text{VSF}=\text{VSF}^{CB}-\text{VSF}^{T} \quad (17)$$

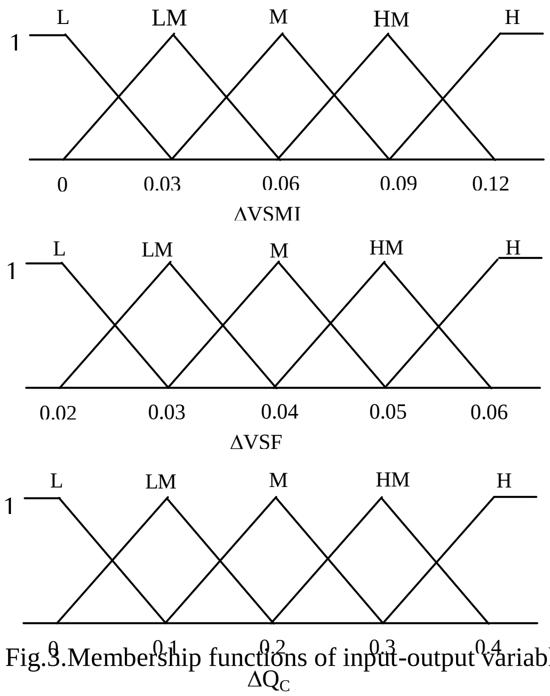

Fig.3.Membership functions of input-output variable.

The membership function and its ranges for fuzzy inputs (ΔVSMI, ΔVSF) and output (ΔQ_C)are shown in Fig. 3. The corresponding linguistic variables are defined as L (low), LM (low medium), M (medium),HM (high medium) and H (high). For simplicity triangular and trapezoidal membership functions are considered.

In fuzzy logic based approaches, the decisions are made by forming a series of rules that relate the input variables to the output variables using if–then statements.The output is derived on the basis of rules defined by an inference matrix. The number of rules depends on the number of inputs and their linguistic variables. Two inputs (ΔVSMI and ΔVSF) with each five linguistic variable produce twenty five rules for the fuzzy Inference System are shown in Table 1. From the FIS sample output of Fig.4, it is observed that ΔVSMI is M (0.06) and ΔVSF is M (0.04) then output ΔQ_c is M (0.2). The fuzzy output signal is defuzzified by the centre of gravity defuzzification strategy to get the crisp output value[25].

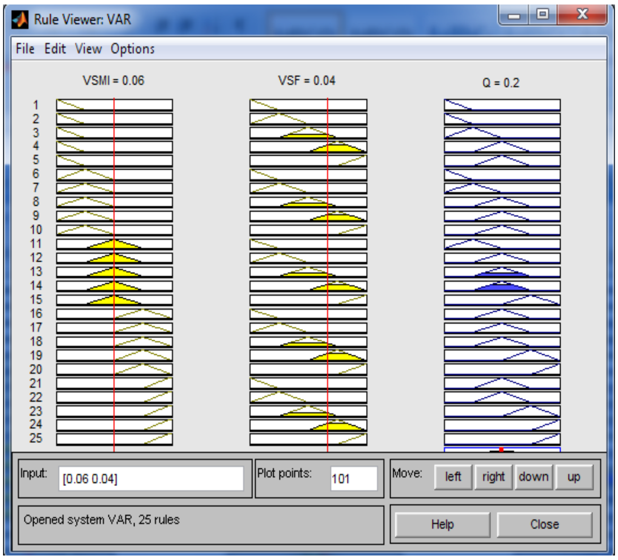

Fig. 4. FIS Sample output

Table 1
Fuzzy inference system rules.

AND		ΔVSMI				
		L	LM	M	HM	H
	L	L	L	LM	M	M
ΔVSF	LM	L	LM	M	M	M
	M	LM	M	M	M	HM
	HM	M	M	M	HM	H
	H	M	M	HM	H	H

3.3.2 VAR limit control

In order to minimize VAR devices investment cost, the number of VAR support location should be reduced. So, the VAR support should be provided on the critical load buses (Q_C^{CBS}). The VAR limit control updates the VAR support required at the Q_C^{CBS} subject to a maximum of reactive load power at the critical buses

(Q_L^{CBS}) using following Eq. (18).

$$Q_C^{CBS} = Q_C^{CBS} + \Delta Q_C \qquad (18)$$

$$\text{if, } Q_C^{CBS} \geq Q_L^{CBS}, \text{ then set } Q_C^{CBS} = Q_L^{CBS}$$

The maximum Q_C^{CBS} is limited to Q_L^{CBS} for avoiding over compensation.

The proposed system is tested with different system configurations. In each configuration, SVR model estimates the VSMI^{CB} and VSF^{CB}. These estimated values are compared with threshold values of VSMI^{T} and VSF^{T}. If both the error components ΔVSMI and ΔVSF are less than or equal to zero, then the system remains in stable. If any one or both the error components are positive, then the FLC determines the ΔQ_C and the VAR limit controller provides Q_C^{CBS} . This calculated VAR support is injected in the corresponding critical buses and the new values of VSMI^{CB} and VSF^{CB} are recalculated. These values are compared again with threshold values, and this process is continued until the error components ΔVSMI and ΔVSF become zero or negative.

3.3. Generation of training and testing data

The training and testing data of the SVR are generated for different system configurations as follows.

- The system under normal operating condition.
- The load active and reactive powers are changed ($\pm$ 30% of the base case values) and supplied by slack generator.
- The load active and reactive powers are changed ($\pm$ 30% of the base case values and +50% generator active powers).
- The system under N-1 contingency.
- The system under N-1 contingency with load and generator changes.

  The power factor at each bus is maintained constant during pattern generation. Each randomly generated pattern is then verified by a conventional power flow program to make sure that each of the cases provides a feasible power flow solution and obtain the operating points. The cases, for which the power flow does not meet the steady state operating requirements, are removed. The acceptable cases are subjected to CPF.

4. Proposed algorithm.

The algorithm of the proposed system is briefly described in the following steps:

1. Different system configurations are created randomly by perturbing the load and line as described in the subsection 3.3.

2. The valid random cases are collected through a conventional power flow program to ensure that only the acceptable cases are subjected to CPF.

3. Determine the most critical bus of the given power system using VSF as explained in section 2.1.

4. An input vector θ_L and Q_L are generated using conventional power flow and respective target vector VSMI^{CB} and VSF^{CB} are determined using CPF.

5. Choose different possibilities, such as kernel type, kernel parameters and SVR parameters (C and *γ)* to train the SVR network.

6. Train the SVR network using the training data set. Test the accuracy of the regression model to unseen test samples and verify the predictor of voltage stability margin.

7. Develop the FLC to obtain ΔQ_C by the mapping $\Delta \mathrm{VSMI}$ and $\Delta \mathrm{VSF}$ as explained in section 3.3.1.

8. Choose threshold values VSMI^T and VSF^T experimentally and set $\mathrm{Q}_C^{CBS} = 0$

9. Compute error components $\Delta \mathrm{VSMI}$ and $\Delta \mathrm{VSF}$ using Eq. (17) for a new system configuration. If both the error components are ≤ 0, then the system is stable and stop the computation. Else, compute ΔQ_C by a fuzzy logic controller.

10. Determine Q_C^{CBS} using Eq. (18). It changes the operating condition of the system and improves the values of VSMI^{CB} and VSF^{CB}, then go to step 9.

5. Simulation results and discussions

The proposed algorithm is applied to the IEEE 14 bus and IEEE 30 bus systems. These are the standard test systems used by the researchers to validate their results. The numerical data for IEEE 14 bus and IEEE 30 bus systems are taken from the reference [26]. Initially, critical buses are computed by VSF for each test case with heavy loading conditions as explained in section 2.1. The ranking of the critical buses of the test systems is shown in Table 2. It is identified that buses 14 and 30 are the most vulnerable buses for IEEE14 and IEEE30 bus system respectively.

Table 2
Ranking of critical buses of the test systems.

Test system	Critical buses for VAR support(Q_C^{CBS})
IEEE-14 Bus	14, 9, 5, 4, 10
IEEE-30 Bus	30, 29, 26, 24, 19, 20, 21

Patterns of about 6470 and 8010 are generated in IEEE 14 bus and IEEE 30 bus respectively. Out of these patterns 5823 and 7209 patterns (90%) are randomly selected for SVR training, while the left 647 and 801 patterns (10%) are used for testing the SVR. In each system configuration, the input vectors, bus voltage angle θ_L and load reactive power Q_L at the initial operating point of load buses are computed using the conventional Newton-Raphson method.The voltage stability indices, VSMI^{CB} and VSF^{CB} are then computed by the continuation power flow method. In this paper, conventional power flow and continuation power flow solutions are obtained using the Power System Analysis Toolbox (PSAT). The PSAT is a MATLAB based open source software tool for electric power system analysis and control [27]. All the computations are performed on a personal computer with 2.5GHz Intel Core i5-2450M CPU and 4 GB of RAM in MATLAB 7.8 software.
MATLAB supported SPIDER SVM tool is used for training the SVMs in the regression. This paper use multi-output SVR for multiple outputs as VSM^{CB} and VSF^{CB}. The training performance of the SVR module depends on proper selection of SVR parameter such as cost function *C* and *γ* and kernel types. The various kernel types considered for SVM regression are the Radial Basis Function (RBF), linear, Gaussian and polynomial. This paper uses RBF kernel type because of its superiority over the others and the optimal value of *C* and *γ* are chooses 100 and 0.2 for obtaining highest cross-validation accuracy [20].The trained SVR can be used to predict the VSMI^{CB} and VSF^{CB} for the unseen test cases.

5.1. SVR performance in estimation of VSMI and VSF

Figs.5and 6 shows that the accuracy of the estimated VSMI^{CB} and VSF^{CB} by the trained SVR in IEEE14 bus and IEEE 30 bus system respectively. The graphs plot the "Error of VSMI^{CB} and VSF^{CB}" against the testing patterns by the SVR for the unseen test cases. The comparison of mean square errors (MSE) and the computational time for training and testing of SVRs and ANN model for both IEEE 14 bus system and IEEE 30 bus system are tabulated in Table 3. It shows that SVR is superior to ANN because, less training and testing error and time.

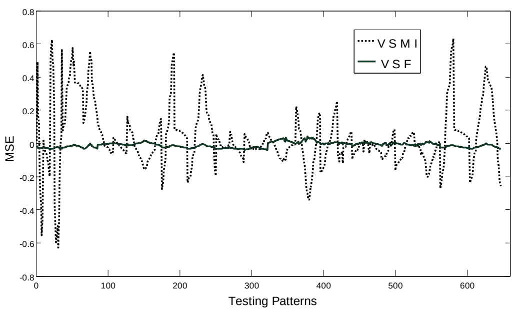

Fig.5. Error of testing patterns in IEEE 14 Bus system.

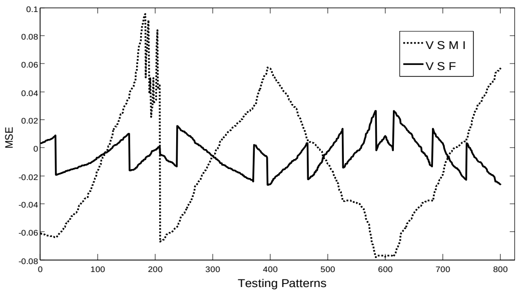

Fig.6. Error of testing patterns in IEEE 30 Bus system.

Table 3
Comparative analysis SVR with ANN in IEEE 14 Bus and 30 bussystems.

Test system	Parameters	ANN	SVR
IEEE 14 bus	No of neurons	6	-
	Training MSE	0.5537e-2	0.6532e-5
	Testing MSE	0.4762e-3	0.6142e-5
	Training time(S)	16.235	5.9256
	Testing time(S)	3.256	1.5631
IEEE 30 bus	No of neurons	7	-
	Training MSE	0.4721e-3	-0.5901e-5
	Testing MSE	0.4212e-3	-0.4159e-5
	Training time(S)	18.8742	5.7264
	Testing time(S)	3.9834	1.2637

The proposed tool not only assesses the voltage stability, also provide VAR support needed using FLC, when the system enters near the unstable condition. The fuzzy inputs ΔVSMI and ΔVSF are computed using Eq. (17) and are obtained from trained SVR. The threshold value of $VSMI^T$ and VSF^T depends on the power system configuration and the operating state, hence they are computed experimentally.

Table 4
Threshold Values

Test system	$VSMI^T$	VSF^T
IEEE-14 Bus	0.9600	0.0250
IEEE-30 Bus	0.9500	0.0200

The threshold value of $VSMI^T$ and VSF^T are chosen between the values of $\lambda_{\max}^c$ and $\lambda_{\max}$ through empirical observation. It is treated as constant for all the operating conditions. The chosen threshold values for $VSMI^T$ and VSF^T are given in Table 4.The proposed tool quickly provides the required reactive power support at the critical buses to enhance the voltage stability. The load buses require VAR support called critical buses in each test systems are shown in Table 2. It is also noted that in all the test cases the VAR support at the critical buses are limited to the local reactive power demand requirement. The proposed tool is then tested for different bilateral and multilateral transactions in every test system.

5.2. Cost of VAR compensation

It is assumed that the reactive compensators are installed at critical buses. The charge for using capacitors is assumed proportional to the amount of the reactive power output purchased [28].It can be expressed asEq.(19)

$$C_{cj}(Q_{cj}) = r_{cj}Q_{cj} \tag{19}$$

Where,
Q_{cj}: injected reactive power at the bus j in *(MVAh)*.r_{cj} is the price of reactive power per *MVAh*. The amount injected reactive power depends on the system operating condition and the voltage stability margin requirement. The price of reactive power depending on some factors such as capital cost,period of a lifetime and average utilization factor. For example, investment cost of VAR support device is \$22000/*MVAh*,lifetime of 30 years and average use of 2/3, r_{cj} can be calculated as follows:

$$r_{cj} = \frac{Investment\ cost}{Operating\ hours}$$

$$r_{cj} = \frac{\$22000}{30*365*24*\frac{2}{3}} = 0.1255\ \$/\ \mathrm{MVAh})$$

5.3. VAR support estimation

In the IEEE 14 bus system, the following bilateral and multilateral transactions are considered.

1. 5MW of power injected at generator bus 6 and the same amount is consumed by the load at bus 10.
2. 10MW of power injected at generator bus 2 and the same amount is consumed by the load bus 13.
3. 10 MW of power injected at generator bus 2 and the same amount is consumed by the load bus 9.
4. 12MW of power injected at generator bus 2 and the same amount is consumed by the load bus 2 with outage the line (9-10).
5. 5MW of power injected at generator bus 6 and the same amount is consumed by the load bus 6 with outage the line (6-11).
6. 5 MW of power injected at generator buses 3 and 6 respectively, and 5 MW consumed by the load buses 5and 13 respectively.
7. 10 MW of power injected at generator buses 2 and 6 respectively, and 10 MW consumed by the load buses 5and 13 respectively.

8. 10 MW and 5MW of power injected at generator buses 2 and 3 respectively, and 10 MW and 5MW consumed by the load buses 10and 12 respectively.

9. 10 MW and 5MWof power injected at generator buses 2 and 3respectively, and 10 MW and 5MW consumed by the load buses 10and 12 respectively with outage the line (6-12).

Table 5
VAR support of IEEE 14-bus system using ANN.

Trans action	Q_C^{CBS} (p.u)					Total VAR support (p.u)	VAR support Cost $/MVAh	BC		AC		VAR support provided time (Sec)
	14	9	5	4	10			$VSMI^{CB}$	VSF^{CB}	$VSMI^{CB}$	VSF^{CB}	
1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9802	0.0201	0.9802	0.0201	0.0000
2	0.0340	0.1062	0.0122	0.0200	0.0394	0.2116	0.0265	0.9323	0.0509	0.9681	0.0246	2.5342
3	0.0200	0.0764	0.0102	0.0232	0.0302	0.1600	0.0200	0.9305	0.0507	0.9677	0.0206	2.8225
4	0.0366	0.1260	0.0134	0.0325	0.0456	0.2541	0.0318	0.8799	0.0485	0.9667	0.0202	5.6721
5	0.0250	0.0914	0.0348	0.0260	0.0112	0.1884	0.0236	0.8674	0.0635	0.9668	0.0232	2.0457
6	0.0180	0.0744	0.0100	0.0221	0.0292	0.1537	0.0192	0.9409	0.0485	0.9693	0.0244	3.0153
7	0.0300	0.1062	0.0122	0.0228	0.0394	0.2106	0.0264	0.9068	0.0776	0.9641	0.0234	3.1024
8	0.0200	0.0764	0.0302	0.0232	0.0102	0.1600	0.0200	0.9363	0.0576	0.9628	0.0249	2.9100
9	0.0500	0.1660	0.0580	0.0400	0.0160	0.3300	0.0414	0.9017	0.0662	0.9705	0.0249	8.2561

Table 6
VAR support of IEEE 14-bus system using SVR.

Trans action	Q_C^{CBS} (p.u)					Total support VAR (p.u)	VAR support Cost $/MVAh	BC		AC		VAR support provided time (Sec)
	14	9	5	4	10			$VSMI^{CB}$	VSF^{CB}	$VSMI^{CB}$	VSF^{CB}	
1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9845	0.0201	0.9845	0.0201	0.0000
2	0.0340	0.1060	0.0121	0.0200	0.0392	0.2111	0.0264	0.9232	0.0509	0.9682	0.0226	2.4563
3	0.0198	0.0761	0.0102	0.0231	0.0300	0.1592	0.0199	0.9395	0.0507	0.9734	0.0201	2.7125
4	0.0365	0.1260	0.0132	0.0323	0.0452	0.2532	0.0317	0.8806	0.0485	0.9691	0.0200	5.3729
5	0.0249	0.0913	0.0346	0.0258	0.0110	0.1876	0.0235	0.8698	0.0635	0.9768	0.0211	2.0065
6	0.0178	0.0742	0.0100	0.0220	0.0292	0.1532	0.0192	0.9489	0.0485	0.9702	0.0234	2.9133
7	0.0300	0.1061	0.0122	0.0225	0.0391	0.2099	0.0263	0.9088	0.0776	0.9649	0.0214	2.8026
8	0.0200	0.0763	0.0300	0.0228	0.0101	0.1591	0.0199	0.9263	0.0576	0.9628	0.0213	2.8105
9	0.0499	0.1660	0.0578	0.0397	0.0155	0.3279	0.0412	0.9057	0.0662	0.9756	0.0247	7.3678

The one line diagram of IEEE 30 bus system with the splitting of Area 1, 2 and 3 is given in fig.7. The following bilateral and multilateral transactions are considered for the system.

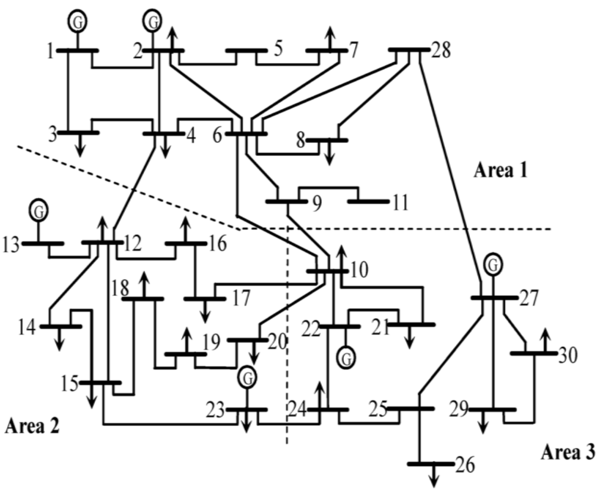

Fig.7. Single line diagram of IEEE 30 bus system.

1. Generator at bus 2 in area 1 supplies 10 MW to the load at bus 15 in area 2.
2. Generator at bus 2 in area 1 supplies 10 MW to the load at bus 17 in area 2.
3. Generator at bus 2 in area 1 supplies 10 MW to the load at buses14 and 17 in area 2
4. Generator at bus 13 in area 2 supplies 10 MW to the load at bus 15 in area 3.
5. Generator at buses13and 23 in area 2 supplies 10 MW to the load at buses 10 and 21 at area 3.
6. Generator at bus 13 in area 2 supplies 10 MW to the load at bus 10in area3 with line 10-21outage.
7. Generator at bus 27 in area 3 supplies 10 MW to the load at bus 8 in area 1.
8. Generator at buses27 and 22 in area 3 supplies 10 MW and 5MW to the load at buses3 and 7in area 1with line 6-9 outage.
9. Generator at bus 27 in area 2 supplies 10 MW to the load at bus 19 in area 2.

The simulation results obtained for various configurations of IEEE 14 bus system using ANN and SVR are provided in table 5 and 6 respectively. The table contains the VAR supports provided in the critical buses (Q_C^{CBS}), the total VAR supports, VAR support cost , $VSMI^{CB}$ andVSF^{CB} values for system before compensation (BC), after compensation(AC) and VAR support providing time. Similarly Table 7 and 8 contains simulation results for IEEE 30 bus using ANN and SVR respectively.

Table 7
VAR support of IEEE 30-bus system using ANN.

Transaction	Q_C^{CBS} (p.u)						Total VAR support (p.u)	VAR support Cost $/MVAh	BC		AC		VAR support provided time (Sec)
	30	29	26	24	19	20			$VSMI^{CB}$	VSF^{CB}	$VSMI^{CB}$	VSF^{CB}	
1	0.0049	0.0030	0.0094	0.0322	0.0189	0.0044	0.0728	0.0091	0.9456	0.0443	0.9509	0.0200	2.2004
2	0.0128	0.0063	0.0170	0.0516	0.0273	0.0058	0.1208	0.0152	0.9448	0.0441	0.9566	0.0183	2.7212
3	0.0181	0.0057	0.0154	0.0476	0.0316	0.0056	0,1240	0.0156	0.9258	0.0372	0.9536	0.0061	3.8931
4	0.0140	0.0069	0.0181	0.0546	0.0286	0.0061	0.1282	0.0161	0.8896	0.0918	0.9584	0.0332	5.6721
5	0.0080	0.0044	0.0046	0.0201	0.0136	0.0035	0.1542	0.0194	0.9296	0.0399	0.9554	0.0097	3.0153
6	0.0051	0.0031	0.0096	0.0328	0.0191	0.0044	0.0741	0.0093	0.9399	0.0441	0.9607	0.0215	3.1024
7	0.0045	0.0028	0.0090	0.0313	0.0185	0.0043	0.0704	0.0088	0.9400	0.0405	0.9560	0.0202	1.9324
8	0.0114	0.0058	0.0156	0.0482	0.0258	0.0056	0.1125	0.0141	0.9135	0.0387	0,9559	0.0125	6.7821
9	0.0118	0.0059	0.0156	0.0483	0.0258	0.0060	0.1134	0.0142	0.9135	0.0395	0.9560	0.0130	3.9543

Table 8
VAR support of IEEE 30-bus system using SVR.

Transaction	ΔQ_C^{CBS} (p.u)						Total VAR (p.u)	VAR Cost	BC		AC		VAR support provided time (Sec)
	30	29	26	24	19	20		\$/MVAh	$VSMI^{CB}$	VSF^{CB}	$VSMI^{CB}$	VSF^{CB}	
1	0.0047	0.0030	0.0094	0.0321	0.0186	0.0042	0.0721	0.0090	0.9459	0.0423	0.9602	0.1820	2.1259
2	0.0127	0.0063	0.0170	0.0514	0.0271	0.0056	0.1201	0.0151	0.9471	0.0421	0.9585	0.0167	2.5322
3	0.0180	0.0055	0.0153	0.0475	0.0314	0.0054	0.1231	0.0154	0.9335	0.0321	0.9534	0.0060	3.7654
4	0.0139	0.0068	0.0180	0.0543	0.0284	0.0059	0.1272	0.0159	0.8946	0.0715	0.9584	0.0132	5.4362
5	0.0079	0.0043	0.0043	0.0201	0.0134	0.0034	0.1534	0.0192	0.9372	0.0388	0.9675	0.0097	3.0112
6	0.0050	0.0031	0.0095	0.0326	0.0190	0.0042	0.0734	0.0092	0.9402	0.0421	0.9661	0.0167	3.0021
7	0.0044	0.0027	0.0090	0.0312	0.0183	0.0042	0.0698	0.0087	0.9423	0.0401	0.9668	0.0126	1.9030
8	0.0114	0.0057	0.0154	0.0481	0.0257	0.0053	0.1116	0.0140	0.9234	0.0367	0.9678	0.0125	6.7001
9	0.0117	0.0059	0.0155	0.0481	0.0252	0.0058	0.1122	0.0141	0.9200	0.0386	0.9568	0.0130	3.9523

In the IEEE 14 bus system, for transaction 1, $VSMI^{CB}$ value is greater than $VSMI^{T}$ and the VSF^{CB} value is less than the VSF^{T}. According to Eq. (17) there is no need for VAR support. But in remaining transactions, the $VSMI^{CB}$ value is less than $VSMI^{T}$ and VSF^{CB} value is greater than the VSF^{T}, which leads the system to instability condition. Hence there is a need for VAR support to be provided for the system to reach the stable condition.

In all transactions of the IEEE 30 bus system, the $VSMI^{CB}$ value is less than $VSMI^{T}$ and VSF^{CB} value is greater than the VSF^{T}, then the system reaches the instability condition. Hence there is a need for VAR support to be provided for the system to reach the stable condition. The inference from the Tables 5,6,7and 8 is clearly evident that the total VAR support requirement, their cost and VAR support providing time in the system using SVR is found better than ANN based system.

6. Conclusion

This paper has developed a SVR model along with FLC based tools for online VSM assessment and improvement. The voltage stability indices, $VSMI^{CB}$ and VSF^{CB} in the power system has been calculated using the SVR at every monitoring period. Moreover, a fuzzy logic methodology has been formulated to estimate the required VAR support to improve the voltage stability in a power system. The proposed tool has been used to estimate the voltage stability and required VAR support under normal operating conditions, N-1 contingencies as well as deregulated environment. The validity of the proposed model has been demonstrated by applying it to the IEEE 14bus and 30bus systems. The results from ANN and SVR performance and VAR supports of all transactions of the power systems network reveals that the SVR model is more effective and computationally feasible for online voltage stability assessment and improvement.

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