ANN BASED ONLINE VOLTAGE STABILITY MARGIN ASSESSMENT IN DEREGULATED POWER SYSTEM

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Abstract: *Recently the operation of power system strategies have changed significantly due to the introduction of deregulation in electricity markets. Today, the power system are being operated with high stress, hence sufficient voltage stability margin and reactive power support are necessary to be managed to ensure secured operation of power system. This paper proposes an Artificial Neural Network (ANN) along with Fuzzy Logic Controller (FLC)based tool for online voltage stability monitoring and estimation of VAR support requirement at the critical buses of power system for improving voltage stability margin at different operating conditions. The ANN input vector is in the form of bus voltage angle and reactive power load. The voltage stability margin (VSM) and voltage stability factor (VSF) of the most vulnerable bus are used as target for ANN. The proposed tool can successfully estimate the voltage stability margin and VAR support for various transactions in deregulation environment and also under N-1 contingency. The ANN input and output patterns are generated from offline process for various simulated loading conditions using conventional continuation power flow method. The proposed method has been successfully applied to the IEEE 14 bus and IEEE 30 bus test system.*

Keywords Voltage stability margin, Artificial neural network, Fuzzy logic controller, VSM, VSF 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, tend to operate the system 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 disturbance [3]. A power system enters a state of voltage instability when a disturbance results in a progressive and 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]. One of the main responsibilities of the independent system operator (ISO) is to establish an equitable and fair transmission services in an open-market structure to provide a reliable and secure power systems [6].

In order to prevent the occurrence of voltage collapse, it is essential to accurately predict the operating condition of a power system. So, ISO need 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 [7-10]. The main difficulty in these methods is that Jacobian matrix of power flow equation becomes singular at voltage stability limit. The continuation power flow overcomes this problem [11-12]. The continuation method based voltage stability analysis techniques are fairly accurate 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 artificial neural network, fuzzy logic, 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 sufficiently accurate online response.

In reference [13], authors have investigated voltage magnitudes and the phase angles are the best predictors of online voltage stability margin assessment. The phase angles and load reactive power are used as the best predictors of online voltage stability margin assessment in [14]. In reference [15], a single ANN with fewest input features used for estimating voltage stability margin with sufficient accuracy and high execution speed. Fuzzy logic approach has been used to determine the maximum loadability limit in [16]. The comparative study of various voltage stability indices for the estimation of loadability margin is presented in reference [17].

In power system, voltage and reactive power support are linked to each other. The main factor causing instability is the inability of the power system to meet the demand for reactive power. 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 ensuring voltage stability. A multi-objective genetic algorithm is used for voltage stability enhancement using rescheduling of generator and optimal placement of FACTS devices briefed in [18]. A reactive power control approach based on fuzzy sets theory, for voltage stability enhancement by monitoring L-index has been presented in [19].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 [20]. However, they have not computed voltage stability margin and also the calculated VAR support was provided at all load buses of the power system and this leads to higher VAR support requirement for the projected load demand.

From the observation of vast literature shows that the researchers have considered assessment of voltage stability or voltage stability margin estimation or VAR support estimation separately in the monopoly power system. This paper employs bus voltage angle and load reactive power as input attributes and two output voltage stability indices VSM and VSF to predict the voltage stability margin and determine the minimum VAR support required for enhancing voltage stability margin in the restructured power system. This paper presents the development of artificial neural network 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 voltage stability margin at different loading and system configurations in restructured power system.

The rest of the paper is organized as follows. Section 2 describes the voltage stability indices and calculation of VSM and VSF using CPF. The design of the proposed tool by using ANN along with fuzzy logic controller 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 concludes the paper.

2. Voltage Stability Indices
2.1 Voltage Stability Margin (VSM)
Voltage stability margin is defined as a megawatt (MW) distance between the current operating point and maximum loading condition according to the system loading parameter [15] as illustrated graphically in Fig.1. To find successive load flow solution using continuation power flow, the load flow equation is reformulated by inserting loading parameter λ. So, locally parameterization technique can be applied. Using constant power load, the general form of power flow equations are:

$$P_i = \sum_{k=1}^{n} V_i \ V_k \ Y_{ik} \cos(\partial_i - \partial_k \gamma_{ik}) \tag{1}$$

$$Q_i = \sum_{k=1}^{n} V_i \ V_k \ Y_{ik} \sin(\partial_i - \partial_k \gamma_{ik}) \tag{2}$$

Where,

$Pi = P_{Gi} - P_{Li}$, $Qi = Q_{Gi} - Q_{Li}$

P_i = Injected active power at i^{th} bus.

Q_i = Injected reactive power at i^{th} bus

P_{Gi} = Active power generation at i_{th} bus.

Q_{Gi} = Reactive power generation at i^{th} bus.

P_{Li} = Active power load at i^{th} bus.

Q_{Li} = Reactive power load at i^{th} bus.

V_i = Voltage magnitude at bus i.

∂_i = Voltage angle at bus i.

V_k = Voltage magnitude at bus k.

∂_k = Voltage angle at bus k.

Y_{ik} = Admittance matrix [Ybus].

γ_{ik} = Admittance angle.

The loading parameter λ is used to simulate the active and reactive power load/generation increases, the equation of P_i, Q_i and P_{Li}, Q_{Li} can be modified as

$$P_i = P_{Gi}(\lambda) - P_{Li}(\lambda), Q_i = Q_{Gi}(\lambda) - Q_{Li}(\lambda)$$

Then,

$$P_{Li}(\lambda) = P_{Li0} + \lambda[S\Delta_{base} \cos(\varphi_i)] \tag{3}$$

$$Q_{Li}(\lambda) = Q_{Li0} + \lambda[S\Delta_{base} \sin(\varphi_i)] \tag{4}$$

Where,

$$S\Delta_{base}\cos(\varphi_i) = P_{Li0}$$
$$S\Delta_{base}\sin(\varphi_i) = Q_{Li0}$$

P_{Li0}, Q_{Li0} = original load at bus i active and reactive respectively, $S\Delta_{base}$ = Apparent power at original load.

φ_i = power factor angle of load at bus *i*.

So, Equations 3 and 4 can be written as

$$P_{L_i}(\lambda) = P_{L_{io}}[1+\lambda]; \; Q_{L_i}(\lambda) = Q_{L_{io}}[1+\lambda] \qquad (5)$$

Where, $P_{L_{io}}$ and $Q_{L_{io}}$ are base case load demands at i^{th} bus.

The VSM is expressed as,

$$VSM = \frac{|S_M| - |S_O|}{|S_O|} \qquad (6)$$

Where, $|S_M|$ and $|S_O|$ denotes the maximum and base case values of the total system apparent powers, respectively. For a power system with 'n' buses, the voltage stability margin can be calculated as:

$$VSM = \frac{|S_M| - |S_O|}{|S_O|} = \frac{\Sigma_{i=1}^{n}\sqrt{P_{L_{imax}}^2 + Q_{L_{imax}}^2} - \Sigma_{i=1}^{n}\sqrt{P_{L_{io}}^2 + Q_{L_{io}}^2}}{\Sigma_{i=1}^{n}\sqrt{P_{L_{io}}^2 + Q_{L_{io}}^2}} \qquad (7)$$

Using (5), $P_{L_i max}$ and $Q_{L_i max}$ are obtained by:

$$P_{L_{imax}} = P_{L_{io}}[1+\lambda_{max}]; \; Q_{L_{imax}} = Q_{L_{io}}[1+\lambda_{max}] \qquad (8)$$

Where, λ_{max} is the maximum system loading parameter. $P_{L_i max}$ and $Q_{L_i max}$ denotes the maximum active and reactive power load at the ith bus corresponding to λ_{max}. Substituting $P_{L_i max}$ and $Q_{L_i max}$ from Eq. (8) into Eq.(7), one can easily show that the VSM is indeed equal to λ_{max}. In other words, we have:

$$VSM = \lambda_{max} \qquad (9)$$

2.2 Voltage Stability Factor (VSF)

The differential change in voltage magnitude at each bus for a given differential change in total active power demand is defined as VSF [11].

$$VSF \text{ of bus } i = \frac{dV \text{ for bus } i}{\text{sum of } dP_S \text{ for all buses}} \qquad (10)$$

$$VSF_i = \frac{dV_i}{dP_{TOTAL}} \qquad (11)$$

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. As dP_{TOTAL} is same for all buses and hence, the dV_i determine the VSF. The bus with the highest VSF can be treated as the most critical bus in the system. The most critical bus is the one that is nearest to experiencing voltage collapse. This index will be zero when the critical bus is far away from voltage instability.

2.3 Calculation of VSM

The VSM (λ_{max}) and VSF are computed by using continuation power flow 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.CPF finds successive load flow solutions according to the given load scenario. It consists of prediction and correction steps. From a known base solution, a tangent predictor is used so as to estimate the next solution for a specified pattern of load increase. The corrector step then determines the exact solution using Newton-Raphson technique. After that a new prediction is made for a specified increase in load based upon the new tangent vector. Then corrector step is applied. This process goes until critical point is reached. The critical point is the point where the tangent vector is zero. In Fig. 1, the VSM is the distance from the current operating point (λ_1) to the critical point on the λ –V curve. 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 (λ_{max}^c) is less than that of pre-contingency (λ_{max}^n) due to N-1 contingency.VSM^T to be kept in the system for voltage stability.
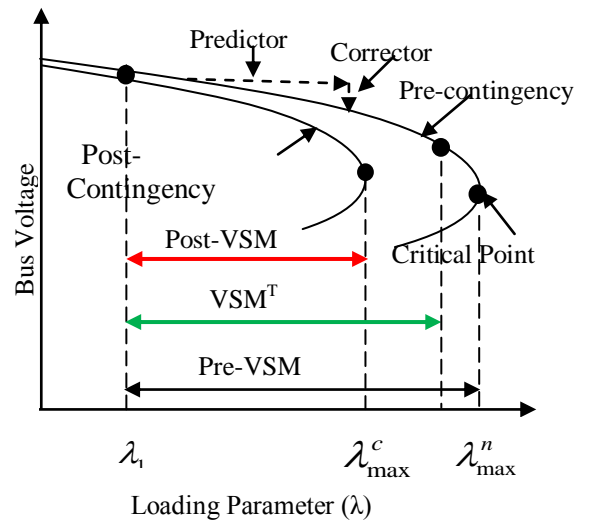

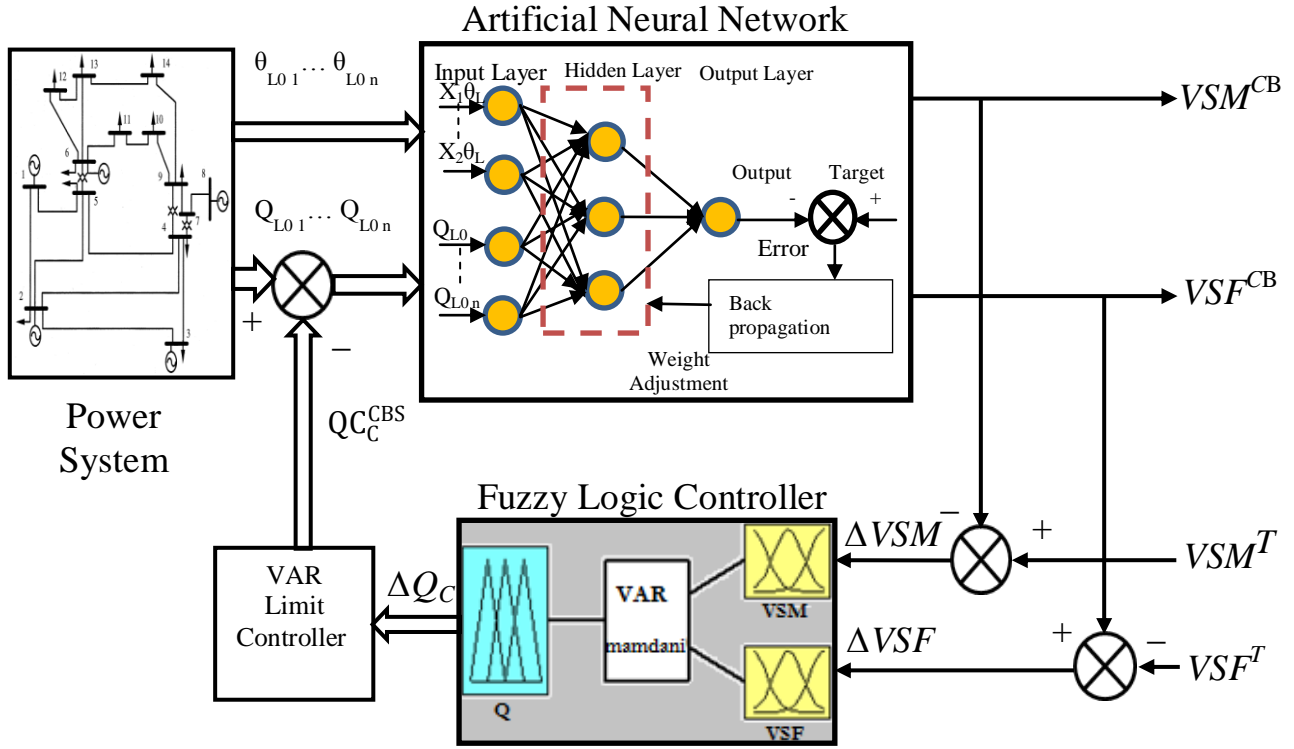Fig.1. Definition of VSM^T, Pre-VSM and Post-VSM.

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

3. Proposed system

Fig.2 conceptually shows the structure and process of the proposed online tool. It is developed using an ANN, fuzzy logic controller and Q-limit control logic. A multilayer feed forward ANN model evaluates the voltage stability state of the power system by monitoring the values of VSM and VSF at the critical bus in different system configurations. The weakest bus is the one that is nearest to experiencing voltage collapse. It is a recognized fact that the voltage stability assessment by VSM and VSF at the most critical bus and enhancement at the most critical bus by VAR support improves the voltage stability of the entire power system. In other words, the information available at the most critical bus is an indication of how far the system is away from the instability point [20].

The VSM value of the most vulnerable bus is same for all load buses in the system. When the power system operating conditions are closer to voltage instability limit, a fuzzy logic along with Q-limit logic controller compute the required VAR support to be provided to enhance the voltage stability of the system. The design of an ANN and Fuzzy logic controller is described as follows.

3.1. Artificial Neural Network methodology

Among the numerous artificial neural networks which have been proposed, the most widely utilized type of neural network topology is the multilayer feed-forward network, because it is suitable for dealing with the nonlinear problems. This network, also called multi-layered perceptron (MLP), An MLP neural network consists of one input layer, one output layer and one or more hidden layers. Processing elements in an ANN are known as neuron. Each neuron is connected to other neurons through communication links, each with an associated weight.

The neuron calculates its output by finding the weighted sum of its input and then applying an activation function which produces an activation level inside the neuron. Generally the activation function is sigmoidal function and is linear for the hidden and output layers, respectively. After calculating the output layer is compared to a target and the error is applied in a backpropagation process to adjust the weights for minimize the total squared error of the output. A trial-and-error procedure is usually employed to determine the number of neurons in the hidden layers.

3.2. Design of fuzzy logic controller
3.2.1 Fuzzy modeling

Fuzzy Logic is a methodology to solve the problems which are too complex to be understood quantitatively. It is based on fuzzy set theory, introduced by Prof. Zadeh [21]. 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 VSM (ΔVSM) and change in VSF (ΔVSF) as inputs and gives the required reactive power at a load bus (ΔQ_C) as output. The fuzzy inputs ΔVSM and ΔVSF are determined from Eq. (12).

$$\Delta VSM = VSM^T - VSM^{CB}; \; \Delta VSF = VSF^{CB} - VSF^T \qquad (12)$$

The membership function and its ranges for fuzzy inputs (ΔVSM, ΔVSF) and output (ΔQ_C) are shown in Figure.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 (ΔVSM and ΔVSF) with each five linguistic variable produce twenty five rules for the fuzzy Inference System is shown in Table 1. For illustration purpose, two rules are explained below:
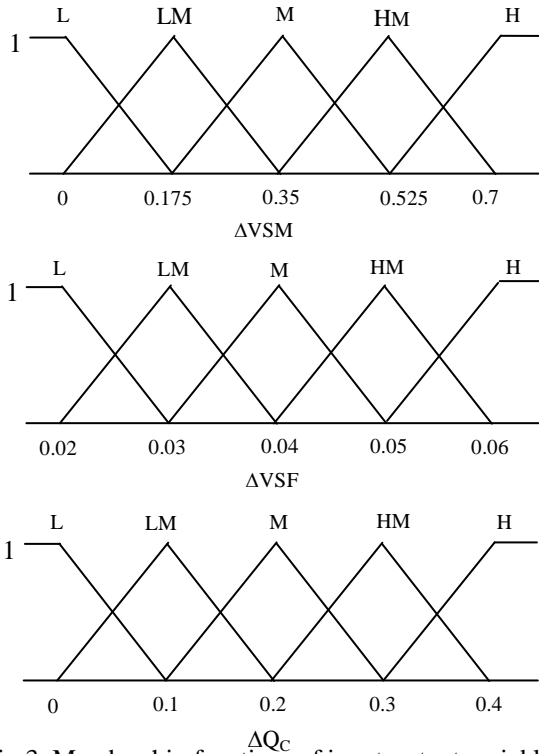

Fig.3. Membership functions of input-output variable

If ΔVSM is 'low' and ΔVSF 'medium' then required change in the VAR support (ΔQ_c)is 'low medium'.
If ΔVSM is 'high' and ΔVSF is 'high' then required change in the VAR support (ΔQ_c) is 'high'.
Fuzzy output signal is defuzzified by the centre of gravity defuzzification strategy to get the crisp output value [22].

Table 1
Fuzzy inference system rules

AND		ΔVSM				
		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

3.2.2 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 buses. The VAR limit control updates the VAR support required at the critical buses (Q_C^{CBS}) subject to a maximum of reactive load power at the critical buses

(Q_L^{CBS}) using following Eq. (13).

$$Q_C^{CBS} = Q_C^{CBS} + \Delta Q_C \qquad (13)$$

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

The maximum VAR support required at the critical buses is limited to Q_L^{CBS} for avoiding over compensation.

The proposed system is tested with different system configurations. In each configuration, ANN model estimate the VSM^{CB} and VSF^{CB}. These estimated values are compared with threshold values of VSM^T and VSF^T. If both the error components ΔVSM 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 fuzzy logic determines the ΔQ_C and the VAR limit controller provides the required VAR support at the critical buses(ΔQ_C^{CBS}). This calculated VAR support is injected in the corresponding critical buses and the new values of VSM^{CB} and VSF^{CB} are recalculated. These values are compared again with threshold values, and this process is continued until the error components ΔVSM and ΔVSF become zero or negative.

3.3. Generation of training and testing data

The training and testing data of the ANN is 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.

4. Proposed algorithm.

The solution algorithm for voltage stability estimation and required VAR support provided for enhance voltage stability can be briefly described in the following steps:

1. Determine the weakest bus of the given multi-bus system using VSF.
2. Different system configurations are created randomly by perturbing the load, generator and line as described in the subsection 3.3.
3. The random cases are gathered through a conventional power flow program to ensure that only the acceptable cases pass into the CPF.
4. An input vector $\theta_{L0,}$ and Q_{L0} are generated using conventional power flow and related target vector VSM^{CB} and VSF^{CB} are generated using CPF.
5. Select the set of training parameters such as number of epochs, learning increment and rate, performance goal with Mean Squared Error (MSE) and minimum and maximum gradient.
6. Train the network using the training data and validate its performance with testing data. If the performance is unsatisfactory, adjust the number of hidden layers, neurons and activation functions and repeat this process till satisfactory performance is obtained.
7. Evaluate the performance of the testing data through mean absolute error (MAE) as in Eq.(14).

$$ \text{MAE } \% = \frac{1}{M} \sum_{i=1}^{M} \frac{\left| y_i - y_0 \right|}{y_0} * 100\% \qquad (14) $$

Here, y_0 is the target VSM and VSF obtained from the CPF program and y_i is the VSM and VSF estimated by the ANN. M is the number of cases.
8. Develop the fuzzy logic model to obtain ΔQ_C by mapping ΔVSM and ΔVSF.
9. Choose threshold values VSM^T and VSF^T by experimentally and set $Q_C^{CBS} = 0$.

10. Compute error components ΔVSM and ΔVSF using Eq. (12) for a new system configuration. If both the error components are ≤ 0, then the system is stable, stop. Else, compute ΔQ_C by the FLC.

10. Determine Q_C^{CBS} using Eq. (12). It changes the operating condition of the system and adjust the value of VSM^{CB} and VSF^{CB}, then go to step 10.

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 [23]. Initially critical buses are computed by VSF for each test case with heavy loading conditions as explained in section 2.2. The ranking of the critical buses of the test systems are 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(ΔQ_C^{CBS})
IEEE-14 Bus	14, 9, 5, 4, 10
IEEE-30 Bus	30, 29, 26, 24, 19, 20, 21

In each system configuration, the input vectors, bus voltage angle (θ_L) and load reactive power (Q_L) at the initial operating point of the load buses are computed from the conventional Newton-Raphson method. For real time application, bus voltage angles and load reactive power can be obtained from phasor measurement units [24]. The voltage stability indices, VSM$_{CB}$ 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 by using Power System Analysis Toolbox (PSAT). PSAT is a MATLAB based open source software tool for electric power system analysis and control [25]. 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.

5.1. ANN performance

There are 6470 and 8010 patterns were generated in IEEE 14 bus and IEEE 30 bus respectively by varying the real, reactive loads and generator active power randomly from its base case value. Out of these patterns 5823 and 7209 patterns (90%) are randomly selected for ANN training, while the left and 647 and 801 patterns (10%) are used as the testing data to verify the ANN

performance in each test system. The network was trained for a maximum of 300 epochs or until the network training mean-squared error falls below 1e-4. A learning rate of 0.01 and a momentum constant of 0.9 was used in this study. A single ANN is trained for input features and output indices by the set of the training patterns. The number of hidden layers and the number of neurons in that layer were determined experimentally to be one hidden layer with six neurons for 14-bus and seven neurons for 30-bus system. The trained ANN can be used to predict the VSM and VSF of the most critical bus for unseen test cases.
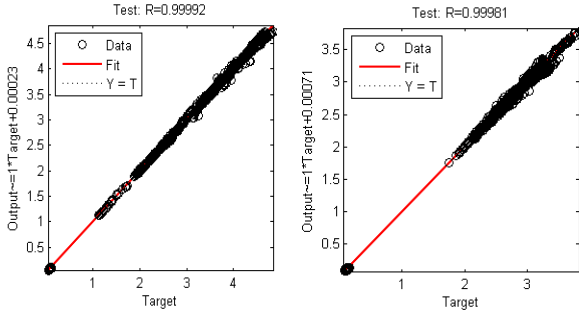

Fig.4. ANN VSM and VSF estimation performance of IEEE 14 bus and IEEE 30 bus.

Fig. 4 shows the accuracy of the estimated VSM and VSF by the ANNs trained in IEEE14bus and IEEE 30 bus system respectively. The graphs plot the "Target VSM and VSF" against the "Forecasted VSM and VSF" by the ANN, for the unseen test cases. If the target VSM and VSF completely matches with the forecasted VSM and VSF, all points should lie on the diagonal line. Table 3 lists the Mean Absolute Error % for the unseen test cases in each test system.

Table 3
Mean Absolute Error for the test cases

Test system	Mean Absolute Error %
IEEE 14-bus	$5.66574e^{-4}$
IEEE 30-bus	$7.33671e^{-5}$

The proposed tool not only assess the voltage stability and also provide VAR support needed when system enters near the unstable condition by using fuzzy logic controller. The fuzzy inputs ΔVSM and ΔVSF are computed using Eq. (12) and are obtained from trained ANN. The threshold value for VSM^T and VSF^T depends on the power system configuration and the operating state, hence they are computed experimentally.The values of VSM and VSF for IEEE 14 bus system under base case system condition are 3.973 and 0.0151 respectively. If these values are chosen as VSM^T and VSF^T, then the VAR support to be provided become excessive. On the other hand, VSM and VSF values in

the same system under line outage (4-9) with 30% real power loading all load buses are 3.2828 and 0.0799 respectively. If these values are chosen as VSM^T and VSF^T, then they do not ensure that the power system is maintained in the stable condition. The threshold values are chosen within these two operating conditions through empirical observation. A similar procedure was adopted for the choice of threshold values for the IEEE 30 bus system. Once the threshold values are chosen for a given system, it is treated as constant for all the operating conditions. The chosen threshold values for VSM^T and VSF^T are given in Table 4.

Table 4
Threshold Values

Test system	VSM^T	VSF^T
IEEE-14 Bus	3.8230	0.0250
IEEE-30 Bus	5.2321	0.0200

The proposed tool quickly provides the required reactive power support at the critical buses to enhance the voltage stability. The required VAR support provided in the 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 and can be expressed in [26].

$$C_{cj}(Q_{cj}) = r_{cj}Q_{cj} \qquad (15)$$

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 life time 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:

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

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

Table 5

VAR support of the IEEE 14-bus system

Trans action	VAR support of the critical buses (ΔQ_C^{CBS}) (p.u)					Total VAR support (ΔQ_C)	VAR support cost $/MVAh	Before Compensation		After Compensation	
	14	9	5	4	10			VSM^{CB}	VSF^{CB}	VSM^{CB}	VSF^{CB}
1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	3.9403	0.0201	3.9403	0.0201
2	0.0340	0.1060	0.0121	0.0200	0.0392	0.2111	0.0264	3.6679	0.0509	3.8465	0.0226
3	0.0198	0.0761	0.0102	0.0231	0.0300	0.1592	0.0199	3.7327	0.0507	3.8672	0.0201
4	0.0365	0.1260	0.0132	0.0323	0.0452	0.2532	0.0317	3.4961	0.0485	3.8408	0.0200
5	0.0249	0.0913	0.0346	0.0258	0.0110	0.1876	0.0235	3.4463	0.0635	3.9205	0.0211
6	0.0178	0.0742	0.0100	0.0220	0.0292	0.1532	0.0192	3.7384	0.0485	3.8512	0.0234
7	0.0300	0.1061	0.0122	0.0225	0.0391	0.2099	0.0263	3.6028	0.0776	3.8303	0.0214
8	0.0200	0.0763	0.0300	0.0228	0.0101	0.1591	0.0199	3.6802	0.0576	3.8254	0.0213
9	0.0499	0.1660	0.0578	0.0397	0.0155	0.3279	0.0412	3.5825	0.0662	3.8560	0.0247

Table 6
VAR support of the IEEE 30-bus system

Transac tion	VAR support of the critical buses (p.u)						Total VAR support (ΔQ_C)	VAR support cost $/MVAh	Before Compensation		After Compensation	
	30	29	26	24	19	20			VSM^{CB}	VSF^{CB}	VSM^{CB}	VSF^{CB}
1	0.0049	0.0030	0.0094	0.0322	0.0189	0.0044	0.0728	0.0091	5.2068	0.0443	5.2525	0.0200
2	0.0128	0.0063	0.0170	0.0516	0.0273	0.0058	0.1208	0.0152	5.1742	0.0441	5.2388	0.0183
3	0.0181	0.0057	0.0154	0.0476	0.0316	0.0056	0,1240	0.0156	5.1056	0.0372	5.2215	0.0061
4	0.0140	0.0069	0.0181	0.0546	0.0286	0.0061	0.1282	0.0161	4.8720	0.0918	5.2485	0.0332
5	0.0080	0.0044	0.0046	0.0201	0.0136	0.0035	0.1542	0.0194	5.0914	0.0399	5.2323	0.0097
6	0.0051	0.0031	0.0096	0.0328	0.0191	0.0044	0.0741	0.0093	5.1839	0.0441	5.2610	0.0215
7	0.0045	0.0028	0.0090	0.0313	0.0185	0.0043	0.0704	0.0088	5.2037	0.0405	5.2357	0.0202
8	0.0114	0.0058	0.0156	0.0482	0.0258	0.0056	0.1125	0.0141	5.1717	0.0387	5.2348	0.0125
9	0.0118	0.0059	0.0156	0.0483	0.0258	0.0060	0.1134	0.0142	5.0029	0.0395	5.2356	0.0130

5.3. VAR support estimation

In IEEE 14 bus system, the following bilateral and multilateral transactions have been 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 line 9-10 is outage.

5. 5MW of power injected at generator bus 6 and the same amount is consumed by the load bus 6 with line 6-11 is outage.

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 10 and 12 respectively.

9. 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 with line 6-12 is outage.

The total VAR supports are obtained by injecting the VAR requirement at the critical buses (ΔQ_C^{CBS}) and VAR support cost of ANN is given as Table 5. In transaction 1, VSM^{CB} value is greater than VSM^T and the VSF^{CB} value is less than the VSF^T. According to Eq. (13) there is no need for VAR support. But in transaction 2, the VSM^{CB} value is less than VSM^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. The required VAR support at the critical buses are shown in the second row of Table 5 and the total amount of VAR support (ΔQ_C) 0.2111is need to be provided for the system to reach the stable condition. Similarly VAR support provided for the remaining transactions of IEEE 14 bus system as shown in Table 5.

The one line diagram of IEEE 30 bus system with the splitting of Area 1, 2 and 3 are given in fig.5. The

following bilateral and multilateral transactions are considered for the 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 buses 14 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 buses 13 and 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 10 in area 3 with line10-21outage.

7. Generator at bus 27 in area 3 supplies 10 MW to the load at bus 8 in area 1.

8. Generator at buses 27 and 22 in area 3 supplies 10 MW and 5MW to the load at buses 3 and 7in area 1with line 6-9 outage.

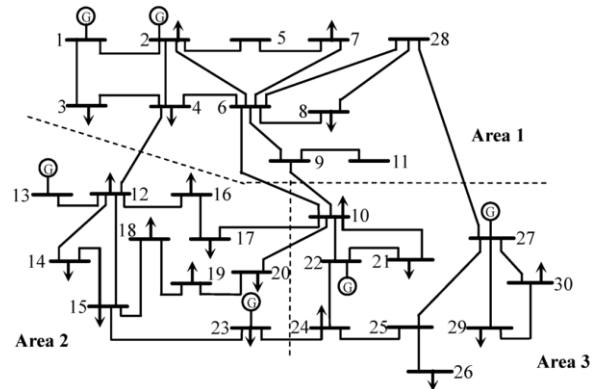9. Generator at bus 27 in area 2 supplies 10 MW to the load at bus 19 in area 2.

Fig.5. Single line diagram of IEEE 30 bus system.

The total VAR supports are obtained by injecting the VAR requirement at the critical buses (ΔQ_C^{CBS}) and VAR support cost of ANN is given as Table 6. In all transactions, the VSM^{CB} value is less than VSM^T and VSF^{CB} value is greater than the VSF^T, then the system reaches the instability condition. The required VAR support at the critical buses and the total amount of VAR support (ΔQ_C) provided for the system to reach the stable condition for the all transactions of IEEE 30 bus system are shown in the Table 6.
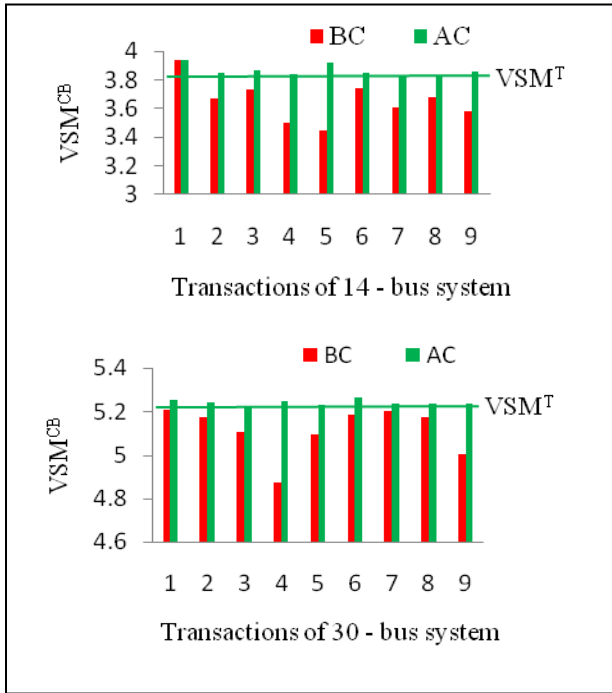
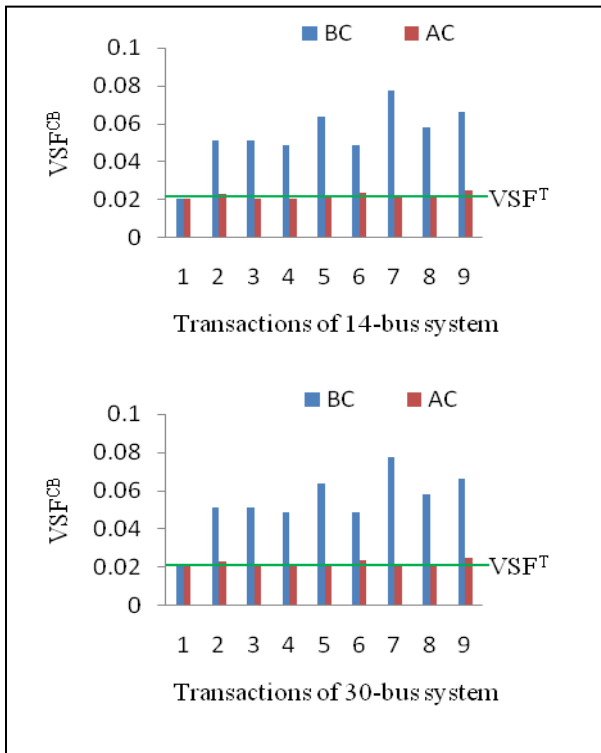Fig.6. VSM^{CB} before and after VAR support in test systems.

Fig. 7. VSF^{CB} before and after VAR support in test systems.

The VSM^{CB} and VSF^{CB} values obtained for each transaction of IEEE14 bus and IEEE 30 bus system before compensation (BC) and after compensation (AC) are graphically displayed through bar charts in Figs. 6 and 7 respectively. From these figures, it is observed that the operating point of transaction1 of 14-bus system is in the safe region, hence this case do not require VAR support. However, for the remaining cases of all test systems, the VSM^{CB} and VSF^{CB} values are in the critical region. Therefore, require VAR support to be provided at the critical buses of the each test system in order to traverse into the safe region. Thus, the proposed tool effectively monitor voltage stability through trained ANN and sufficient VAR support provided during unhealthy condition of the power system.

6. Conclusion

This paper has been developed an artificial neural network along with a fuzzy logic based tool for online voltage stability assessment and improvement. The voltage stability indices, VSM and VSF for most critical bus in the power system can be calculated using the ANN 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 14 bus and IEEE 30 bus systems. The results from ANN performance and VAR support calculation of all transactions of the power systems network shows that the proposed algorithm is effective and computationally feasible for online voltage stability assessment and improvement.

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