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Power systems wide-area voltage stability assessment considering dissimilar load variations and credible contingencies

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Abstract This paper reveals that the existing techniques have some deficiencies in the proper estimation of voltage stability margin (VSM) when applied to a power system with different load change scenarios. The problem gets worse when credible contingencies occur. This paper proposes a real-time wide-area approach to estimate VSM of power systems with different possible load change scenarios under normal and contingency operating conditions. The new method is based on an artificial neural network (ANN) whose inputs are bus voltage phasors captured by phasor measurement units (PMUs) and rates of change of active power loads. A new input feature is also accommodated to overcome the inability of trained ANN in prediction of VSM under $N-1$ and $N-2$ contingencies. With a new algorithm, the number of contingencies is reduced for the effective training of ANN. Robustness of the proposed technique is assured through adding a random noise to input variables. To deal with systems with a limited number of PMUs, a search algorithm is accomplished to identify the optimal placement of PMUs. The proposed method is examined on the IEEE 6-bus and the New England 39-bus test system. Results show that the VSM could be predicted with less than 1% error.

Keywords Artificial neural network (ANN), Phasor measurement unit (PMU), Voltage stability margin (VSM)

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1 Introduction

Voltage stability is defined as the ability of the power system to maintain steady voltages when it is subjected to perturbations [1]. In general, a power system is designed to operate under various conditions; however, it is inevitable that complex power systems will experience difficulties in the operation process some of which lead to the voltage collapse. In the sequel of many major blackouts [2, 3], tackling system voltage instability has attracted researchers' attention [4–7].

Among several methods developed so far to calculate voltage stability limit [8–11], continuation power flow (CPF) is one of the most efficient methods. In CPF method, new forms of power flow equations are introduced to overcome the convergence problem of conventional power flow algorithms near the stability limit point [11]. CPF method, although offers accurate outcomes, is time-consuming and undesirable for real-time applications. In [12], a modified coupled single-port model was proposed to monitor voltage stability of the system. Results show improvement in monitoring voltage stability in comparison with the conventional CPF method. In [13] and [14], two methods were developed to analyze voltage stability based on the Thevenin equivalent concept. What is missing in these methods is considering systems different conditions like contingencies.

As the CPF method is an offline method, it is not appropriate to be used it for online applications. In this manner, several data mining tools such as support vector machine, artificial neural networks (ANNs), fuzzy systems, and expert systems together with conventional techniques have been proposed to develop online monitoring of voltage stability [15–18]. Among these methods, ANN is a fast response technique promising to be used in real-time applications [16]. The capability of ANN in capturing nonlinear characteristics of the power system makes it suitable for real-world practices [19, 20]. ANN, as a "black-box" tool, includes input and output neurons. The performance of ANN is dominantly affected by the input feature selection. In the context of voltage stability assessment, [21] has selected active and reactive line flows as ANN inputs. In [22], active and reactive powers of load buses were used in the ANN input vector. Reference [23] used voltage magnitude of load buses and active and reactive powers of load and generation buses. In [13], performances of different inputs of the ANN were compared and it was deduced that the best performance of ANN is attained using bus voltage phasors as the input vector.

Dealing with a broad range of contingencies, such as line outages, is a challenge in voltage stability analysis. In $N-1$ contingency states, the trained ANN may fail to accurately estimate voltage stability margin (VSM) because of the change in the system configuration and characteristics. This may become worse in $N-2$ contingencies. Research attempts in [20–23] have used an ANN to evaluate voltage stability in the normal condition and a separate ANN for contingency states. This may be inappropriate for a large power system with a huge number and different types of contingencies.

In the previous works, voltage stability of power systems has been evaluated by using state variables of the current operating point. The long-term voltage stability phenomenon is highly dependent on the load change scenarios [1]. Since in large-scale power systems the loads vary in different scenarios, incorporating the rates of change in loads in the ANN design process can be a viable alternative [11]. To the best knowledge of the authors, this subject has not been covered in previous research efforts.

In view of the above concerns and requirements, this paper develops a novel ANN-based approach with explicit inputs reflecting load change scenarios in addition to bus voltage phasors. This combination of features is used since:

1) Proximity of voltage collapse could be estimated by using voltage magnitude.
2) Power flow could be predicted by means of phase angles [16].
3) Rates of load change give a direct implication to the devised ANN that which loads or regions has more effect on the system voltage stability limit. Note that the load change rate can be obtained by having two sequent power quantities captured by measurement and monitoring system.

The proposed method is able to estimate VSM in normal and contingency conditions by using a single ANN. The ability to determine voltage stability status in normal and contingency at the same time is the main advantage of the proposed method in comparison with the other online methods. To keep the ANN accuracy in contingency conditions, a specific input standing for contingency number is accounted for. As in the large-scale systems the number of contingencies is intractable, the performance of the proposed method would be affected. Accordingly, a new algorithm is introduced to reduce the number of contingency states supposed to be added in training phase of the ANN. The effectiveness of the proposed algorithm is examined on IEEE 6-bus test system and New England 39-bus test system.

The rest of the paper is organized as follows: some fundamental considerations of voltage stability are discussed in Section 2. An introduction to the ANN and the proposed methodology are presented in Section 3. Section 4 outlines simulation results. Section 5 summarizes the conclusions.

2 Fundamentals of voltage stability analysis

One of the main features that affects voltage stability of a power system is the limitation in transferring active and reactive powers through transmission lines. To explain the basics of voltage stability, a simple radial system is shown in Fig. 1 where a constant voltage source plays the role of infinite bus. Transmission line and load are represented by Z and Z_L, respectively. By decreasing Z_L, more power could be transferred to the load, until the maximum power is transmitted. Afterward, by further decrease of Z_L (demanding more power), the voltage drop will be more dominant and the power transferred to the load will eventually decrease. This process, shown in Fig. 2, is known as

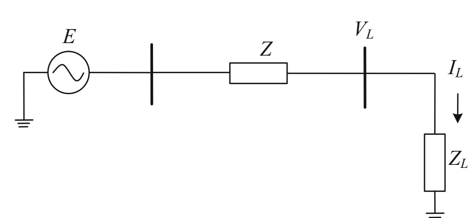

Fig. 1 A simple radial network

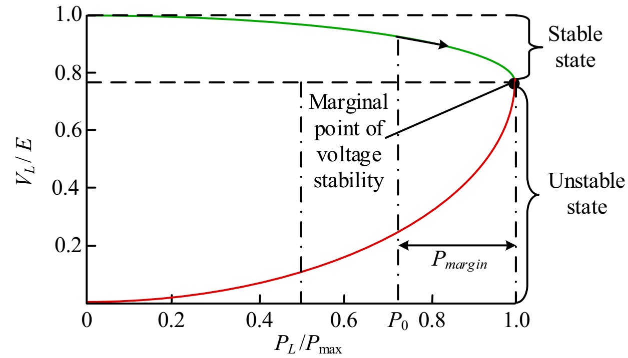

Fig. 2 *P-V* curve of simple radial system

the *P-V* curve. The current active power delivered to the load and the maximum possible active power transfer are P_0 and $P_{\max}$, respectively. VSM is defined as:

$$VSM = \frac{P_{\max} - P_0}{P_{\max}} \tag{1}$$

VSM is selected as a voltage stability indicator because of its simplicity of deduction for system operators and the speed of calculation [16, 17].

As a reliable method to obtain VSM, CPF method is often used [11]. In CPF method, a model of load, (2) is incorporated into the network (3) [16].

$$\begin{cases} P_L^i = P_{L0}^i + \lambda P_{Ld}^i \\ Q_L^i = Q_{L0}^i + \lambda Q_{Ld}^i \end{cases} \tag{2}$$

$$\begin{cases} P_i = V_i^2 G_{ii} + V_i \sum\limits_{i \neq j} V_j (G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) \\ Q_i = -V_i^2 B_{ii} + V_i \sum\limits_{i \neq j} V_j (G_{ij}\cos\theta_{ij} - B_{ij}\sin\theta_{ij}) \end{cases} \tag{3}$$

where P_L^i and Q_L^i are active and reactive power delivered to the load bus i; λ is a real number that defines loading of the system; P_{Ld}^i and Q_{Ld}^i are the rates of load changes in active and reactive power of the load bus i; P_i and Q_i are the active and reactive power injected to node i; V_i is the voltage magnitude at bus i; θ_{ij} is the voltage angle difference between buses i and j; G_{ij} and B_{ij} are the real and imaginary parts of the ij^{th} element of the system admittance matrix. The rates of change in active and reactive power are defined as deviations of the active and reactive powers as λ changes. In CPF method, by increasing λ, system load is increased until the load reaches maximum load limit. In bifurcation node, λ, P_L, and Q_L are equal to $\lambda_{\max}$, $P_{L\max}$, and $Q_{L\max}$, respectively.

3 Proposed methodology

The first step towards developing an appropriate ANN for the voltage stability monitoring is clarification of the goal of ANN and the problem in question. The problem defined in previous attempts is: "For a specific system condition, what would be the stability margin?" Specifying system condition includes obtaining system parameters and variables, such as voltage magnitude, active and reactive powers of the loads, etc. However, the problem in question in this paper is: "For a specific system condition and rates of load changes, what would be the stability margin?" The aspect of various load change scenarios is emphasized here since, based on the authors' experiences, real power systems do not have a unique and identical load increase pattern in all load points. This feature leads to significant deficiencies of the existing ANN models in proper estimation of VSMs. Neither increasing ANN training samples nor applying different configuration of ANN could handle this complexity. To overcome this difficulty, the rates of various load changes should be predicted and inserted as inputs into the ANN.

To compute VSM, MATLAB-based open source software tool PSAT is employed by applying CPF method on sample cases. After generating appropriate sample cases for training, validating, and testing the designed ANN, MATLAB neural network toolbox is employed to estimate VSM [21, 24].

3.1 ANN structure

In this study, the standard multilayer perceptron (MLP) neural network consisting of one input layer, one output layer, and one hidden layer including 10 neurons is employed to predict VSM of the power system shown in Fig. 3. The Levenberg-Marquardt back-propagation algorithm is selected for the training phase of ANN.

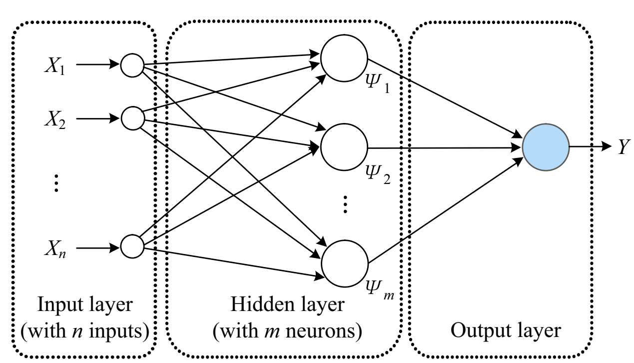

Fig. 3 Simplified diagram of MLP neural network

3.2 Input variables selection

The issue of selecting input variables is a basic and determinative aspect in obtaining the best performance of the model. Regarding ANNs, there is no straight method to specify which input could lead the model to the highest efficiency [25]. The difficulty of selecting input features is due to the following items:

1) There are many available variables of which those improving performance of the model should be selected.
2) Selected variables should have less correlation to avoid redundancy.
3) Selected variables should have a potential in estimation of VSM; worthless features may even lead to malfunction.

As indicated before, the combination of voltage angles and magnitudes of system buses as the input of ANN is the most effective feature combination in comparison to others, such as voltage magnitudes and reactive powers, etc. [16]. This deduction does not hold in the problem at hand since different rates of load changes are accommodated. Under these circumstances, a third input feature is needed. To do so, the rates of load changes are selected as the third input feature. In this way, ANN could directly learn how to respond along with different load change scenarios.

3.3 Data set generation

A wide range of possible states of the system and load change scenarios while having the minimum number of samples should be accounted for in generating ANN training data set. To do so, random variables are added to active and reactive powers of loads, active power of generators, voltage magnitude of PV buses, and the rate of load changes in load buses, respectively, as follows.

$$\begin{cases} P_L^i(j) = P_{L0}^i[1 + 2\Delta_{P_L}(0.5 - \varepsilon_{P_L}^i(j))] \\ Q_L^i(j) = Q_{L0}^i[1 + 2\Delta_{Q_L}(0.5 - \varepsilon_{Q_L}^i(j))] \end{cases} \tag{4}$$

$$\begin{cases} P_G^i(j) = P_{G0}^i[1 + 2\Delta_{P_G}(0.5 - \varepsilon_{P_G}^i(j))] \\ V_G^i(j) = V_{G0}^i[1 + 2\Delta_{V_G}(0.5 - \varepsilon_{V_G}^i(j))] \end{cases} \tag{5}$$

$$P_{Ld}^i(j) = P_{Ld0}^i[1 + 2\Delta_{P_{Ld}}(0.5 - \varepsilon_{P_{Ld}}^i(j))] \tag{6}$$

where P_{L0}^i, Q_{L0}^i, P_{G0}^i, V_{G0}^i, P_{Ld0}^i are the base cases of active and reactive power of load, active generation power, voltage magnitudes of generators, and the rate of changes in load bus i, respectively; $P_L^i(j)$, $Q_L^i(j)$, $P_G^i(j)$, $V_G^i(j)$, $P_{Ld}^i(j)$ are j^{th} samples of aforementioned variables. Random numbers in the range of zero up to one ($\varepsilon_{P_L}^i$, $\varepsilon_{Q_L}^i$, $\varepsilon_{P_G}^i$, $\varepsilon_{V_G}^i$, $\varepsilon_{P_{Ld}}^i$) are added to base values to generate new samples. Δ is the per unit value of range of variation and it is a known value. So, (4)–(6) represent random variables located within their associated feasible ranges. As an example for $P_L^i(j)$, if Δ equals to 0.3 (i.e. 30% variation from the base load) and $\varepsilon_{P_L}^i(j)$ equals to 0.9, the active power load at bus i in the case j equals to 76% of the base case active power.

Loads increase in a fixed power factor fashion, that is:

$$\frac{P_L^i(j)}{Q_L^i(j)} = \frac{P_{Ld}^i(j)}{Q_{Ld}^i(j)} \tag{7}$$

where $Q_{Ld}^i(j)$ is the rate of change in reactive power of the i^{th} bus in j^{th} sample. While $P_{Ld}^i(j)$, $P_L^i(j)$, $Q_L^i(j)$ are dependent on random variables, $Q_{Ld}^i(j)$ is a function of aforementioned variables and there is no need to use any extra random variable to generate $Q_{Ld}^i(j)$.

3.4 Evaluation of model performances

Typical measures applied for the performance evaluation of ANNs are residual squared error (R^2) and mean square error (MSE) [23, 26]. In this paper, R is used to measure the performance of the designed ANN. This index is defined as:

$$R = \sqrt{1 - \frac{\sum_{(x_i, y_i) \in S} (y_i - y_p)^2}{\sum_{y_i \in S} (y_i - y_m)^2}} \tag{8}$$

where x_i is the input parameters of ANN (voltage phasors and rates of load changes); y_i is the value of VSM determined by CPF method; y_p is the predicted value of VSM estimated by ANN; y_m is the mean value of VSM determined by CPF method, and S ANN samples set.

R is equal to one when the trained ANN is able to exactly predict all VSMs. Inaccurate estimation of VSM leads to lower values of R measure.

3.5 Incorporation of system configuration changes

Power system components (e.g. lines, generators, and etc.) need periodical maintenances. In addition, there are always unexpected outages in the system due to component failures or protection system incorrect actions. Power systems likely face with the condition that one, two, or more components are out of service. Dealing with power system assessments in contingency conditions is hence crucial for the system operators [5, 27]. Note as well that since the higher order of contingencies are of trivial probabilities, usually single and double outage contingencies are merely accounted for in system studies. However, power system resilience analysis calls for low probability but very sever disturbances.

The designed ANN should be able to deal with $N-1$ and $N-2$ contingency situations. This requirement could be fulfilled in two ways:

1) Implicit method in which the ANN samples include contingency cases; however, no input directly introduces contingency condition to ANN [16, 17].
2) Explicit method in which the ANN samples include contingency samples; moreover, an extra input(s), which specifies contingency identification, is added to the input features. In this manner, each sample corresponds to a specified contingency. Results show that this method can improve the ANN performance.

3.6 Flowchart for VSM estimation using ANN

In the process of obtaining VSM using ANN, the number of samples used for training phase should be tractable. However, the number of possible contingencies is too huge for a real-scale power system. To deal with this difficulty, an algorithm is introduced in the following to eliminate unnecessary contingencies from the list of credible ones. The flowchart of the algorithm is shown in Fig. 4. The flowchart of the algorithm includes three steps.

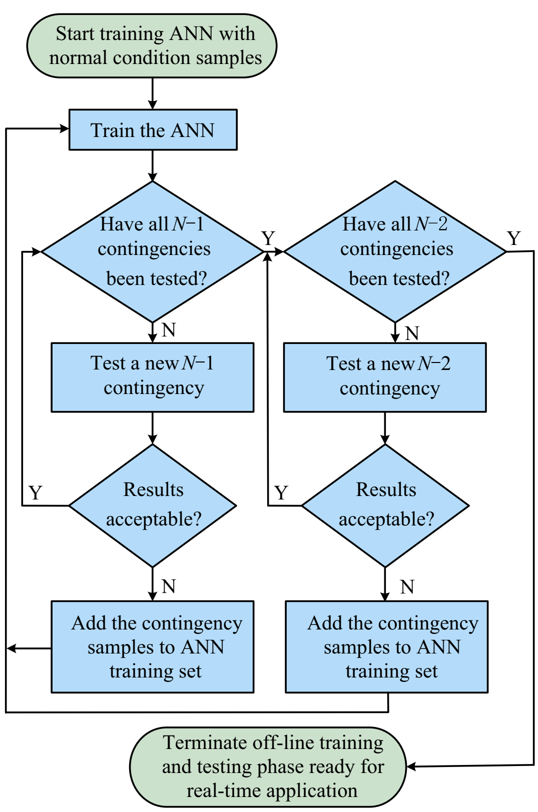

Fig. 4 An algorithm to reduce ANN training samples in large power systems

Step 1: Train ANN with normal state samples.

Step 2: Choose some samples among $N-1$ contingencies. If the trained ANN is able to predict VSM, there is no need to add these contingencies to sample cases of ANN. Otherwise, the contingencies are added to sample cases and ANN is retrained. This step may be applied for all $N-1$ contingencies. In this stage, some of contingencies, with low effects on the voltage stability or with impacts similar to those of contingencies already included in the training, are omitted.

Step 3: The same process of *Step 2* is applied to $N-2$ contingencies. In comparison to $N-1$ contingencies, an $N-2$ contingency brings about more severe impacts only when the two outaged elements are electrically (and likely geographically) close to each other. Otherwise, $N-2$ contingency has no further mutual impact compared to two respective $N-1$ contingencies. In such a case, usually one of contingencies has more effect on voltage stability and it would determine the limitation of voltage stability. That is why analysis of $N-2$ contingencies will start after investigating all $N-1$ contingencies. Thus, majority of $N-2$ contingencies would be eliminated in this stage and just a few are added to the training data set. However if in a large-scale system, the number of $N-2$ contingencies is intractable, contingency screening and selection procedures can be taken in use to handle the computational difficulty.

In summary, the ANN is trained to respond normal, $N-1$, and $N-2$ contingencies. If the system experience a contingency in real-time, then the input standing for the contingency number implicitly assist ANN to lead to a more accurate result. In this manner, the designed method is well capable to deal with contingencies.

4 Simulation results

According to the nature of long-term voltage stability, test cases are designed as such they can specify the effect of load change during a long-term voltage stability assessment. The IEEE 6-bus standard and the New England 10-machine 39-bus test systems are examined for the numerical analysis purposes [28].

4.1 Illustrative example

In this section, the IEEE 6-bus test system shown in Fig. 5 is used to demonstrate the VSM estimation by means of the proposed method.

The first step is generating sample cases. To do so, random variables are added to the system base cases. The tolerances of active and reactive powers are set at ±30%. This means that Δ equals to 0.3 in (4). The tolerance of

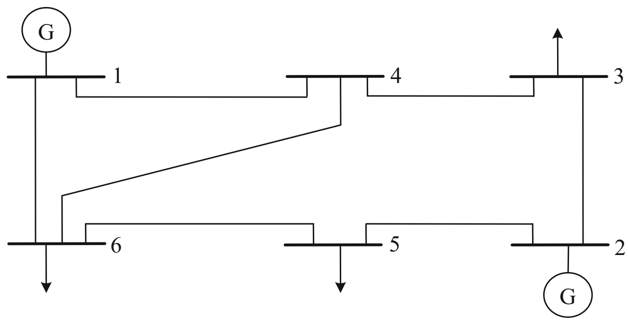

Fig. 5 Single-line diagram of IEEE 6-bus test system

generators voltage magnitude is set at ±3%. The tolerance of the rate of change of active power is set at ±30%. The number of generated cases is 3000. These cases are randomly divided into three groups: training, validation, and testing cases. 70% of the whole cases are used for training phase, while each of the validation and testing phase include 15% of cases. Training and validation phases are done concurrently. The validation phase is used to stop training before over fitting occurs. Only normal condition is considered in this stage and contingency analysis will be discussed later. Using CPF method for each of the sample case, VSM is obtained and used as the target of the designed ANN.

The next step is to adopt ANN inputs. In this regard, voltage magnitudes and angles of all buses except the slack bus plus the rate of active power changes of all load buses are selected as the inputs. Slack bus voltage magnitude and angle are fixed during simulations, so it is omitted from the input list. Thus, we have thirteen inputs and a single output target for the ANN.

Training the ANN is conducted thereafter. The trained ANN could be next used to predict unseen cases as the test phase of the ANN. Figure 6 shows the performance of designed ANN during training, validation, and test phase. As it can be seen in Fig. 6, the performance of ANN during test phase is so close to that associated with the training phase. It shows that number of training samples is large enough; so, using more samples to obtain better results is unnecessary and may lead to over fitting.

Now, contingency states are to be included in the process. In this paper, only line outages are considered for both $N-1$ and $N-2$ contingencies. To do so, $N-1$ contingency is added to the normal state of the system. Note that the algorithm described in Section 3.6 is not taken in use here as the system at hand is small enough. As explained in Section 3.5, either implicit or explicit method should be used to include the impact of contingencies. Performance of the implicit technique is shown in Fig. 7. Comparing with Fig. 6, it is deduced that the performance of ANN is degraded in the implicit method. Because bus

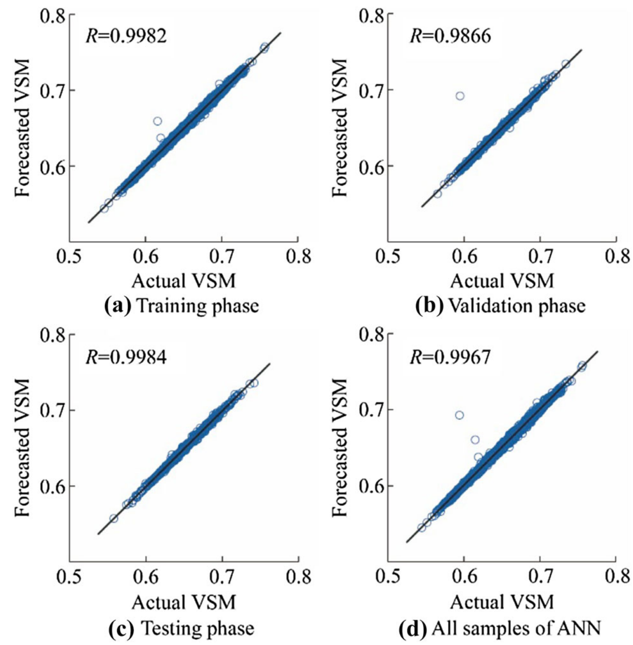

Fig. 6 Regression analysis of the forecasted VSM versus the actual value

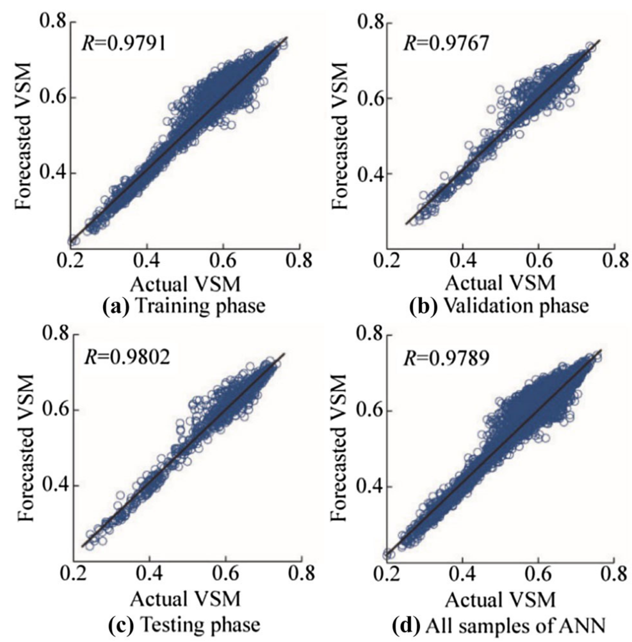

Fig. 7 Regression analysis of the forecasted VSM versus the actual value under N–1 contingencies using the implicit method

voltage phasors do not provide enough discrimination for contingencies and ANN is trained inappropriately.

In the explicit method, an input which defines contingency number is added to input features. Thus, 14 inputs are introduced which include five bus voltage magnitudes, five bus voltage angles, three rates of power change of load buses, and a contingency number. The obtained results are given in Fig. 8. As can be seen, the performance of the designed ANN is remarkably much more accurate in the explicit method.

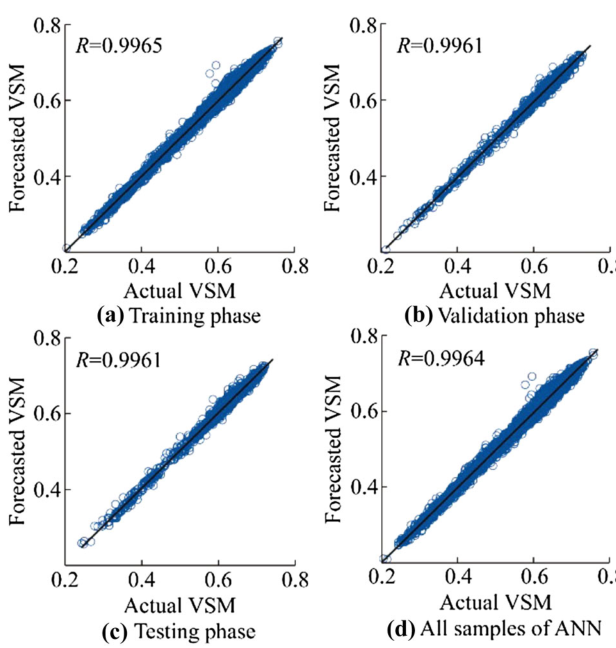

Fig. 8 Regression analysis of the forecasted VSM versus the actual value under N–1 contingencies using the explicit method

4.2 New England 39-bus test system

The proposed method is applied on the New England 39-bus test system shown in Fig. 9. Note that as the voltage stability problems and studies has geographically limited interdependencies, examining systems larger than IEEE 39-bus system in voltage stability focused literature is not common and brings no new insights. In this case, the difficulty is dealing with numerous contingencies; hence, the algorithm proposed in Section 3.6 is utilized. The structure of the devised ANN is presented in Fig. 10. Inputs X_1 up to X_{38} are bus voltage magnitudes. Inputs X_{39} up to X_{76} are bus voltage angles. Inputs X_{77}, X_{78}, X_{79} represent the rate of change of active powers of three regions of the system. Practically, in power systems, loads of a same region change in a same manner. So, the New England 39-bus test system is divided into three regions and loads of each region change in an identical rate. This assumption is technically sensible while it can be even relaxed by increasing the number of regions. Input X_{80} represents contingency number.

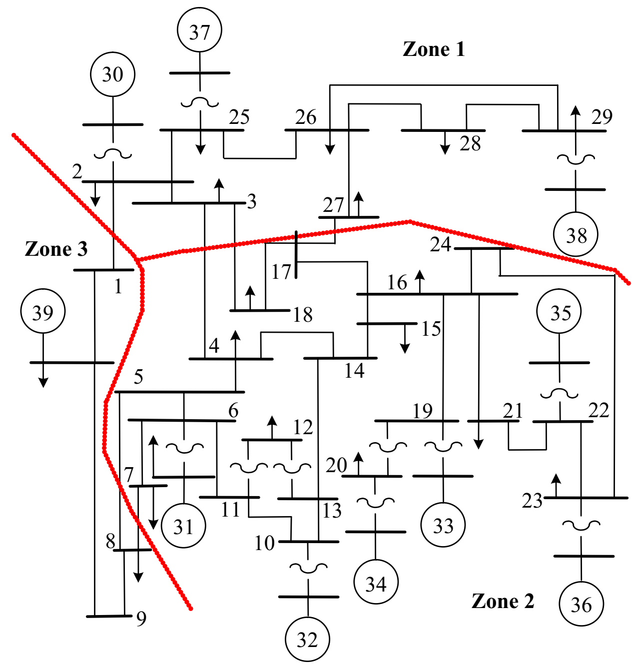

Fig. 9 Single-line diagram of New England 39-bus test system

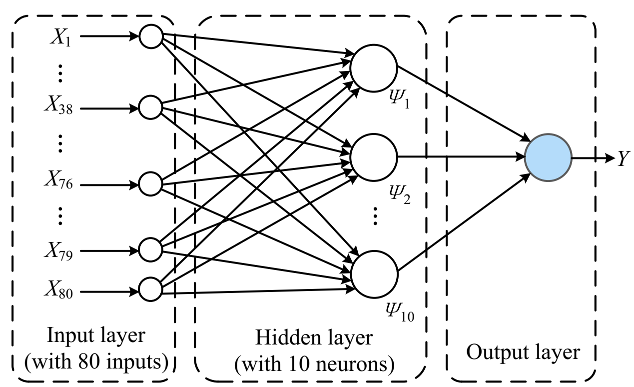

Fig. 10 ANN structure for New England 39-bus system

The number of samples used for training, validation, and testing phase of the ANN is 3000 (70% for training, 15% for validation, and 15% for testing).

Figure 11 shows the performances of three methods in estimation of VSM while no contingency is regarded. These methods are:

Method 1: Inputs are voltage phasors and rates of change of active powers. Also, different load change scenarios are used in the training phase.

Method 2: Inputs are voltage phasors. Different load change scenarios are used in the training phase.

Method 3: Inputs are voltage phasors. However, only a single load change scenario is used in the training phase. Actually, this is the conventional method assuming a unique load variation pattern for the whole system.

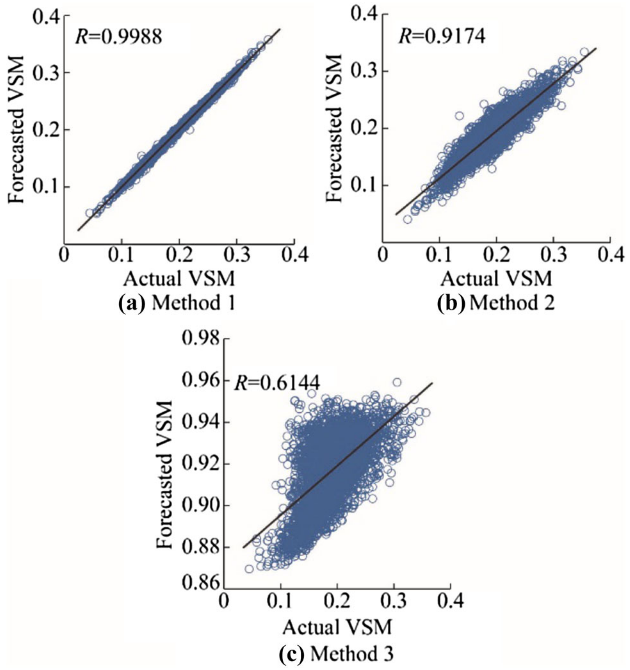

Fig. 11 Regression analysis of the forecasted VSM versus the actual value

Referring to Fig. 11, it is concluded that the conventional Method 3 fails in the proper estimation of VSM (R = 0.6144). Thus, adding various load change scenarios to the train sample set is an inevitable requirement in real-world practices. Comparison of two other techniques reveals that the direct consideration of various load change scenarios in the ANN (Method 1) outperforms Method 2 in which load change scenarios are only seen among in the training set.

The next step is to add $N-1$ contingency samples to the main training samples. Recalling the proposed flowchart, only contingencies which are not properly estimated by the ANN are added to the training samples. Doing so, 48 single contingencies are reduced to 27. Figure 12a shows the capability of the designed ANN to estimate the VSM under normal and $N-1$ contingencies.

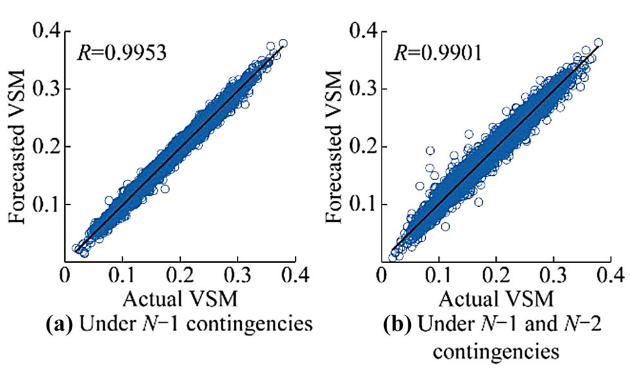

Fig. 12 Regression analysis of the forecasted VSM versus the actual value using the explicit method

Next, $N-2$ contingencies are similarly covered. From the viewpoint of voltage stability assessment, the most severe $N-2$ contingencies are outage of transmission lines terminating to a given load bus. These double contingencies with a count of 45 are initially considered and next filtered out. Finally, 10 double contingency is recognized valuable to be added to the training samples. Figure 12b shows the regression results of the designed ANN in response to the normal, $N-1$ contingency, and $N-2$ contingency states.

4.3 ANN training time

Among the aspects of real-time application of VSM assessment approaches is the computational time. Talking about ANN, one computational time is important: How long does the devised ANN take to estimate VSM?

Table 1 shows the computational time of ANN training and execution (VSM estimation) in the IEEE 6-bus and the New England 39-bus test systems. The simulations are conducted on an Intel 2.2 GHz CPU with 8 GB RAM. Expectedly, the ANN fits well to be implemented in a real-time manner.

4.4 Effect of measurement errors on proposed method

It is inevitable that every measurement includes some level of error. According to the standard IEEE C37.118 [29], the total vector error (TVE) is introduced to describe the allowable tolerance of phasor measurement error as:

$$TVE = \sqrt{\frac{(\mathrm{Re}\{\boldsymbol{V}_m\} - \mathrm{Re}\{\boldsymbol{V}_r\})^2 + (\mathrm{Im}\{\boldsymbol{V}_m\} - \mathrm{Im}\{\boldsymbol{V}_r\})^2}{(\mathrm{Re}\{\boldsymbol{V}_r\})^2 + (\mathrm{Im}\{\boldsymbol{V}_r\})^2}} \tag{9}$$

where $\mathrm{Re}\{\boldsymbol{V}\}$ and $\mathrm{Im}\{\boldsymbol{V}\}$ indicate the real and imaginary parts of vector $\boldsymbol{V}$, respectively; m and r stand for measured and exact value of the vector, respectively.

In order to analyze the effect of measurement error on the proposed method, normally-distributed random noises are added to inputs of ANN. Based on the standard IEEE C37.118, random noise terms are added to both magnitude and phase angle of phasors in a way that TVE does not exceed 1%. As given in Table 2, results show that the proposed algorithm is robust to the noise and the performance index of the designed ANN is more than 90%.

Table 1 Training and execution time of ANN

Mode	Training time (s)	Estimation time (s)
6-bus system	4.9410	0.0156
39-bus system	54.5970	0.0312

Table 2 *R* value of designed ANN considering noisy inputs

Phase	*R* value
Training phase	0.9364
Validation phase	0.9244
Testing phase	0.9304

4.5 Optimal phasor measurement unit (PMU) placement

Most of the power systems around the world have only limited number of PMUs and there is far distance with the complete phasor observability of electric power networks. The reason was the high price of PMU devices in the past and is the limited available wide-band communication media todays. Accordingly, the optimal placement with the objective of VSM analysis could be a practically fruitful alternative [30]. Usually, it is not computationally feasible to test every possible combinations of PMU placement (2^N, where N is the number of buses). A search algorithm could thus be employed to obtain a proper combination. To do so, the New England 39-bus test system is studied.

Among many methods proposed to find the optimal placement of PMUs for complete observability of the system [31, 32], integer linear programming (ILP) method is the most commonly used [33]. In [34], optimal PMU placement of the New England 39-bus system ensuring complete observability is reported. Each PMU by means of current phasors and line parameters makes its hosting bus and all adjacent buses observable (zero injection bus effect is overlooked because of its low reliability and high propagated error). Doing so here, buses 2, 6, 9, 10, 11, 14, 17, 19, 22, 23, 25, 29, 34 are selected as candidates for PMU placement ensuring entire observability. Among candidate buses, the search algorithm is to find the best placement of a given number of PMUs achieving the best performance of the proposed method.

Initially, the place of first PMU among 13 buses is specified. Afterward, the second PMU is placed in a bus out of 12 remaining buses. This process will continue until the last available PMU. Note as well that this procedure looks for appropriate schemes within the context of the final full observability PMU placement plan.

The performance of the proposed method using 1 to 4 PMUs are shown in Fig. 13. Results show that in the New England 39-bus system by 4 PMUs out of 13 ones, an appropriate performance in VSM estimation is achieved. Note that we mimic the real situation in which just the outputs of measurement system are real/valid values to be used in the studies. Hence, only the data captured by PMUs are assumed to be available here. Expectedly, with more PMU devises installed across the network, more comprehensive data is available for training the ANN and a better performance of VSM estimation is attained.

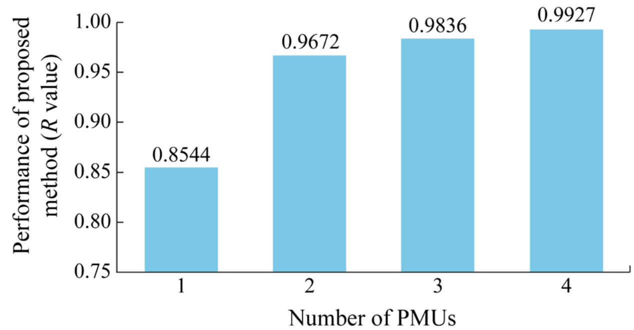

Fig. 13 *R* value performance measure versus various number of PMUs

5 Conclusion

This paper revealed that an ANN with bus voltage phasors as inputs is unable to estimate VSM when various load change scenarios are expected. To deal with this problem, the rates of change of active powers were adopted to be added to the input vector of ANN. The designed ANN was trained off-line and used for real-time VSM estimation. For the sake of practicality, two explicit and implicit methods have been discussed for incorporation of contingencies. The results indicated that the explicit method has more reliable performances. In large-scale power systems, the immense number of contingencies could be cumbersome. An algorithm was accordingly developed to reduce the number of contingencies in large-scale power systems. Results show that the performance of the proposed method is more than 99% in all case studies and is not affected by the size of the system. In addition, the effect of noise on the ANN inputs has been tested and the results clarified that the VSM could be obtained in noisy environments by using the proposed method.

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