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Online Distribution System's Voltage Stability Margin Monitoring Using Neural Networks and Optimization Algorithm

Nazmohammad Sarikhani[a*], Arman Ghanbari Mazidi[b]

[a] *Islamic Azad University, Aliabad Katoul Bramch, Aliabad Katoul, Iran*
[b] *Islamic Azad University, Bandar-e Abbas Bramch, Bandar-e Abbas, Iran*

Keywords

Voltage stability,
RBFNN,
Association rules,
Estimation,
Feature selection.

Abstract

Due to the major blackouts caused by voltage collapse, the voltage stability problem has become one of the most significant challenges in the planning and operation of the modern electric power systems. Voltage instability has increasingly become a significant risk for the secure operation of electric power systems. In the heavily loaded electric power systems, the events causing voltage instability, lead to a progressive decrease in bus voltage magnitudes which may result in network islanding and blackout. For such systems, online voltage security assessment to preserve a desirable level of voltage security margin is a vital requirement for maintaining system security. This paper proposes an intelligent method for online voltage stability margin (VSM) estimation based on Radial Basis Function Neural Network (RBFNN) and association rules (AR). The proposed method includes four main modules: feature extraction, feature selection, estimator and training module. In the feature extraction module, the loading parameter of the network like voltage magnitude, active and reactive power have been extracted to be used as a raw input of estimator. In the feature selection module, the AR method has been employed to select the best set of the extracted features in the previous module. In the estimator module, RBFNN has been utilized and in the training module, bee's algorithm (BA) has been used to train the RBFNN. automatically select the number, location, and spread of basis functions to be used in RBF networks. The proposed method is applied to the New England 39-bus power system model and the obtained results have shown that the proposed method has excellent accuracy in VSM estimation.

1. Introduction

Power systems are designed to maintain an acceptable voltage profile throughout the network under normal operating conditions as well as after changes in the operating conditions, which could be due to load changes, disturbances, or faults. Voltage instability occurs in power systems when the voltage at a load bus drops well below its nominal value and cannot be brought back by voltage control mechanisms such as reactive power compensators. Large disturbances, unsustainable increase in load demand, or large decrease in power supply may lead to voltage collapse events in power systems. When a power system is heavily stressed, uncontrollable cascaded events may take place leading to unacceptable levels of voltage drops throughout the network. Therefore, all power distribution grids posses an inherent problem when operating under heavily stressed conditions and are susceptible to voltage instability in absence of adequate compensation schemes [1, 2].

To be able to operate power systems in a more intelligent and smarter way, it is essential to be able to ascertain quantitatively the level of stress in the system at any given operating condition. This must be done in terms of metrics that are able to provide a quantitative measure of stability at any given operating condition and the risk of losing it. Over the past several years, massive efforts have been devoted to the development of practical measures of the distance from the current operating state to the voltage collapse point, thereby providing an early warning of a critical situation. Voltage stability of a system can be analyzed by static approaches, dynamic approaches or machine learning algorithms. The static approaches are based on the steady state power flow model of the power systems and many aspects of voltage stability problems can effectively be analyzed using these methods; however, such simplified

* Corresponding Author:
E-mail address: mohammad.sarikhani2018@gmail.com – Tel, (+98) 9373768500 – Fax, (+98) 33226774

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approaches usually lead to unreliable results as shown in [3]. In order to get a much more realistic picture of the voltage stability phenomena, it is necessary to take system dynamics into account. On the other hand, the application of dynamic methods may be too time-consuming for online use [4, 5].

In recent years, machine learning algorithm applications like artificial neural networks (ANN), fuzzy systems and support vector machine (SVM) in the field of power system security assessment have received more interest due to its ability for handling highly complex problems. In the technical literature, there are many works reported on the online voltage stability assessment, exploring the capability of machine learning algorithms for approximating a functional relationship between voltage stability indicators and the measurable power system parameters.

In [6- 10] ANNs have been used to VSM assessment in distribution systems. ANN is used in these works, typically to establish a relationship between a voltage stability indicator and the measurable power system parameters affecting the indicator. Regarding the ANNs training, the mostly used training algorithm is the Back-Propagation (BP) algorithm, which is a gradient-based method. Hence some inherent problems existing in BP algorithm are also frequently encountered in the use of this algorithm. Firstly, the BP algorithm will easily get trapped in local minima especially for those non-linearly separable pattern classification problems, so that back-propagation may lead to failure in finding a global optimal solution. Second, the convergent speed of the BP algorithm is too slow even if the learning goal, a given termination error, can be achieved. In addition, there is no systematic way to select the topology and architecture of a neural network. In general, this has to be found empirically, which can be time consuming [11].

In [12, 13] SVM have been used to VSM assessment in distribution systems. Recently, researchers are utilizing the SVMs due to its performance in acquiring remarkable results. However, the SVM accuracy depends on the selecting of the kernel function and the parameters (e.g. cost parameter, slack variables and the margin of the hyper plane.) Failure to find the optimal parameters for an SVM model influences its recognition accuracy [14]. Computational cost is another disadvantageous of utilizing the SVM [15].

Based on the published papers about the online VSM estimation, there are some facts which should be considered during the design of estimator. One of these issues is the feature selection and lowering the input vector dimension. Most of the previous methods have used whole input data as the input of estimator. These methodologies require a large number of inputs which significantly increases the machine size and diminishes its accuracy. In this paper, the AR is used to select the most effective features collection. Another issue is related to the choice of the estimation approach to be adopted. The developed method uses RBFNN for the estimation task. RBFNN has excellent performance in prediction of nonlinear time series, function approximation, pattern recognition and estimation [16- 18].

The rest of the paper is organized as follows. The use of VSM for voltage stability monitoring is described in Section two. Section three presents the proposed method. Section four shows some simulation results and finally section five concludes the paper.

2. Voltage Stability Margin

Voltage instability results from the attempts of loads to draw more power than can be delivered by the transmission and generation systems [19]. Suppose that a sample power system is operating stably at a certain loading level. Figure 1 shows the variation of the voltage magnitude of a particular load bus in the system against a loading parameter λ, representing an independent system parameter that is slowly varied, such as active and reactive loads and/or active generation dispatch. For the system loading below the maximum, there are two solutions, one with higher voltage (stable), and the other with lower voltage (unstable). As the system loading increases following a certain direction, these solutions approach each other and finally coalesce at a critical point. This nose point or saddle-node bifurcation (SNB) point corresponds to the maximum transmissible power. Increasing the system loading beyond this point could lead the entire system to voltage collapse.

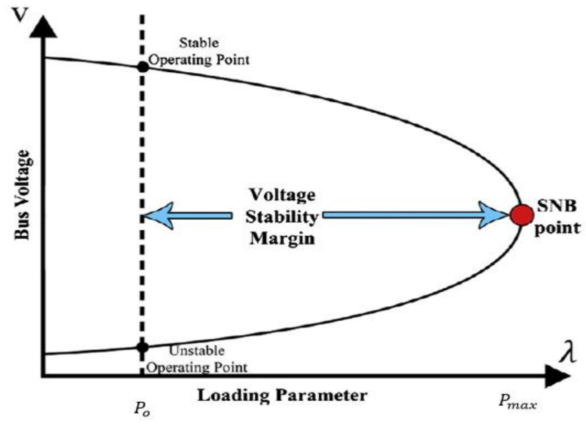

Figure 1. Illustration of the VSM [19]

In this paper, the VSM is defined as the distance from the current operating state to the voltage collapse point according to the system loading parameter; therefore, as illustrated in Fig. 1, for calculating this margin, the SNB point should be located. As reported in the literature, the SNB point can be identified using either direct or continuation methods [20]. Direct methods find this point by solving an augmented system of equations. These methods have been shown to be efficient and accurate in locating the saddle node bifurcation points; however, they need a good initial guess and may fail if all the system limits are considered [19].

Continuation methods, by contrast, do not have the mentioned limitations and also provide more information. Starting from an initial point, these methods trace the equilibrium points of a power system state as its parameters change in a quasi-continues manner. Continuation methods are robust and accurate, but they are computationally expensive, especially for large power systems [19]. Machine learning methods provide an attractive alternative to overcome the problem of computational burden of the continuation algorithms, since after training, machine learning methods can estimate its outputs very fast due its parallel architecture.

3. Proposed Method

This paper proposes a new method for estimating VSM based on application of optimized RBFNN and feature selection algorithm. The VSM is calculated by estimating the distance from the current operation state to the maximum voltage stability limit point according to the system loading parameter. Almost all voltage collapse incidents have occurred in heavily loaded systems. Furthermore, research has shown that voltage stability is strongly influenced by system loads [20]. On the other hand, synchronous generators are a primary source of the reactive power and are to a great extent, responsible for maintaining a good voltage profile across the power system [20]; therefore, the following seems to be a suitable set of initial input variables for predicting the VSM:

- Voltage magnitudes and generated active powers of the PV buses.
- Active and reactive powers of all the system loads.
- Generated reactive powers of all the system generators.
- Generated active power of the slack bus.

Figure 2 shows the traditional RBFNN based VSM estimation system. In this system, raw data is fed to RBFNN. In this figure, F_i $(i = 1,2,\ldots,N)$ indicate the extracted feature such as voltage magnitude at the specific bus. Also N indicate the number of all extracted features from power network.

Power system measurements are very redundant and the number of variables is extremely high. This abundance of variables significantly compromises estimation tasks for several reasons. Weak informative features act as artificial noise in data and limit the accuracy of the classification algorithms. In addition, the variance of a statistical model is typically an increasing function of the number of variables, whereas the bias is a decreasing function of this quantity [21-24]. Thus, restricting the input space to a small subset of the available input variables has obvious economic benefits in terms of data storage, computational requirements and cost of future data collection; furthermore, reducing the number of input variables leads to better model understanding in some cases. The optimal input variable set will contain the fewest input variables required to describe the behavior of the output target, with a minimum degree of redundancy and with no uninformative variables. Thus, AR has been employed to select the best set of extracted features. AR selects a reasonable subset of features then it improves both the recognition accuracy and the complexity of the problem. The algorithm for feature selection based on AR for estimation is given in Figure 3. Our algorithm consists of four phases. More details about AR can be found in [25].

//Input: D, training data set.
minsup, minimum support threshold.
minconf, minimum confidence threshold.
maxlen, maximum number of conditional attributes.
C, class attribute.
minfrequent, minimum frequency of attributes in set of association rules.
//Output: F, a set of frequent features.
1. R = Apriori(*D, minsup, minconf, maxlen*)
2. **For** each rule r ∈ R do
3. **If** consequence(r) != C Then
4. delete r from R
5. **End**
6. **End**
7. **For** each attribute Attr from D do
8. **For** each rule r ∈ R do
9. **If** condition(r) = Attr $_i$ **Then**
10. c ount_Attri ++
11. **End**
12. **End**
13. add Attr $_i$and count_Attri to F
14. **End**
15. **For** each feature f ∈ F do
16. **If** *FrequentFeature*(f) < *minfrequent* **Then**
17. delete f from F
18. **End**
19. **End**
20. **Return** F

Figure 3. Feature selection in the proposed method

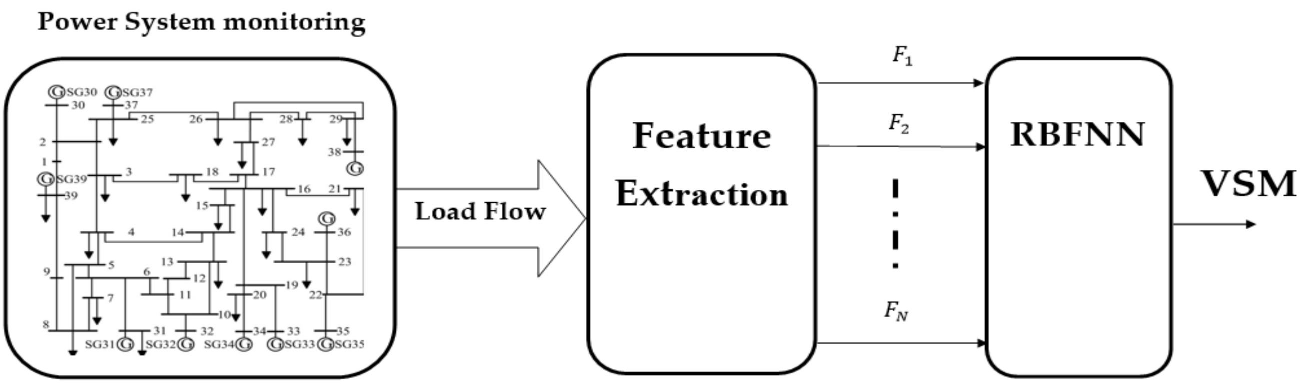

Figure 2. Traditional RBFNN based VSM estimation system

The first phase is at line 1. This phase is for conventional association rule mining with Apriori algorithm from training data set (D). This phase requires three parameters, which are minimum support threshold (minsup), minimum confidence threshold (minconf), maximum number of attributes that can be appeared at the conditional (or antecedent) of the association rules (maxlen), and minimum frequency of features or attributes that appeared in association rules (minfrequent). This last threshold is for discarding features with low importance.

Phase 2 is the part from lines 2 to 6. This phase is the rule pruning, which is the deletion of rules that have attributes in their consequence part disagree with the specified subset of class attribute (C). This phase is for selecting from association rules the frequent patterns containing both predictive features and class attribute.

Phase 3 is the part from lines 7 to 14. The operation of this phase is to count the frequency of features appeared in association rules that are obtained from phase 2. We design these steps to iterate over each attribute and count the appearance frequency of attributes that appear in the conditional part of the association rules.

Phase 4 is the part from line 15 to 19. This phase is the features selection from subset of frequent features of rules (F) by deleting features that have percentage of frequency appearance in the set of association rules lower than the specified minimum frequency threshold. Finally, the algorithm returns the subset of features that has been considered high importance to class attribute prediction based on the analysis of their appearance in the set of association rules induced from the training data set.

By selecting of the best collection of features, the dimension of input data to RBFNN will decrease from N to lower value M ($N > M$). Therefore, training period of the RBFNN will be decreased as it is shown in Fig 5. In this figure, $F_{S,i}$ ($i = 1,2,,\ldots,M$) indicates the i^{th} selected feature and M indicates the total number of selected features.

The estimation basically consists of two phases: training and testing. In the training stage, parameters are calculated according to the chosen learning algorithm. The issue of the learning algorithm and its speed is very important for the RBFNN model. In [26] a new learning algorithm based on BA is proposed for RBFNN training. The excellent performance of this method is proved by several numerical experiment. Therefore in this paper we propose the application of this new learning algorithm to train the RBFNN in the field of VSM estimation. Fig. 5 shows the main structure of the proposed method.

The most commonly used measure to evaluate the performance of an estimator is Root Mean-Squared Error (RMSE) between the actual and the estimated signal. In the proposed method, the BA should find the best parameters of RBFNN to enhance the estimation accuracy or decrease the RMSE value. Eq. (3) shows the fitness function.

$$RMSE = \sqrt{\frac{\sum_{p=1}^{NP}(VSM_{act}(p)-VSM_{est}(p)).^{2}}{NP}} \qquad (1)$$

where VSM_{act} represents the actual VSM, VSM_{est} represents the estimated VSM by RBFNN, p represents the pattern number and NP denotes the total number of patterns.

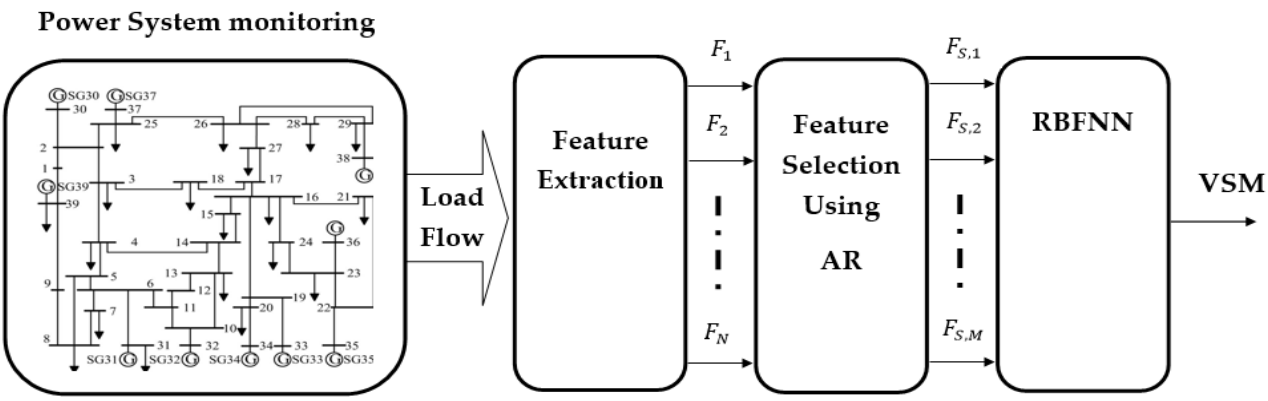

Figure 4. Feature extraction and selection in the proposed method

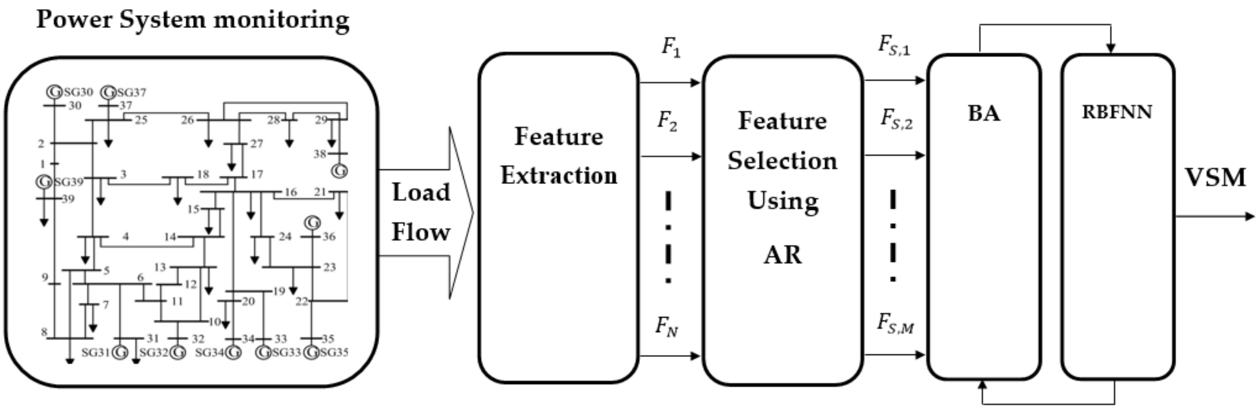

Figure 5. The main structure of the proposed method

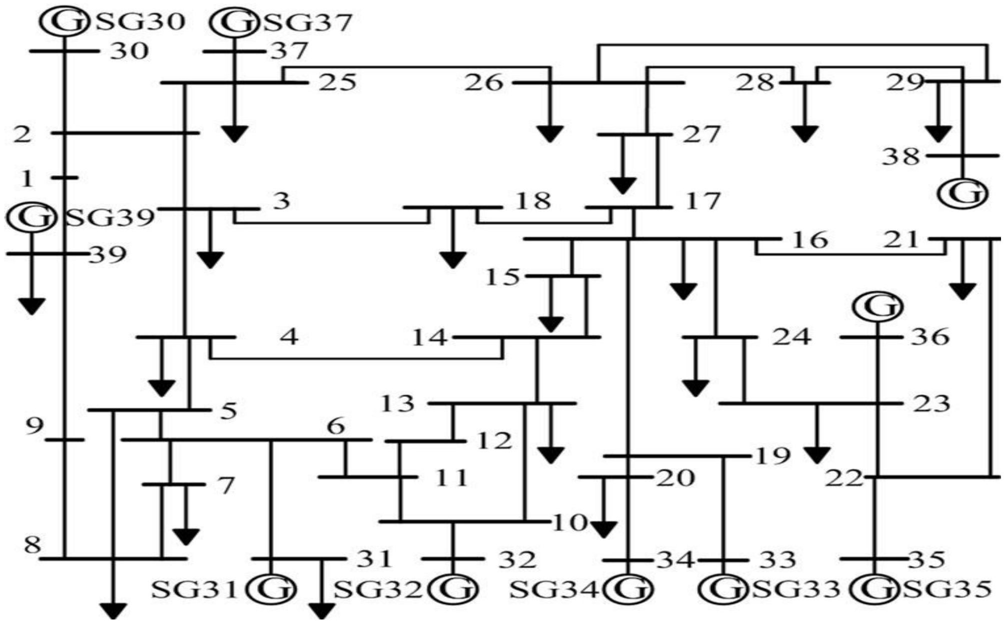

Figure 6. Test system [27]

4. Simulation Results

To demonstrate the performance and effectiveness of the proposed method, it is applied to New England 39-bus system. The single-line diagram of the est system is shown in Figure 6. The bus and line data of the system can be found in [27]. This system consists of 29 PQ buses, 46 lines and 10 synchronous machines equipped with IEEE type-1 voltage regulators. The following loading parameters were selected as the initial input variables for an RBFNN to estimate the VSM in the New England 39-bus system:

- Voltage magnitudes and generated active powers of all 9 PV buses.
- Active and reactive powers of all 19 system loads.
- Generated reactive powers of all 10 system generators.
- Generated active power of the slack bus.

Therefore, initial input vector has 67 (9 + 9 + 19 + 19 + 10 + 1) arrays.

4.1. Data Generation

In order to train the RBFNN, it is necessary to prepare sufficient and suitable training data. Each training data set consists of loading parameters of the network as input pattern and associated VSM as output pattern. The VSM is calculated by estimating the distance from the current operation state to the maximum voltage stability limit point according to the system loading parameter. Each training set corresponds to a specific operating point. For this purpose, several load-generation increase patterns are created. For each load increase pattern denoted as loading pattern, continuation power flow (CPF) calculation is carried out by increasing load and generation through specified steps (i.e. %2) until the point of voltage collapse and load ability limit. Each loading pattern is represented by a vector a showing trend of load increase on load buses. The dimension of vector α is equal to the number of load buses. The element α_k calculated by Eq. (2) represents the share of load increase at bus #k with respect to the total system load increment.

$$\alpha_k = \frac{P_{load,k}}{\sum_{k=1}^{n} P_{load,k}} \qquad (2)$$

As shown in Figure 1, for each loading pattern a there is a corresponding P–V curve with an associated loading limit (P_{max}) denoted as loadability limit. Therefore, each loading pattern corresponds to a loadability limit. During load-generation increase toward point of voltage collapse, at different steps of load increment, system takes several operating points with different corresponding loading parameters and VSM. Each operating point is characterized by two parameters; load level P_0 and loading pattern α. Load level P_0 creates network loading parameters while loading pattern results in load ability limit P_{max}. VSM evaluated by Eq. (3) is a combinatorial feature of the two characteristics and is associated with the corresponding loading parameters.

$$VSM_{o,i} = P_{max,i} - P_{o,i} \qquad (3)$$

where $P_{max,i}$, is the loadability limit associated to loading pattern α_i, and $P_{o,i}$ is the system load level at the operating point. In the trajectory of load increase based on a specific loading pattern, system takes several operating points with different load levels, loading parameters and associated VSM. Network topology, reactive power compensation and loading pattern are the major factors affecting load ability limit and voltage security margin. In order to embed the effect of network topology and reactive power compensation into the learning ability of RBFNN, for some operating points, some lines are taken out and reactive power is changed to produce new voltage profiles and VSM for adding to training patterns. The investigated conditions are:

1. Initial point of simulation
2. Load increment-under normal condition
3. Load decrement-under normal condition
4. Small load variation
5. Line 15–16 is out

6. Load increment-line 15–16 is out
7. Reconnection of line 15–16
8. Small load variation
9. Injection of 300 MVAr capacitive at bus 4
10. Load increment-with injection of 300 MVAr

In order to prepare several loading parameters with different VSM as training patterns, 26 loading patterns with different associated load ability limits in the range of 7000–12800MW are defined. For each loading pattern, system load is increased incrementally by step of 5% until the point of voltage stability limit resulting in individual load ability limits. With respect to each specific loading pattern, in the trend of load increment toward voltage stability limit a certain number of loading parameters are created by continuation power flow calculation. In order to involve the effect of network topology and reactive power limit on the voltage profile and its associated VSM, for each loading pattern some lines or reactive sources are taken out as single contingencies. Each loading parameter including the effect of all system parameters and controllers belongs to a specific load level P_0 with a corresponding load ability limit (P_{max}) and stands as a representative for system VSM. As a result, 5135 loading parameter corresponding to different load levels and VSMs are created. For this study, we have used 40% of data for training the RBFNN, 10% for validation and the rest for testing. The obtained VSMs at different conditions are shown by Figure 7.

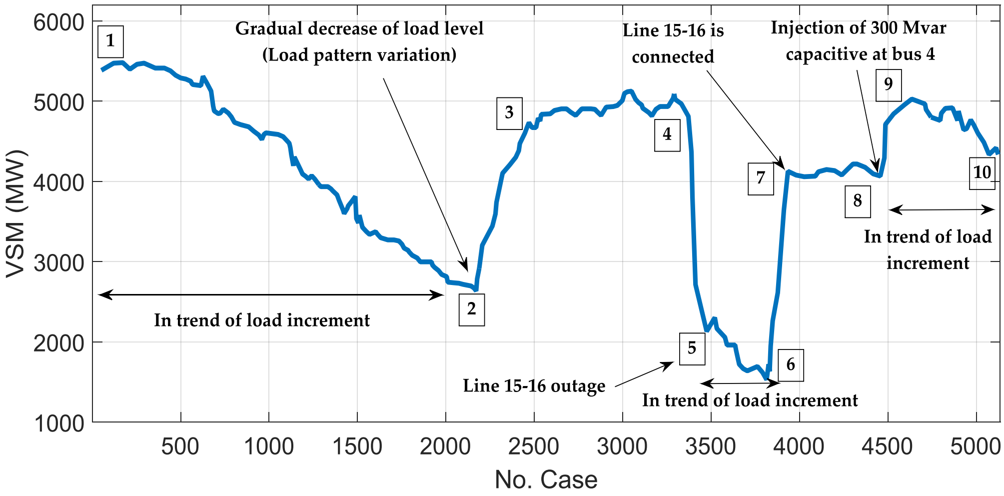

Figure 7. The obtained VSMs at different conditions

4.2. Performance of the Proposed Method

In this section, the performance of proposed method in VSM estimation is investigated. In this study, we used AR to reduce the number of RBFNN inputs for VSM estimation problem. Using AR, we found the best feature collection including 9 features. These features are:

- Active power of bus 12 and 28.
- Generated active power of the slack bus and bus 4.
- Voltage magnitudes at buses 2, 4 and 8.
- Generated reactive power of the generators at bus 3 and 9.

These 9 features have been used as best input of RBFNN. Also the bee's algorithm used as learning algorithm. Selecting the most effective feature collection lead to higer accuracy in voltage stability estimation. Also the volume of the computation will reduce significantly. The obtained results using raw data and proposed method are listed in Table 1. In this table, RBFNN represent the RBFNN with traditional learning algorithm and optimized RBFNN (BA-RBFNN) refers to RBFNN with optimal parameters where its parameters are found by bee's algorithm. It can be seen that performance of the proposed method is much better than other methods. The proposed method is able to estimate the VSM on test dataset with minimum error (RMSE=24.53). The obtained results show the effectiveness of feature selection and optimization. performance of the proposed method is shown by Figures 8 to 10. It can be seen that the proposed method has excellent performance in VSM estimation. Figure 10 shows the error rate of the proposed method. In this figure, vertical axis shows the error rate in MW. It can be seen that the error value is very small.

Table 1. Performance of the proposed method

Estimator	Input	Input size	RMSE	
			Training dataset	Test dataset
RBFNN	Raw data	69	30.75	35.38
RBFNN	Selected features	**9**	27.29	31.04
BA- RBFNN	Raw data	69	28.52	32.61
BA- RBFNN	**Selected features**	**9**	**22.67**	**24.53**

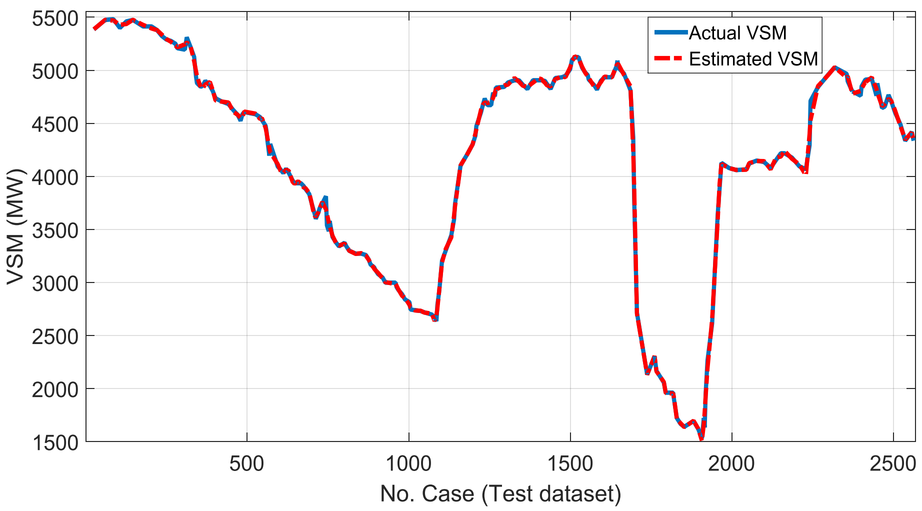

Figure 8. Performance of the proposed method

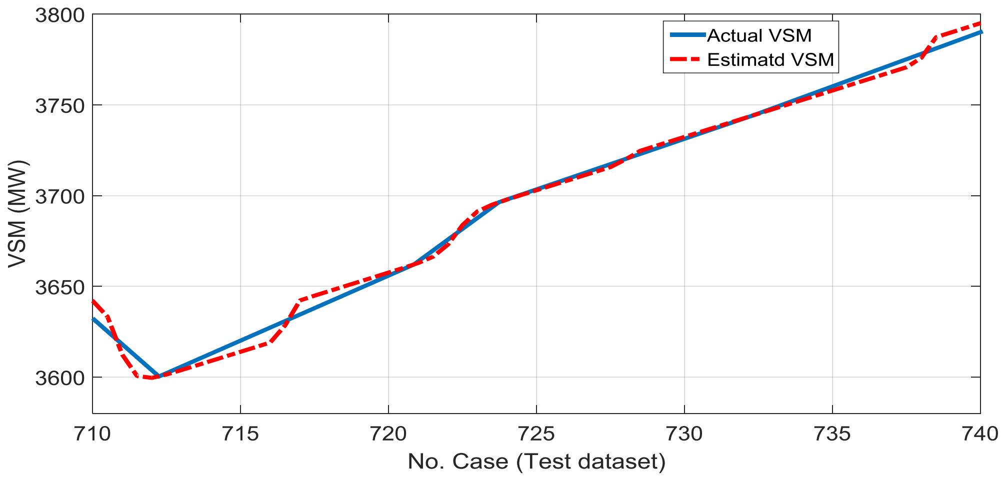

Fig 9. Performance of the proposed method with more details

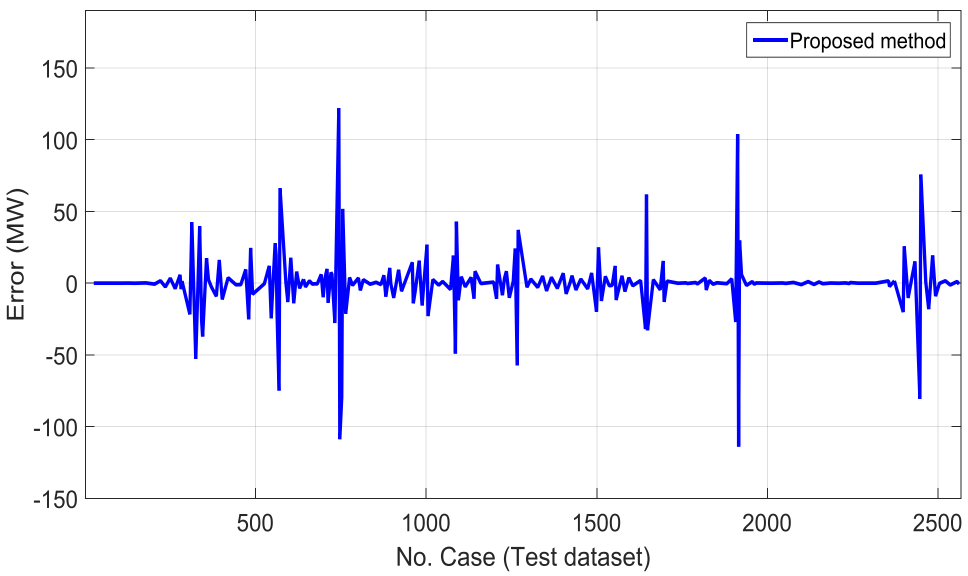

Figure 10. Error of the proposed method

4.3. Comparison with Other Methods

Considering the importance of the continuous monitoring of the power network condition, in recent years extensive studies have been conducted to estimate VSM successfully. Direct comparison with other works is difficult for p VSM problems. This is mainly because of the fact that there is no single unified data set available. A different setup of conditions (for example, normal condition, small load variation, line outage) will lead to different performance. Besides, there are many different kinds of benchmarking system used for VSM estimation. This causes difficulties for direct numerical comparison.

For comparison, we applied two recently introduced methods on New England 39-bus system and compared with our method. Ref [28] have introduced a three steps algorithm for VSM estimation using multilayer Perceptron neural network (MLPNN), Multi-Resolution Wavelet Transform (MRWT) and principle component analysis (PCA). In this method, voltage profile is adopted as the original input data for VSM estimation. In this approach, in order to provide high discrimination between network voltage profiles, MRWT is utilized to extract the features of voltage profiles. Also, in order to eliminate the redundant features, principle component analysis (PCA) has used to select the most relevant features extracted by MRWT. MLPNN is adopted to estimate system VSM using the dominant extracted features of the voltage profile by MRWT and PCA. The original input pattern consists of 47 variables including the detail and approximation wavelet coefficients of voltage profiles. By applying PCA transformation on extracted features, they are reduced to 14 dominant components.

In [29] a method based on multi-layer perceptron (MLP) neural network and loading parameters has been proposed to estimate the VSM. In this method, using Gram–Schmidt orthogonalization process along with an ANN-based sensitivity technique, a feature selection method has been proposed to find the fewest input variables required to approximate the VSM.

Employing the Gram–Schmidt (GS) orthogonalization process along with an ANN-based sensitivity technique, 7 features including generated reactive power of the generator at bus 3, voltage magnitudes at buses 2, 3 and 4 and generated active power of the slack bus identified as the most effective.

The obtained results using various methods are listed in Table 2. The mentioned results are average of 50 independent runs. In this table, the RMSE, run time based on second and standard deviation (SD) of RMSE are listed. It can be seen that best performance is achieved by the proposed method. The SD of various methods show that the proposed method has more robust performance compared to other methods. The SD of the proposed method is zero and it means that the proposed method can estimate the VSM with high accuracy in each run. Also the run time of the proposed method is significantly better rather than other methods. Lower RMSE, lower run time and robust performance during different runs are advantages of the proposed method in comparison with other methods. The difference between actual and estimated VSM using different methods are shown in Figure 11. In this figure, the horizontal axis shows the case number and the vertical axis shows the error rate. It can be seen that the proposed method has lower error in comparison to other methods.

Table 2. Comparison with other methods

Method	RMSE	Run time (sec)	SD
MRWT+PCA+MLPNN [28]	27.85	6.95	$\pm$ 0.741
MLP+ GS [29]	29.21	4.31	$\pm$ 0.825
Proposed method	**24.53**	**1.86**	**0**

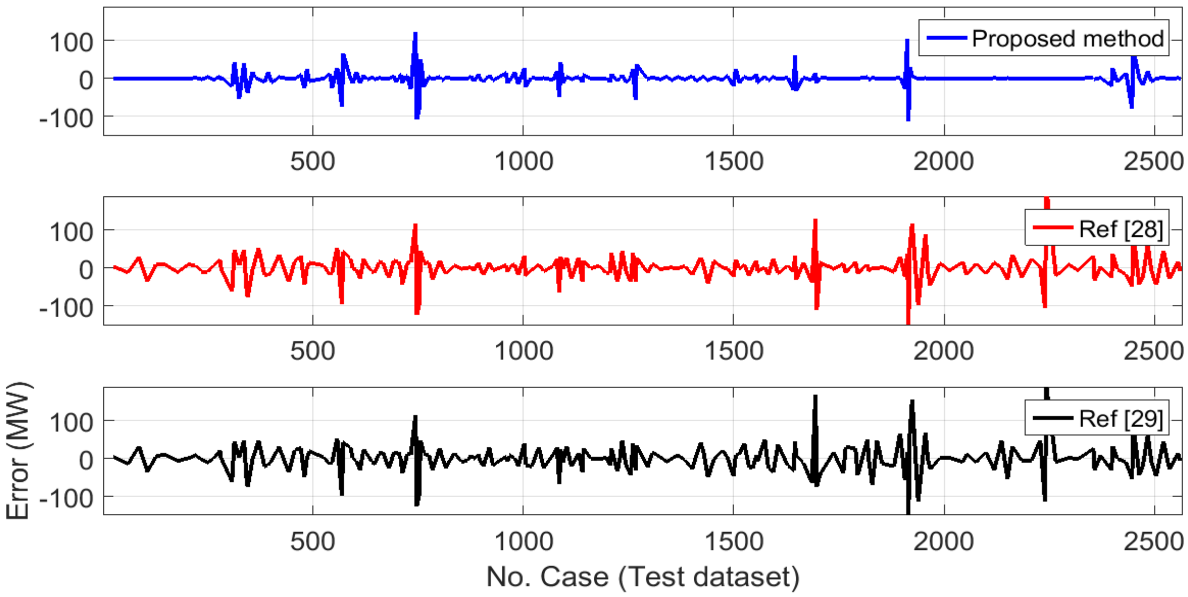

Fig 11. The difference between actual and estimated VSM using different methods

4.4. Comparing Performances of the Feature Selection Techniques

The performance of the proposed feature selection method has been compared with other feature selection methods, for investigating the capability of the proposed feature selection method. In this respect, filter method [30], composition of feature relevancy (CFR) [31], discriminative embedded unsupervised feature selection (DEUFS) [32] and improved binary genetic algorithm with feature granulation (IBGAFG) [33] are considered. The obtained results are shown by Table 3. It can be seen that the proposed method has better accuracy than other systems. In all cases the RBFNN parameters are optimized by BA.

Table 3. Comparison the performance of different feature selection methods

Estimator	NO. features	RMSE
Filter+BA-RBFNN	11	29.76
CFR +BA-RBFNN	6	26.90
DEUFS +BA-RBFNN	14	30.18
IBGAFG +BA-RBFNN	7	28.12
Proposed method (AR+BA-RBFNN)	**9**	**24.53**

4.5. Comparison with Different Estimators

The performance of the proposed system has been compared with other estimators for investigating the capability of the proposed estimator, as indicated in Table 4. In this respect, probabilistic neural networks (PNN), multilayered Perceptron (MLP) neural network with Levenberg–Marquardt algorithm (LM) learning algorithm and support vector machine (SVM) are considered. In this experiment, we used selected feature subset as the input of the estimator. It can be seen from Table 4 that the proposed method has better accuracy than other methods.

Table 4. Comparison the performance of different estimators

Estimator	NO. features	RMSE
AR+PNN	9	27.12
AR +MLP	9	26.50
AR+SVM	9	25.87
Proposed method (AR+BA-RBFNN)	**9**	**24.53**

5. Conclusion

Because of growing interconnections and geographical spread, today's power systems are becoming increasingly larger and more complex. Online voltage stability assessment of such multi-area power systems in near real-time is becoming a challenging task. In this study a fast and accurate method proposed for VSM estimation. We used New England 39-bus power network to evaluate the performance of the proposed method.

The best machine learning method will have poor performance if input features are not properly selected. Therefore, in the first experiment, AR has been used to select the most effective features. The AR should select the best and most effective features and minimize the number of input dimensions to the lowest and most optimal set. Also bee's algorithm used to find the optimal parameters of RBFNN. RBFNN, with optimal structure and selected features was able to estimate the VSM with RMSE=24.53 correctly.

In the next experiments, the performance of the proposed method has been compared with other methods. In this experiment, we applied two recently introduced methods called MRWT+PCA+MLPNN and MLP+ GS on New England 39-bus power network. The obtained results showed that the proposed method had higher accuracy, lower run time and more robust performance in comparison with other methods available in the literature. Also we compared the performance of RBFNN with other machine learning methods and the obtained results showed that RBFNN had better performance in comparison with previous machine learning methods. In the next experiment, the performance of the proposed feature selection algorithm compared with other feature selection methods. The obtained results showed that AR had better performance in comparison with other methods. The obtained results showed that the proposed estimation method has high accuracy, robust performance and short run time.

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