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Neuro-Fuzzy Based Algorithm for Online Dynamic Voltage Stability Status Prediction Using Wide-Area Phasor Measurements

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Abstract

In this paper, a novel neuro-fuzzy based method combined with a feature selection technique is proposed for online dynamic voltage stability status prediction of power system. This technique uses synchronized phasors measured by phasor measurement units (PMUs) in a wide-area measurement system. In order to minimize the number of neuro-fuzzy inputs, training time and complication of neuro-fuzzy system, the Pearson feature selection technique is exploited to select set of input variables that have the strongest correlation with the output. Study on the network features such as phase angle and voltage amplitude has shown that among two interesting features, phase angle has maximum information about the performance of the network and solely can be used for training purposes. This is extra advantage of the proposed method that minimum data is needed to predict dynamic voltage stability status The efficiency of the proposed dynamic voltage stability prediction method is verified by simulation results of New England 39-bus and IEEE 68-bus test systems. Simulation results show that the proposed algorithm is accurate, computationally very fast and reliable. Moreover, it requires minimum data and so it is desirable for Wide Area Monitoring System (WAMS).

Keywords: Dynamic voltage stability prediction; Wide area monitoring system; Neuro-fuzzy algorithm; Feature selection technique

1. Introduction

Voltage stability is an important subset of power system stability factors which refers to the ability of a power system to maintain steady voltages at all buses in the system after being subjected to a disturbance caused by a given initial operating condition [1]. Voltage instability problems may occur for a variety of causes such as increased loading on transmission lines, on-load tap changer dynamics and reactive power constraints [2]. For convenience of analysis and gaining insight in to the nature of voltage stability problems, it is useful to characterize voltage stability in terms of Large-disturbance and Small-disturbance voltage stability [1]. Small disturbance voltage stability is the ability of a power system to maintain voltages for small disturbances such as changes in load or voltage at a bus; while, large-disturbance voltage stability refers to the ability of a power system to maintain voltages for large disturbances such as faults on the power system. Voltage stability can be analyzed using static or dynamic tools. Static analysis based on load flow methods, are widely used to determine the voltage stability margin indexes and to achieve fast approximate analysis of long-term voltage stability [3]. Despite the fact that static analysis provides suitable information about static voltage stability margin, it neglects all dynamic elements and considers that instability is caused by the active power or reactive power unbalance. On the other hand, voltage instability is a dynamic phenomenon under large or small disturbance. The static analysis methods are not able to correctly evaluate small disturbance voltage stability problems. Study on dynamic voltage stability has been presented by different researchers [3-5]. From small signal point of view, voltage stability is achieved when damping ratio of critical mode is positive and as a result the system oscillations are damped. Otherwise, a pair of complex and critical eigenvalue of the system will place in the right half of complex plane and consequently, damping is negative which leads to undamped oscillations of power system [4]. Complexity and nonlinearity of power systems, especially on consumer side, online identifying and detecting operation point status of these systems has become more vital. Whereas, online information regarding power system status, provides an appropriate tools for power system operators to better implementation corrective and preventive strategies such as using compensators or changing load and generation arrangement to improve power system stability. Thus, together with load prediction which has attracted considerable attention, predicting operation status of power system is also important. As a result, in recent studies Neural network as a reliable and intelligent method has received widespread attention from researchers for dynamic stability prediction [3,6-8]. Another necessity in running online algorithm is availability of information about the whole network. In recent years, the presence of PMUs with modern communication facilities has been one of the most encounters in development of smart grids [9,10]. With this technology, it is possible for real time application to measure voltage magnitude and phase angle information more rapidly and precisely. In this paper a classification for operation status of power systems respect to dynamic voltage stability boundary is presented and relation between each operating point and mentioned classification is predicted by using a hybrid strategy include of PMU data, feature selection method and neuro-fuzzy system (NFS). The superiority of the NFS comparing to neural network is that neural networks work as black boxes and cannot use prior knowledge. NFS can utilize almost the same learning methods and achieve the same accuracy as neural network, yet the knowledge in the form of fuzzy rules is easily interpretable for humans [11,12]. Our proposed method has two advantages. First, the tuning algorithms for our proposed method are back propagation learning and least mean square estimation [13,14] which are fast and robust. These algorithms are employed by ANFIS toolbox in Matlab Software. Second, a feature selection algorithm is employed in addition to using NFS. This will decrease number of input features to the NFS leading to a faster response of NFS. The feature selection algorithm used in this paper is based on [15]. Choosing an effective set of input data is important since we need maximum information about the system while minimum numbers of inputs are employed. To have such an advantage, [16] proposed using voltage magnitude and phase angle to train the neural network. It was mentioned that this features are suitable enough to get good training and prediction for a network. In this paper it is demonstrated that even using phase angle, the system stability is reasonably predictable. Furthermore, the number of phase angles can be decreased using a feature selection algorithm. As a result optimum prediction with minimum input data is obtained. Contributions of the paper can be summarized as follows:

Regardless of literatures which voltage stability margin of power system is evaluated, in this paper, voltage stability problem is analyzed and predicted in the form of a classification problem in which NFS algorithm is used as a predictor.

Owing to nonlinear behavior of Eigenvalues of dynamic algebraic Jacobian of power system, analyzing and obtaining HB boundary is more complicated comparing to SNB boundary. Thus, in this paper a solution for investigating power system status based on this boundary without solving dynamic algebraic equations of power system is suggested.

Here, it is shown that the phase angles obtained from PMUs are enough for training when NFS is employed; whereas, voltage amplitude and phase angle were presented as the best training data in [16].

Phase angles in buses that provide redundant data are omitted imposing feature selection algorithm that results in fewer numbers of features used for training.

The remaining parts of the paper are organized as follows. The dynamic voltage stability boundary is presented in section II. The proposed prediction strategy composed of feature selection technique and NFS, based on PMU data is presented in section III. Obtained simulation results for New England 39 bus and IEEE 68 bus test systems are presented and discussed in section IV. Finally, conclusion is made in section V.

1. The dynamic voltage stability boundary

Unlike the static voltage stability analysis methods, the dynamic voltage stability assessment methods, which usually use the time-domain simulation results, accurately model the power system components to detect both short-term and long-term voltage instabilities [5]. The dynamic voltage stability methods investigate the conditions of the system around equilibrium point which means that the system has nonlinear dynamic and performance. To calculate dynamic stability of the system in each equilibrium point on P-V curve, following equation is used. Equation (1) defines nature of the system in each instant which is in the form of parameter dependent differential-algebraic equations [4],

$$\begin{aligned} \dot{x} &= f(x,y,p) \qquad f: R^{n+m+k} \to R^n \\ g(x,y,p) &= 0 \qquad g: R^{n+m+k} \to R^m \end{aligned} \tag{1}$$

where

$x \in X \subseteq R^n$, $y \in Y \subseteq R^m$, and $p \in P \subseteq R^k$. P serves as system operation conditions, including loads, generation, etc. Generation dynamics of power systems are represented by dynamic state variables, x. As an example exciter control systems may be mentioned. Algebraic criterions, such as power flow equations, are fulfilled by instantaneous variables, y. considering constant values for p parameters, an equilibrium point is a solution of the system:

$$\begin{aligned} &\dot{x} = 0 \Rightarrow f(x,y,p) = 0 \\ &\text{subject to constraints } g(x,y,p) = 0 \end{aligned} \tag{2}$$

To evaluate performance of the system and its response to small disturbances, the linearized model of the system at the equilibrium point is calculated. Linearization can be utilized to determine stability margin of the equilibrium point. So one may rewrite the above model as:

$$\begin{bmatrix} \Delta\dot{x} \\ 0 \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \\ \frac{\partial g}{\partial x} & \frac{\partial g}{\partial y} \end{bmatrix} = \begin{bmatrix} J_{11} & J_{12} \\ J_{21} & J_{22} \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} = J \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}, \tag{3}$$
$$p \approx Const, \quad \frac{\partial f}{\partial p} = 0, \quad \frac{\partial g}{\partial p} = 0$$

where J is called the unreduced Jacobian, augmented Jacobian, or augmented system state matrix [4]. Parameter p was assumed to have small and slow variations. Equation (3) can be reduced to ordinary state space equations by eliminating Δy :

$$\Delta\dot{x} = (J_{11} - J_{12}J_{22}^{-1}J_{12})\Delta x = A\Delta x \tag{4}$$

where A is called reduced Jacobian or reduced system matrix. In power system studies, dynamic-algebraic Jacobian matrix is used in order to obtain accurate dynamic voltage stability boundaries [4,17]. For a structural stability problem, there are three different kinds of bifurcation points which they are Hopf bifurcation (HB), Saddle-node bifurcation (SNB) and Singularity induced bifurcation (SIB). In this paper, Hopf bifurcation boundary is used for determining the dynamic voltage stability status of the system in response to a small disturbance. The distance between the base load and the load level leading to the occurrence of HB, is called the voltage stability dynamic loading limit. The problems related to oscillations in the power system are associated with the lack of damping in critical modes [18]. Consider a complex eigenvalue of β±α- =ζ. In such circumstances, the damping ratio of such a mode is defined as follows: In the above equation, α and β are the real and imaginary parts of the critical eigenvalues of the reduced dynamic algebraic Jacobian of the power system. In addition, according to the above relation, Hopf bifurcation occurs when the critical eigenvalues damping ratio of the system is zero and this mode corresponds to the situation, where the eigenvalue is placed on the imaginary axis of the complex plane. Moreover, this mode corresponds to undamped oscillations of the power system's parameters, such as voltage or generated reactive power of generators. On the other hand, based on the dynamic algebraic Jacobian of the power system, voltage stability holds when all the eigenvalues are on the left side of the imaginary axis, so in this situation, the damping is positive and system oscillations are damped. Additionally, in the loadings more than the load leading to HB, the damping ratio (σ) is negative, which is in parallel with undamped oscillations. In "Fig. 1" the behavior of the system's critical eigenvalues is shown at different load levels (λ). In this figure, the oscillatory behavior of the power system is shown, which corresponds to the behavior of critical eigenvalues.

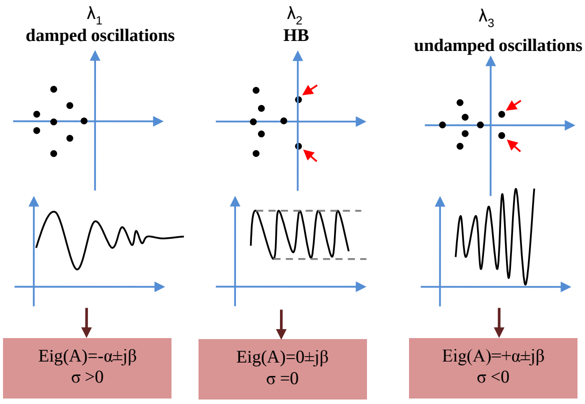


Fig. 1. Relation between the critical eigenvalues of dynamic algebraic Jacobian and power system oscillations

2. Proposed method for dynamic voltage stability status prediction

The proposed prediction method for timely and accurate dynamic voltage stability status prediction consists of synchrophasors recorded by WAMS, feature selection technique and Neuro-Fuzzy classifier as the forecast engine. The flowchart of the proposed algorithm is shown in "Fig.2". In this figure, is a vector containing voltage magnitudes and phase angles of all buses which are obtained from PMUs. Additionally, is the set of selected inputs for dynamic voltage stability status forecast process which are obtained using the proposed feature selection technique. Finally, NFS is employed to predict the dynamic voltage stability status of the system. The other parts of the flowchart are explained in following sections.

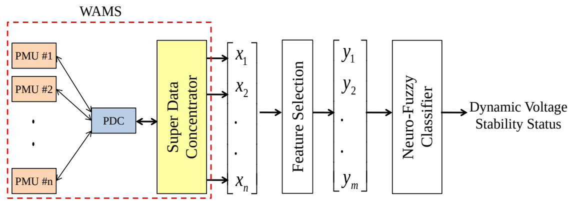


Fig. 2. Proposed algorithm for dynamic voltage stability status prediction

A) Wide-area measurement system

WAMS contains PMUs, communication links, phasor data concentrators (PDCs) and super data concentrator and/or control centers. PMUs can provide synchronous measurement with high sampling rate e.g. 30 samples per second, that results in time based tracking of phenomena in the network [9,19]. Therefore, conventional methods have been replaced with WAMS based on PMUs. The PMUs are mounted on different buses and provide magnitude and phase angle of voltages and currents. They also measure frequency and rate of frequency variation. In this paper, we use this superior advantage of PMUs to study dynamic voltage stability of the network and to develop our proposed method.

B) Feature selection algorithm

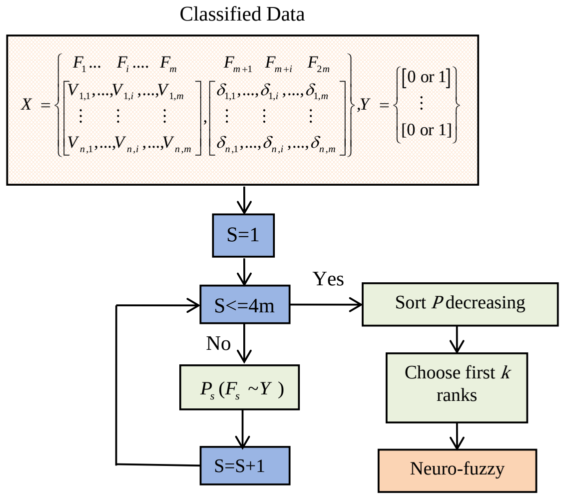
Candidate set of input for a practical power system are not applicable to a forecaster since they may be so large. Moreover, due to presence of irrelevant and redundant inputs the forecast engine might be misled. Redundant data increases the computation time in processor, does not provide more information. The method used in this paper in order to optimize the data set is Pearson future selection algorithm [15]. To introduce the algorithm, assume that we have feature set with values and the classes Y with values y- where in our case X could be any combination of the vector variables (V, δ) and Y is the vector of classified data (0,1)- then Pearson's linear correlation coefficient is computed exploiting following equation:

$$\rho(X,Y)=\frac{E(XY)-E(X)E(Y)}{\sqrt{\sigma^2(X)\sigma^2(Y)}} \qquad (5)$$

The probability of variables correlation is gained using error function as follows:

$$P(X\sim Y)=erf\,(|\rho(X,Y)|\sqrt{n/2} \qquad (6)$$

where n is number of samples. Then, the features are sorted based on value of $P(X\sim Y)$ and the one with maximum rank ($P(X\sim Y)$) has the first place in the list. Depending on the design process, the k (chosen by designer based on complication of the design and number of features which are needed. features with maximum rank could be chosen to train the neuro-fuzzy system. The performance of the feature selection is illustrated in "Fig.3". The general case was depicted where two variables (V, δ) are included in measured data. As the figure shows, correlation of each feature with output is ranked and then the most top ranks are chosen to train neuro-fuzzy system.



Pearson feature selection algorithm

C) Neuro-fuzzy predictor

In this paper we employ neuro-fuzzy inference system to predict the stability of the network. The general model of the neuro-fuzzy system is depicted in "Fig. 4". The method used for neuro-fuzzy system is based on Takagi and Sugeno's method [11,12]. Takagi Sugeno's method was chosen because it can be tuned more flexibly to estimate performance of nonlinear systems. For the involved system with m inputs, fuzzy if-then rules can be presented as:

$$\begin{aligned}&\text{Rule1: if } x_1 \text{ is } A_{1,1} \text{ and } \dots\ x_n \text{ is } A_{1,n},\\ &\text{then } y_1 = w_{1,1}x_1 + w_{1,2}x_2 + \dots, w_{1,n}x_n + r_1\\ &\text{Rule2: if } x_1 \text{ is } A_{2,1} \text{ and } \dots\ x_n \text{ is } A_{2,n},\\ &\text{then } y_2 = w_{2,1}x_1 + w_{2,2}x_2 + \dots, w_{2,n}x_n + r_2\end{aligned} \qquad (7)$$

$w_{k,i}$ is parameter tuned by the neuro-fuzzy system, $k=1,\dots,N$ is number of rules, and $i=1,\dots,n$ is number of inputs of neuro-fuzzy systems. y_k is output of each rule in Takagi Sugeno's type fuzzy systems. The output of each rule is linear combination of inputs plus a constant. This format is useful when training algorithm is used to tune coefficients.

In "Fig. 4", we have five layers that are briefly described as follows. Layer 1 is responsible for the fuzzification of input variables and converts the input variables to linguistic variables. Therefore, each circle in layer 1 is a membership function related to its inputs. If we suppose that we have n inputs and for each input we have m membership function (equal membership function is defined for simplicity in notation, while it can be different in real application), therefore the membership function equation can be written as follows:

$$f_{i,j} = \mu_{i,j}(x_i) \tag{8}$$

where $j = 1,...,m$ is number of membership functions in the i[th] fuzzy set and $f_{i,j}$ is the firing strength of input i in membership function, $\mu_{i,j}$ .In our case, bell-shaped membership function is used.

$$\mu_{i,j}(x_i) = \exp(-(\frac{x_i - a_{i,j}}{b_{i,j}})^2) \tag{9}$$

Variations of $a_{i,j}$ and $b_{i,j}$ produce different membership functions. Here, the back propagation algorithm [13,14] is implemented to tune parameters of membership functions.

In layer 2, the product is used which is denoted by Π. Layer 2 computes the firing strength of each rule. As the figure shows, we have different connections from layer 1 to layer 2 that describe the varieties of rules. Suppose that inputs of the first node in layer 2 are $\mu_{1,1}, \mu_{2,1}, ..., \mu_{n,1}$, then the output of layer 2 is computed by the following product function:

$$R_k = \mu_{1,1}(x_1) \times \mu_{2,1}(x_2) \times .... \times \mu_{n,1}(x_n) \tag{10}$$

Layer 3 normalizes the output of each rule and prepares them for second part of the neuro-fuzzy system for training purpose. Therefore the output of the k^{th} circle in layer 3 is:

$$NR_k = \frac{R_k}{R_1 + R_2 + ... + R_N} \tag{11}$$

where NR_k stands for normalized rules. These values are final value of each rule in fuzzy system. Then, it is exerted to second part of neuro-fuzzy system. From "Fig. 4" we see that we have the same number of nodes as layer 3. For each node we have one input that comes from the previous layer and m inputs that are the original inputs of neuro-fuzzy systems. The output of k^{th} node in layer 4 is:

$$O_k = NR_k(w_{k,1}x_1 + w_{k,2}x_2 + ... + w_{k,n}x_n + r_k) \tag{12}$$

To tune parameters $w_{k,i}$, least mean square error algorithm is used [13,14]. The most important feature of least mean square algorithm is that it always provides global minima. Therefore, the best approximated parameters can be obtained. The final layer, layer 5, is a single node that is summation of all incoming signals,

$$Y = \sum_{k=1}^{N} O_k \tag{13}$$

In our case, desired output is a discrete function $\{0,1\}$ while the output of the neuro-fuzzy system is continuous function. In training phase, desired outputs are exerted to the neuro-fuzzy system, however, when the training phase is finished, we add a threshold to the end of neuro-fuzzy system to provide discrete response.

$$Y_{decision} = \begin{cases} 0 & Y < 0.5 \\ 1 & Y \geq 0.5 \end{cases} \tag{14}$$

Actually, this does not change performance of the neuro-fuzzy system and just discretizes the response so that it can be clearly understandable that system is stable or unstable based on the classification performed in the next sections. In this paper, different input variables are considered and for each one a neuro-fuzzy system is trained and results are analyzed. The measured and classified data are divided to two groups; training data and testing data. This separation is performed so that we have enough data for training and some data for testing the trained system. The separation is performed randomly through all data. The detailed description is given in the simulation part.

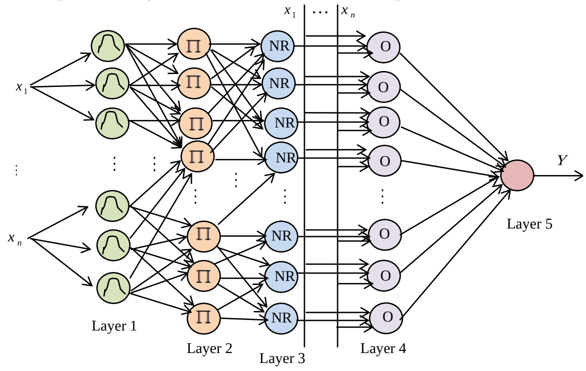


Fig. 3. The structure of neuro-fuzzy system

3. Development of the proposed modeling and simulation results

The proposed dynamic voltage stability prediction method is applied to New England which has 39 buses, 10 machines and 46 branches and IEEE 68 bus test system which has 68 buses, 16 machines and 83 branches. These test systems are used frequently for voltage stability studies of power system [4]. Dynamic and static data of these test systems can be found in [20,21]. The set of candidate inputs for New-England and IEEE 68 bus test systems are 39V+39δ =78 and 68V+68δ =136 candidates, respectively. Moreover, for each proposed class label, 300 samples are generated from which 260 and 40 samples are devoted to training and test phases, respectively. The whole steps to implement neuro-fuzzy predictor are depicted in "Fig. 5". According to mentioned proposed algorithm, it has been assumed that PMUs are installed at buses in the network to measure the voltage synchrophasors. In this paper, these synchrophasors which are used for training the NFS were generated through offline time domain simulations using DIgSILENT software [22]. To produce samples, the small disturbance voltage stability was considered which includes changes in the system load (both the load level and load distribution). Dynamic voltage stability status for each sample is determined using modal analysis [10] with following condition function,

$$\begin{cases} EP \text{ is befor } HP \Rightarrow \quad \text{system is stable,} \quad \text{class: 1} \\ EP \text{ is after } HP \Rightarrow \quad \text{system is unstable, class: 0} \end{cases} \tag{15}$$

where EP is equilibrium point and HP is Hopf Bifurcation boundary.

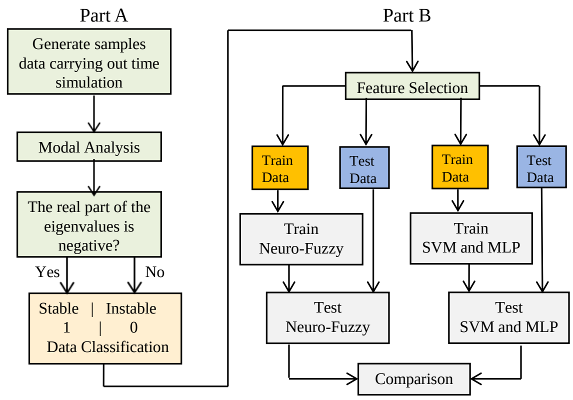


Fig. 4. Dynamic Simulation of system and training procedure

After performing modal analysis, samples are classified under two groups, stable or unstable. Then, the feature selection algorithm is exerted to this classified data to select the most informative features and Finally the selected features is exerted to three different forecast engines include of NFS, support vector machine (SVM) [23] and multi layer perception (MLP) [23] based back propagation (BP) learning algorithms for training purpose. , MLP and SVM neural networks are used as alternative of NFS forecast engine.

A) Simulation results for New England test system

Experiment.1. Selection of Input features

At first, we test neuro-fuzzy system with whole voltage magnitudes and phase angles data and then we show that the voltage magnitudes can be omitted and using just phase angles is enough for suitable training of NFS. In this experiment, Prediction errors obtained by proposed feature selection method for three different forecast engines are shown in "table 1".

These results clearly demonstrate that NFS operates more precisely than other forecast engines specially MLP regarding prediction of operating condition based on proposed classification. Prediction error might cause the operator to fail in making correct decision and to apply a wrong corrective/preventive method which, in turn, may cause damage to the system. For example if the forecast engine predicts class 1 instead of class 2 (a condition when damping is negative and critical eigenvalue is in the right half of complex plane), system damping would be desirable from operator's perspective and it would not be necessary to increase damping. It may result in severe fluctuations and moves the system to vicinity of collapse. Moreover, it can be observed from "Table 1" that we can achieve suitable prediction using only phase angle features. To analyze this issue more properly, the voltage magnitudes and phase angels of some buses are demonstrated in "Fig. 6" when small disturbances (simultaneous increase in loads of buses number 15, 16 and 18) occur.

Table.1.
Obtained prediction error for NFS, SVM and MLP – New-England (Experiment. 1)

Input feature sets	voltage magnitudes and phase angles (V , δ)	phase angles (δ)
No. of features	40	10
No. of rules	40	8
No. of clustering	22	8
Prediction error of NFS(%)	0	0
Prediction error of SVM (%)	3.75	2.5
Prediction error of MLP_{BP} (%)	5	3.75

From "Fig. 6", it can be observed that the variations of the voltage magnitude from stability point to instability point are too small. Here, we have phase angles which have much faster and larger variations comparing to voltage magnitudes. Moreover, it can be concluded from simulation results that the phase angle can provide enough information about stability of the system. Considering these two facts, we suggested to ignoring all the voltage magnitude features from our data. In "Table 2" The phase angle features were chosen using proposed feature selection algorithm are shown and the rank of each candidate is sorted according to their information value for the forecast process.

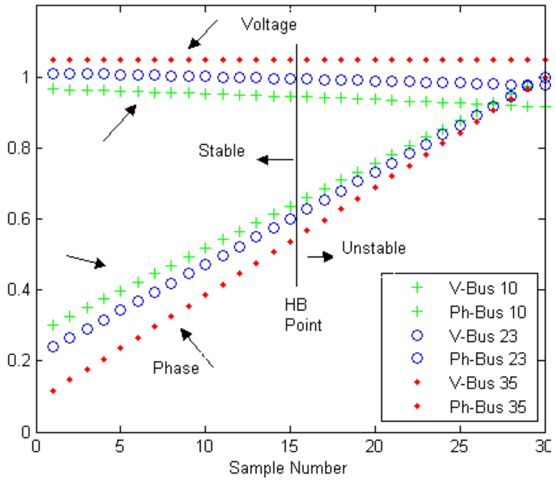


Fig. 5. The sample data from voltage magnitudes and phase angles of some buses during small disturbance

Table.1.
The selected phase angle features after employing feature selection for New England test system

Selected features	δ_{26}	δ_{27}	δ_{25}	δ_{11}	δ_{28}
Rank	0.551	0.543	0.524	0.520	0.519
Selected features	δ_{7}	δ_{30}	δ_{29}	δ_{13}	δ_{8}
Rank	0.513	0.509	0.509	0.500	0.495

Experiment.2. PMU Measurement Error

Despite precision of PMUs, signal processing may produce some errors in the phasor calculations. Difference between the exact applied signal and the measured one is defined as total vector error (TVE). According to IEEE standard [24], the TVE must be less than 1% under steady state condition. To assess performance of the proposed prediction strategy, the effect of noisy samples is evaluated in this experiment. To this purpose, a random error between 0 and 1% was added to voltage phasor of all buses achieved by DIGSILENT before using them as inputs to the NFS, SVM and MLP forecast engines.

"Table 3" shows the results obtained from this experiment. As shown in this table, 14 of 39 initial candidate features are selected after performing the proposed feature selection method. While in the first experiment 10 of 39 initial candidate features are selected. This difference indicates that the complex quality samples lead to increase in the amount of input features of forecast engine. This increase is inevitable in order to increase the accuracy or decrease the error of forecast engine. However, the presented prediction error in "Table 3" shows that the proposed forecast engine (NFS) have zero prediction error while SVM and MLP_{BP} have 5% (4 of 80 test samples are predicted incorrectly) and 7.5 (6 of 80 test samples are predicted incorrectly) prediction error, respectively.

Table.2.
Obtained prediction error for NFS, SVM and MLP considering measurement error– New-England test system (Experiment. 2)

Input feature sets	phase angles
No. of features	14
No. of rules	14
No. of clustering	11
Prediction error of NFS(%)	0
Prediction error of SVM (%)	5
Prediction error of MLP_{BP} (%)	7.5

B) Simulation results for IEEE 68-bus test system

To investigate the capabilities of proposed prediction method, two experiments performed in previous section are carried out on the IEEE 68 bus test system as well. "Table 4", shows prediction results of NFS, SVM and MLP forecast engines for two mentioned experiments. The noise applied in experiment 2 is the same as what applied in experiment 2 of New-England test system. The selected phase angle features for experiment-1 after employing feature selection and rank of each candidate is sorted in "Table 5".

Table.3.
Obtained prediction error for NFS, SVM and MLP – IEEE 68-bus test system

	Experiment-1		**Experiment-2**
Input feature sets	(V, δ)	(δ)	(δ)
No. of features	50	20	34
No. of rules	45	16	30
No. of clustering	30	12	22
Prediction error of NFS(%)	0	0	1.25
Prediction error of SVM (%)	3.75	2.5	6.25
Prediction error of MLP_{BP} (%)	6.25	3.75	8.75

Table.4.
The selected phase angle features after employing feature selection for IEEE 68-Bus test system

Selected features	δ_{55}	δ_{15}	δ_{54}	δ_{16}	δ_{14}
Rank	0.6927	0.6926	0.6926	0.6925	0.6904
Selected features	δ_{17}	δ_{8}	δ_{63}	δ_{36}	δ_{64}
Rank	0.6621	0.6576	0.6552	0.6551	0.6524
Selected features	δ_{37}	δ_{9}	δ_{35}	δ_{20}	δ_{43}
Rank	0.6523	0.6512	0.6503	0.6489	0.6479
Selected features	δ_{19}	δ_{22}	δ_{21}	δ_{58}	δ_{52}
Rank	0.6471	0.6469	0.6469	0.6467	0.6456

According to "Table 4" in experiments 1 and 2 NFS have less prediction error in contrast with SVM and MLP. As a result using NFS with feature selection algorithm is powerful method to predict dynamic voltage stability status of the power system. Also according to the results, using the phase angle features alone is sufficient to predict the voltage stability status. Hence, using the proposed method, the status of power system voltage stability via minimum number of features can be predicted with good accuracy.

4. Conclusion

In this paper, neuro-fuzzy predictor was designed to estimate the dynamic voltage stability status of the system based on wide area synchrophasor data. In order to reduce the number of neuro-fuzzy inputs, training time and complication of forecast engine, the feature selection technique combined with neuro-fuzzy system is proposed to select the set of input variables that have the strongest correlation with the output. The proposed method has been implemented on New-England and IEEE 68-bus test systems. The capabilities of proposed NFS are compared to other neural networks including SVM and MLP for two input feature sets considering noisy input data. The obtained numerical results revealed that proposed prediction method properly specify power system voltage stability status with a few number of phase angle features.

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