SMALL-SIGNAL STABILITY ASSESSMENT OF THE EUROPEAN POWER SYSTEM BASED ON ADVANCED NEURAL NETWORK METHOD

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Abstract: This paper deals with a new method for eigenvalue prediction of critical inter-area stability modes of the European electric power system based on Neural Networks (NN). The existing methods for eigenvalue computations are time-consuming and require the entire system model that includes an extensive number of states. The system features suitable as inputs of the NN are selected based on a new multi step selection technique. After proper training of the NN, the damping and frequency of the oscillations can be predicted very fast and with high accuracy. Hereby, the neural network outputs describe the activations of sampling points in the complex plain, which reflect the nearness of eigenvalues. The interpolation of activations results in regions where the eigenvalues are predicted to be located. The method is suitable for on-line application.

Keywords: Eigenvalues, Oscillation, Neural networks, Small signal modes

1. INTRODUCTION

Inter-area oscillations in large-scale power systems are becoming more common especially for the European Interconnected Power System UCTE/CENTREL. The system has grown very fast in a short period of time due to the recent east expansion. This extensive interconnection alters the stability region of the network, and the system experiences inter-area oscillations associated with the swinging of many machines in one part of the system against machines in other parts. Moreover, for certain load flow conditions, the system damping changes widely, (see) (Bachmann, *et al.,* 1999) and (Breulmann, *et al.*, 2000).
With deregulation of electricity markets in Europe, the utilities are allowed to sell their generated power outside their traditional borders and compete directly for customers. For economical reasons, the operators are often forced to steer the system closer to the stability limits. Thus, the operators need different computational tools for system stability estimation. These tools must be accurate and fast to allow on-line stability assessment.

The computation of the small signal stability is a time consuming process for large networks, which includes the load flow computation, the linearization at the operating point, and the eigenvalue computation.
An alternative method is to use a Neural Network (NN) trained with off-line data for different load flow and system conditions. By using NN, a fast computation of the eigenvalues is possible, providing that the network is properly designed and trained. Recent NN approaches showed highly accurate results regarding the eigenvalue prediction of large-scale power systems (Teeuwsen, *et al.*, 2001). But all of them are trained only for narrow operating conditions of the power system. In fact, when the operating point of a given power system changes, the corresponding eigenvalues may shift significantly. Small changes, e.g. in the network topology, the current load situation or the voltage level, may change the position of the eigenvalues. This change in position leads to the fact that the number of eigenvalues in the weakly damped region is not constant for all considered situations. Therefore, the NN has to be designed as a robust assessment tool

that is not influenced by time of the day, the season, and the power system topology.

The NN introduced in (Teeuwsen, *et al.*, 2001) predicts the eigenvalues itself. But a NN, which is able to manage all the above-mentioned additional influences, must be designed for a varying number of eigenvalues. Hence the NN must have a variable structure, which is a difficult task. To address this issue, the assessment method proposed in this paper is based not on the prediction of eigenvalues per se but on the prediction of regions, which could contain one or more dominant eigenvalues with insufficient damping.

To generate the training data for the NN, an observation area is defined within the complex eigenvalue space. This observation area is located at a low damping level and frequencies where inter-area eigenvalues typically occur. Then, the entire observation area is sampled in the directions of the real and imaginary axes. The distances between the sample points and the eigenvalues are computed and the sample points are activated depending on whether there are eigenvalues nearby or not. The closer an eigenvalue to a sample point, the higher the corresponding activation. Once this is computed for the entire set of patterns, the NN is trained with these activations. After proper training, the NN can be used in real time to compute the sample activations. Then, the activations are transformed into a region where the eigenvalues are obviously located. These regions are characterized by activations higher than a given limit.

2. IVESTIGATED POWER SYSTEM

The power system investigated in this study is the extended UCTE/CENTREL high voltage European network, including the East European and Balkan systems. It consist of approximately 500 generators, several thousand lines and nodes, hundreds of transformers, etc. The generators are described by 5. order models, while different user-defined models are employed for the controllers. The system data is prepared for dynamic investigations in the time range of seconds to a few minutes. Alongside the time domain simulation, the software package used allows the calculation of eigenvalues and eigenvectors.

Fig. 1a-c provides an overview of the inherent system dynamic behavior, the so called mode shapes. Mode shapes depicted in Fig.1 represent the most important inter-area modes, which will be investigated next. The arrows show the direction and the relative intensity of the corresponding swings, because they represent the eigenvectors corresponding to the mechanical motion of generator rotors. The positioning of arrows to the generator geographical locations is arbitrary. However, this kind of visualization provides an excellent overview about the spread of oscillations.

The damping of the first mode in the base state is very good as yet. However, it can change with the operating point over a wide range as shown in Fig. 2.

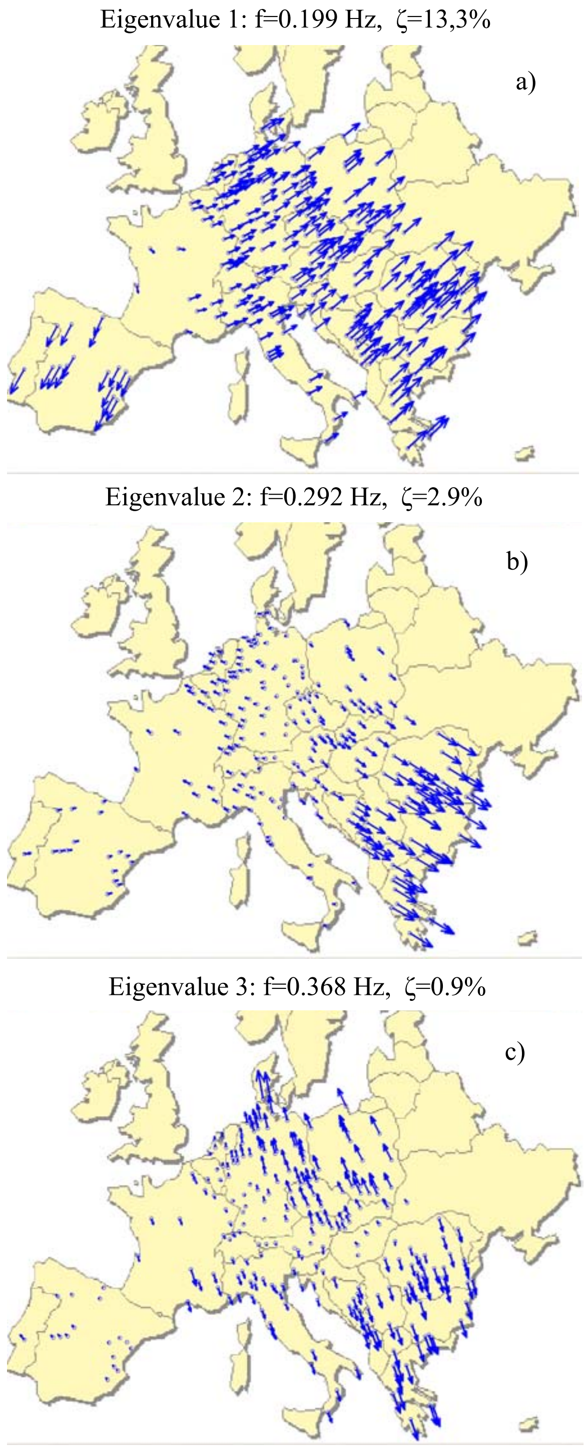

Fig. 1 Modeshapes to the three considered inter-area modes

Fig. 2 contains the eigenvalues for 2500 different load-flow situations. It is calculated by varying the active power transit between different network areas, which corresponds with different utilities. To increase the power generation in one area the necessary number of units were taken into operation. At the same time in the power receiving area the generation was reduced by switching off units. Generally, the load-flow scenarios were adjusted based on practical experience.

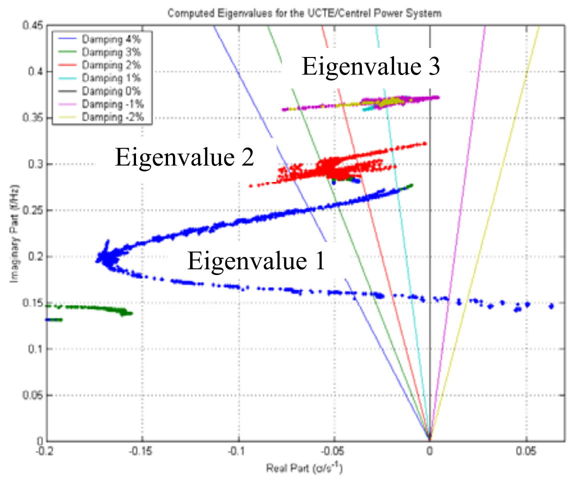

Fig. 2 Considered interarea eigenvalues for 2500 load-flow scenarios

From Fig. 2 follows that all three eigenvalues may experience changes ranging up to unstable values. Furthermore, the impact of transactions on the eigenvalues is strongly non-linear. Obviously, it depends on several factors and cannot be described analytically.

3. NN-BASED APPROACH

It is known that NN are able to learn complex non-linear relationships. Furthermore, as NN inputs usually a reduced number of system features are sufficient. A further advantage of the NN is its very fast computation time. The basic idea for NN-based small signal stability assessment is shown in Fig. 3.

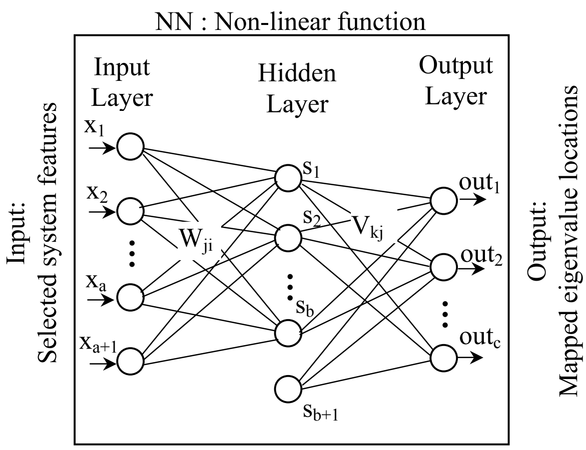

Fig. 3 NN-based Small Signal Stability Assessment

It is clear that eigenvalue calculation using NN will always be afflicted with errors. Therefore, the accuracy ensured by the method must be adequate for the proposed application.

Two basic questions arise:

- How can features for NN be selected?
- How can eigenvalue locations be mapped by NN outputs?

The first question is a general one and will be discussed in the next chapter.

Eigenvalue mapping can be done in different ways. Apparently, the coordinates of eigenvalues can be calculated directly by the NN. This method has been proven in (Teeuwsen, *et al.*, 2001) and is applicable with the following restrictions: the locus of different eigenvalues may not overlap each other and the number of eigenvalues must remain always constant. These follow from the fact that eigenvalues are assigned directly to NN outputs. Another approach considers fixed rectangular regions, which - depending on the distance between region centroid and eigenvalues - are activated or not. The outputs of the NN are in this case the activations of predefined regions (Teeuwsen, *et al.*, 2003a). Enhancement could be achieved with this method by making the region width on the abscissa variable (Teeuwsen, *et al.*, 2003b). A more generalized method considers the activations of sampling points without any fixed partitioning of the complex plain into regions (Teeuwsen, *et al.*, 2003c). This method will be applied to the system described in this paper and will be discussed next. Generally, the advantage of each method, taking into account activation values to be predicted, is the fact that eigenvalues must not be separable. Therefore the number of eigenvalues can vary and overlapping does not lead to problems.

The proposed stability assessment method requires that the observation area in the complex eigenvalue space is defined first. The observation area is located at the region of insufficient damping, where typical inter-area eigenvalues can be found. In this study, the considered damping range is chosen between 4% and –1.0%. Then, this area is sampled along the real axis (σ) with a constant step width. This is done for the given application 5 times for 5 different frequencies *f*. The sampling steps applied are as follows:

$$\Delta\sigma = 0.015\ s^{-1} \qquad \Delta f = 0.14\ \text{Hz}$$

The observation area of insufficient damping is shown in Fig. 4. The sample points are marked by circles.

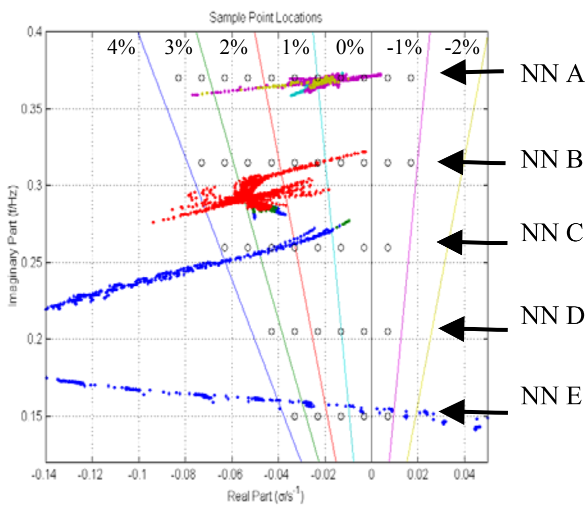

Fig. 4. Partitioning and sampling of eigenvalue plain

The sampling results in a set of 40 sample points. To increase the accuracy of the prediction, the observation area is divided into smaller observation sections (rows of sample points) whereby each row of sample points uses its own NN. Hence, 5 independent NN are used.

After the observation area is sampled, the sample points need to be activated according to the positions of the eigenvalues. Thus, the distance between the eigenvalues and the samples is used to compute activation for the sample points. The eigenvalues are defined by their real component σ_{ev} and their frequency f_{ev}. The sample points are defined by their location (σ_s, f_s). Then, the distance between a given eigenvalue and a given sample is computed as follows:

$$d = \sqrt{\left(\frac{\sigma_s - \sigma_{ev}}{k_\sigma}\right)^2 + \left(\frac{f_s - f_{ev}}{k_f}\right)^2} \quad (1)$$

Because σ and f use different units and cannot be compared directly, both are scaled. Hence, σ and f are divided by the constants k_σ for the real part and k_f for the frequency, respectively. The maximum distance possible between an eigenvalue and the closest sample point occurs when the eigenvalue is located exactly in the geometrical center of 4 neighboring sample points. This is shown in Fig. 5.

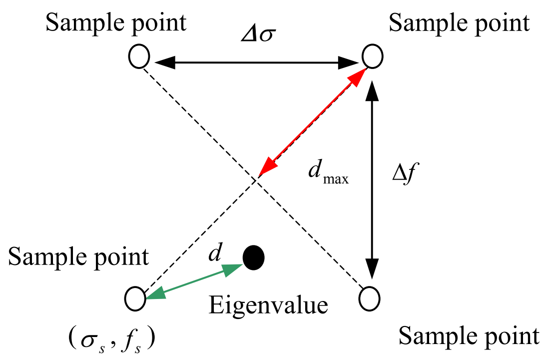

Fig. 5. Definition of the maximum distance d_{max}

According to Fig. 5 and Equation (1), the maximum distance can be computed as

$$d_{max} = \sqrt{\left(\frac{\Delta\sigma}{2} \Big/ k_\sigma\right)^2 + \left(\frac{\Delta f}{2} \Big/ k_f\right)^2} \quad (2)$$

Based on this maximum distance, the activation value a for a sample is defined as a linear function depending on the distance between a sample point and an eigenvalue:

$$a = \begin{cases} 1 - 0.5 \cdot \dfrac{d}{d_{max}} & 0 \le d \le 2d_{max} \\ 0 & d > 2d_{max} \end{cases} \quad (3)$$

This activation a is computed for a given sample point with respect to all eigenvalues resulting from one pattern.

The final activation value act for the given sample point is the summation of all activations a

$$act = \sum_{i=1}^{n} a \quad (4)$$

whereby n is the number of considered eigenvalues. The maximum distance (2) and the activation function (3) lead to the minimum activation for a sample point when an eigenvalue is nearby:

$$act \ge 0.5 \quad (5)$$

The success of the prediction depends strongly on the choice of the scaling parameters. These parameters impact both the training process of the NN and the accuracy of the predicted region as well. Therefore, some experience are necessary to apply the proposed method to particular power systems.

3. FEATURE SELECTION

The first step for creating any artificial intelligence based small signal stability assessment system, however, is the selection of feature used as input. As an important issue to be considered is the fact that the selected features must be exchanged between utilities, i.e. it is required that utilities are willing to offer these quantities to their partner utilities.

Large scale power systems include many features such as transmission line flows, generated powers, demands, etc.. It is obvious that for a large system, the feature set is too large for any effective NN training, see (Teeuwsen, *et al.*, 2001). Hence, feature extraction or selection techniques must be utilized. Even for selection, the features cannot be treated all together. Therefore, in this study a Multi Step Selection (MSS) technique has been used. It is shown in Fig. 6.

The number of potential features in this study reaches approximately nine thousand. Therefore features are divided into five groups. Table 1 shows the assignment of features to the groups. The groups are formed on the basis of physical knowledge. Then, the Principal Component Analysis (PCA) is utilized to reduce the dimension of feature vectors, which is equal to the number of investigated load-flow scenarios, i.e. exactly 2500 (number of pattern). This reduction is necessary because the applied k-means clustering algorithm in the subsequent step shows a better performance with smaller feature vectors. The clustering algorithm puts together similar features, which contain redundant information. Therefore, only one feature is chosen from each cluster for further processing, which is treated according to the selection of single groups. In the end 50 features remain as inputs for the NN. This number is still high and could be further reduced. However, considering possibly missing features in real systems caused for example by signal transmission failures, some redundancy has to be provided. The remaining 50 features belong to different physical quantities and are spread over the whole network.

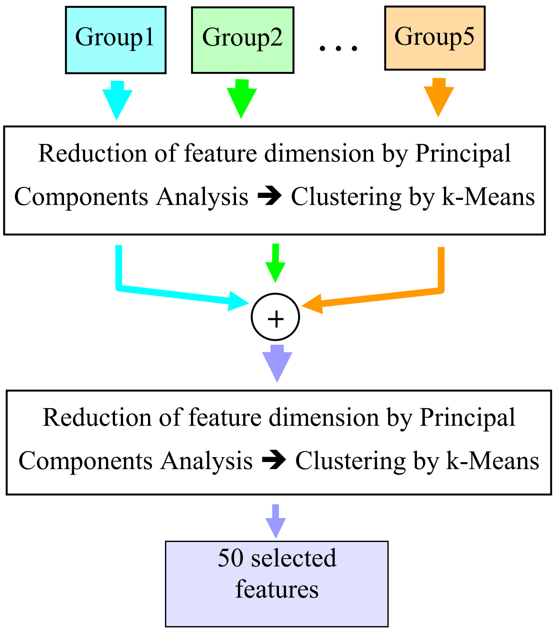

Fig. 6. Applied MSS Feature Selection Method

Table 1 Grouping of features

Features	Occurrence in the Network	Feature Group
Sum of active and reactive power in each high voltage utility	58	1
Rotating energy of generators per utility	29	1
Active power transfer through lines	2.089	2
Reactive power transfer through lines	2.089	3
Magnitude of nodal voltages	2.016	4
Phase angle of nodal voltages	2.016	5
Active power of generators	468	6
Reactive power of generators	468	6
Kinetic energy of generators	468	1

5 APPLICATION AND RESULTS

The sample point activations were computed for the eigenvalues of the 2500 calculated load-flow scenarios. Thus, the desired inputs and outputs of the NN were given. Then the data set were normalized and shuffled randomly before the 5 NN has been trained independently. The training was carried out with a subset of training data, whereas a smaller part of the data was kept back for testing. Once the NN are trained properly, the NN output values representing the activation of the sampling points, need to be transformed into eigenvalue locations. For this purpose all activation values were used to setup an activation surface, which is constructed by linear interpolation between all rows and columns of sample points as shown for a selected pattern in Fig. 7a. Then, a plain surface is drawn at the minimum activation level of 0.5, which is called limit surface. The intersection of the activation surface and the limit surface leads to a region, which is called predicted region (Fig. 7b).

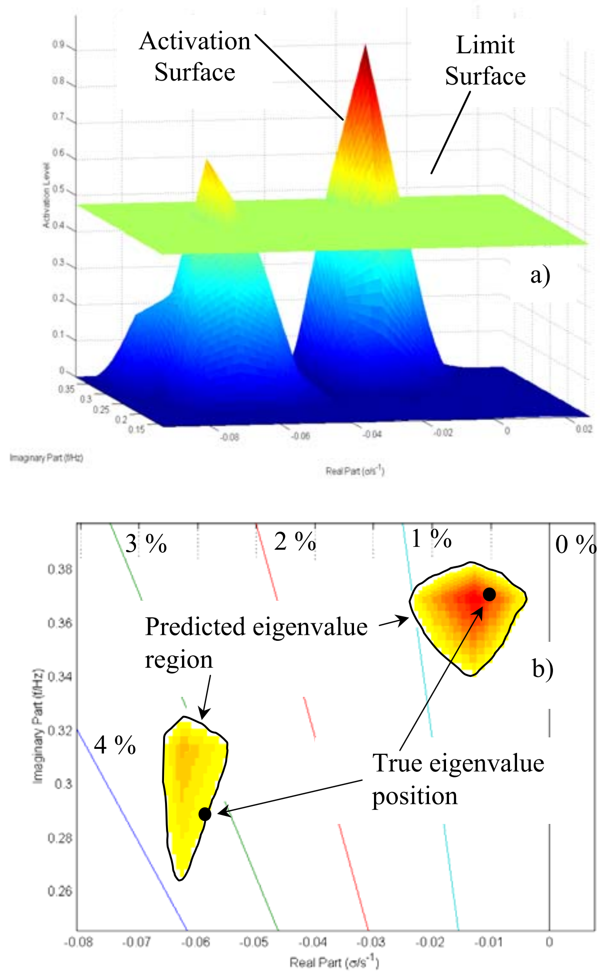

Fig. 7. (a) Activation surface constructed by sample point interpolation and limit surface, (b) View from above: predicted regions in the complex space

If the NN is trained properly, the true eigenvalue position will be within this predicted region as shown in Fig. 7b.

For a more sound error evaluation, the predicted regions are compared with the positions of the eigenvalues for all patterns. If an eigenvalue is located inside a region, the prediction yields correct. If an eigenvalue is located outside the corresponding region or no range and therefore no region is constructed for this eigenvalue, the error is called false dismissal. If a range is constructed, but no corresponding eigenvalue exists within the observation area, the error is called false alarm. The error rates for both kind of errors are calculated according to Eq. (6)

$$E[\%] = 100 \cdot \frac{\text{number of false dismissals or false alarms}}{\text{number of pattern}} \quad (6)$$

Table 2 contains the results for the investigated system.

Table 2 Error rates for NN Training and Testing

Results	Training	Test
Predicted region matches eigenvalue position	99,2 %	97,5 %
False dismissals	0,8 %	2,5 %
False alarm	0,0 %	0,0 %

False alarm was never registered. False dismissals occurred in 2.5% of all cases, which, however, does not necessarily mean that this predictions are not utilizable. The eigenvalues were always located near the predicted region. By using a slightly modified activation function, it is possible to reduce the error rate. Thereby, however, the expanse of the predicted region will increase. Therefore, for an evaluation of the proposed method the width of the region in frequency and damping must be considered too. Fig. 8 shows the definition of region widths $\Delta\zeta_{reg}$ and Δf_{reg}, respectively.

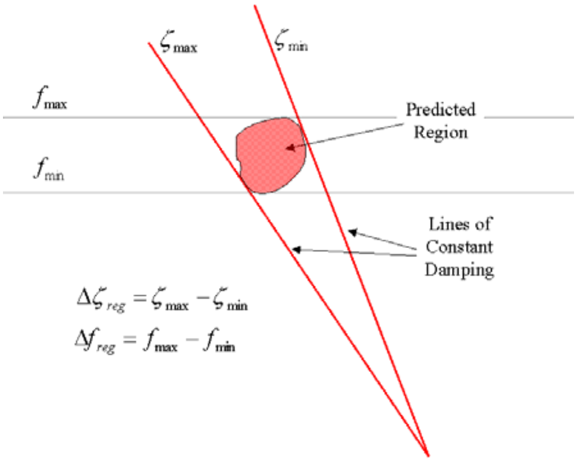

Fig. 8. Definition of the width of a predicted region in damping ($\Delta\zeta_{reg}$) and frequency (Δf_{reg})

The mean and standard deviation of $\Delta\zeta_{reg}$ and Δf_{reg} were computed for all patterns, which include eigenvalues in the observation area. Table 3. contains the results

Table 3 Width of predicted eigenvalue regions

Region width	Training		Test	
	Average	STD	Average	STD
$\Delta\zeta_{reg}$	1,038%	0,430%	1,035%	0,429%
Δf_{reg}	0,055Hz	0,023Hz	0,055Hz	0,024Hz

Assuming that the eigenvalues will always be expected in the center of the predicted region, the method provides an average accuracy of ±0.52% for damping and ±0.023 Hz for frequency. By proper modification of the activation function the accuracy could be further increased at the expense of error rate. Therefore both issues must be compromised according to the current requirements

6. CONCLUSIONS

This paper introduces a new method of eigenvalue prediction for small-signal stability assessment. The method is flexible in terms of the network conditions and can manage a variable number of eigenvalues without loss of accuracy.
The area of interest in the complex eigenvalue space is sampled and the sample points are used to obtain an activation surface after proper NN training. This activation surface can be used to construct a region. In other words, the eigenvalues are located within the predicted region, which is given by the prediction tool.
It has been shown that the method is applicable with good accuracy to the European interconnected power system. One of the key advantages of this new technique results from the fact that only a few selected system features are necessary for eigenvalue prediction. However, in large-scale system the feature selection must be treated with well-founded methods. This paper proposes a multi step selection technique, which applies principal component analysis and the k-means clustering algorithm to pre-select feature groups.
The NN based eigenvalue prediction is very fast and, therefore, is applicable for on-line dynamic stability assessment.

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