Neural Network based Classification Method for Small-Signal Stability Assessment

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Abstract--This paper deals with a new method for eigenvalue prediction of critical stability modes of power systems based on neural networks. Special interest is focused on inter-area oscillations of large-scale interconnected power systems. The existing methods for eigenvalue computations are time-consuming and require the entire system model that comprises an extensive number of state variables. After reduction of the neural network input space and proper training of the neural network, it predicts the stability condition of the power system with high accuracy. A byproduct of this research is the development of a new 16-machine dynamic test system.

Index Terms-- Small-Signal Stability, Inter-Area Oscillations, Eigenvalues, Neural Networks

I. 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 eastward expansion. This extensive interconnection alters the stability region of the network, and the system experiences new 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 [1], [2].

With the deregulation of the 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 prediction. 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 [3].

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, provided that the network is properly designed and trained.

Recent NN approaches showed highly accurate results regarding the eigenvalue prediction of large-scale power systems [4]. 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. Therefore, the NN has to be designed as a robust assessment tool that is not influenced by the time of the day, the season, and the topology of the power system.

A NN, which is able to manage all these additional influences, must be designed for variable number of eigenvalues. Hence the NN must have a variable structure, which is a difficult task. To address this issue, the assessment of the system stability is based on an observation area, which contains the dominant eigenvalues with insufficient damping.

To generate the training data for the NN, the complex eigenvalue space is divided into regions of fixed number. In this case, the NN is trained with the activation level of these regions, which depends on whether there is an eigenvalue within a region or not. After proper training, the NN can be used in real time to decide on the presence of eigenvalues in the selected regions.

II. 16-MACHINE DYNAMIC TEST SYSTEM

The PST16 System used in this study is a newly developed dynamic 16-machine test network. The main focus is on representing characteristic power system dynamics like inter-area oscillations in the time range of a few seconds to minutes.

The PST16 System is modeled by using real data. Three different generator units, such as hydropower, thermal and nuclear types are considered. The rated power of these units is 220 MW, 247 MW and 259 MW, respectively. The power plants consist of a particular number of similar units connected to the network as can be seen in Figure 1.

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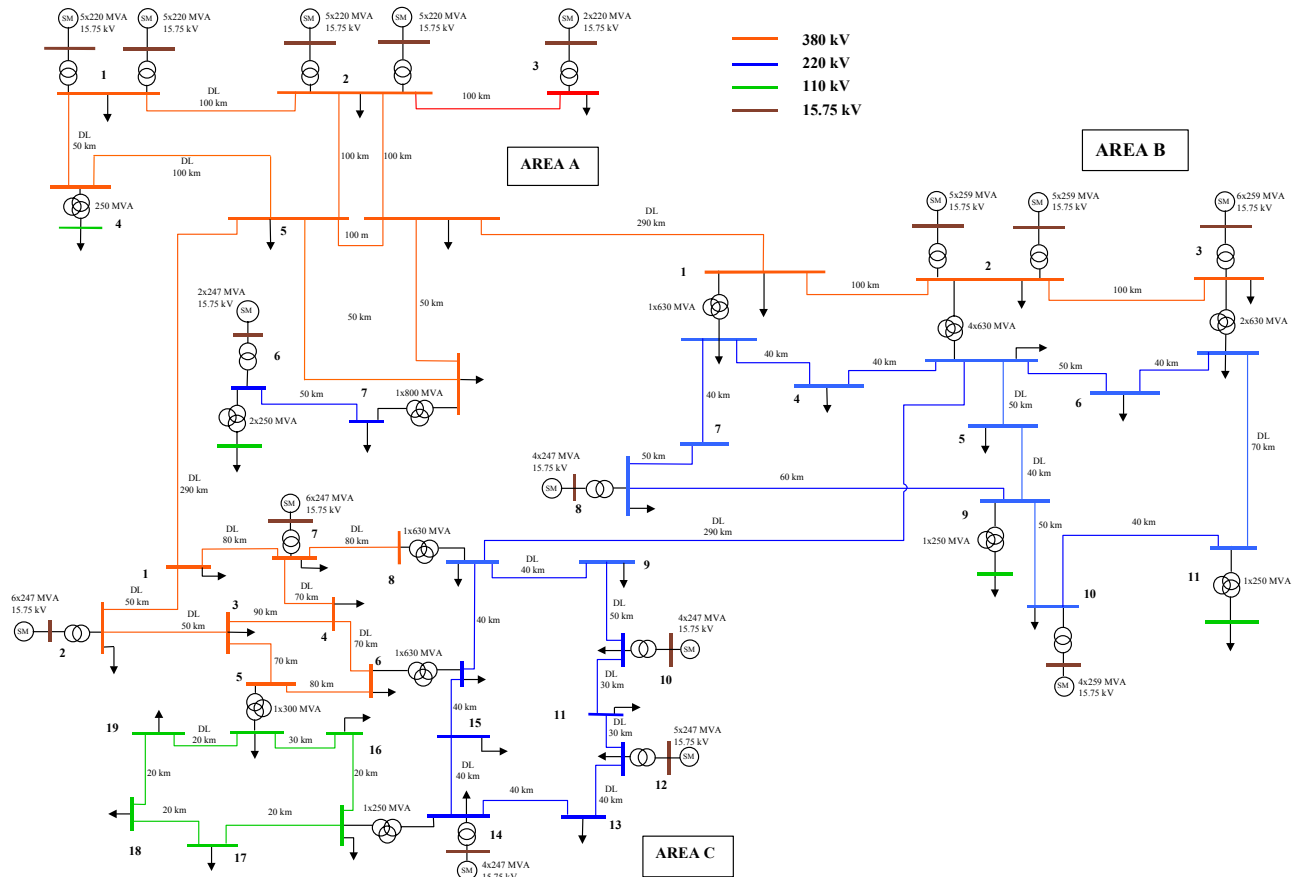
Fig. 1 One-Line Diagram of the PST 16-Machine Test System

The generator models are of 5th order. Different IEEE standard type exciter system models [3] have been used, i.e. for hydro generators ST1A, for thermal driven generators DC1A and for the nuclear units AC1A exciter models. Except for the nuclear units, the turbines and the governing systems are also modeled in detail.

The one-line diagram of the PST16 System is shown in Figure 1. The system consists of three strongly meshed areas. Each has 5-6 generators. Table I includes the fundamental topology information like the number of bus nodes, lines, transformers, and generators for each of the three areas separately. Partly weak transmission lines connect these areas. The connections are weak because the length of the lines is about 280 km. Thus, inter-area oscillations can occur.

However, the system is designed for power exchange between these areas. The first area (Area A) contains mostly hydro power plants and is considered to be a power exporting area. Area B and area C are load demanding areas that import power from area A. The total generation of the system is about 16 GW and the transmission and sub-transmission voltage levels are 380kV, 220kV, and 110kV. Table II shows the concentration of hydro, thermal, and nuclear generators in each area and Table III lists the total load and the total generation per area.

TABLE I
NUMBER OF ELECTRICAL DEVICES FOR EACH AREA SEPARATELY

	Buses	Lines	Transf.	Generators
Area A	17	12	9	6
Area B	21	15	10	5
Area C	28	24	9	5
Total	66	51	28	16

TABLE II
USED GENERATOR TYPES FOR EACH AREA

	Number of Generators		
	Hydro	Thermal	Nuclear
Area A	5	1	0
Area B	0	1	4
Area C	0	5	0

TABLE III
LOAD AND GENERATION FOR EACH AREA SEPARATELY

	Load	Generation
Area A	2,000 MW	4,840 MW
Area B	6,100 MW	5,641 MW
Area C	7,465 MW	5,450 MW
Total	15,565 MW	15,931 MW

To get an insight into the dynamic behavior of the system, time domain simulations as well as eigenvalue calculation can be carried out. Usually engineers prefer investigations in the time domain. However, eigenvalues provide some additional information making this technique more suitable for small signal stability assessment.

First, two different load flow situations were generated by real power exchange between the areas of the test network. Then, for the new operating point, eigenvalues were computed followed by time domain simulation of a small load switching action (10 + j5 MVA at t=2s in the node #13). Figure 2 shows three inter-area eigenvalues for the considered load flow situation. Load situation 1 results from the original state according to the description above. Situation 2 is characterized by an additional real power exchange of about 1300 MW from area A to area C.
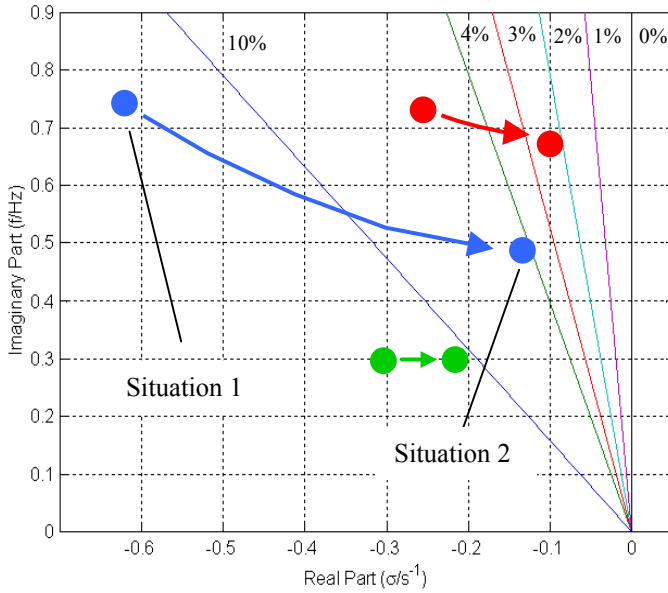

Figure 2: Eigenvalue Shift from Load Flow Situation 1 to Situation 2

Figure 3 shows both the voltage at bus #5 in area A and the real power on the transmission line from bus #5 in area A to bus #1 in area C. Since area A and area C are connected by a double circuit line, the total exchanged real power is about 1720 MW, which is twice the real power shown in Figure 3.

Figure 4 shows the same variables at the same bus for the operating point 2 resulting from additional power exchange in the system. In this scenario, the real power transmitted between areas A and C is much higher than in situation 1. Because of the double circuit between these areas, the total transmitted real power is about 2870 MW, which is close to the maximum transfer capacity of this line. Figures 2-4 show obviously that extreme load flow scenarios can lead to a weakly damped system. Yet the damping in situation 1 is sufficient. Situation 2 results in a weakly damped system behavior. However, it remains still stable. The results in the time domain correspond with the eigenvalues shown in Figure 2. When the transmitted power is increased even more, the system will get unstable.
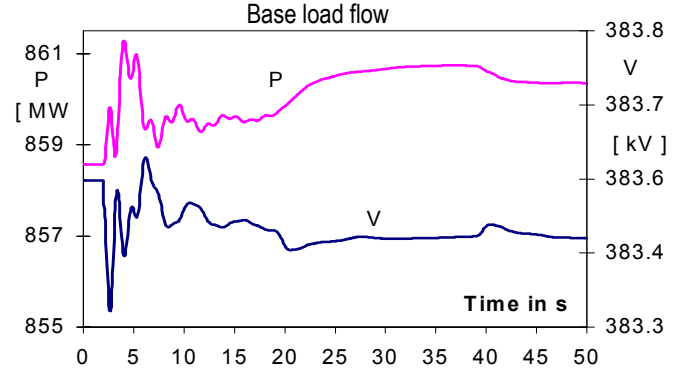

Figure 3: Bus Voltage at Bus #5 in Area A and Real Power on Transmission Line from Bus #5 in Area A to Bus #1 in Area C for Load Flow Situation 1
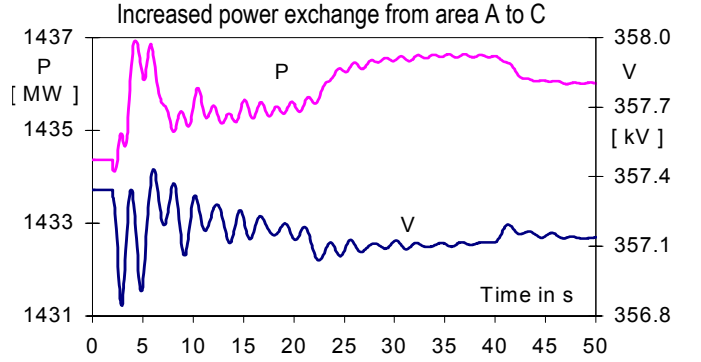

Figure 4: Bus Voltage at Bus #5 in Area A and Real Power on Transmission Line from Bus #5 in Area A to Bus #1 in Area C for Load Flow Situation 2

One of the drawbacks of the time domain simulation is that often system inherent modes are not visible in the plots. For instance, from Figure 4 only one swing frequency can be recognized. It is due to the fact that simulated disturbances excite usually only a few modes. The modal analysis allows a more general conclusion since eigenvalues and eigenvectors are calculated. However, the modal analysis is restricted to linear systems, and thus the nonlinear equations of power system must be linearized. Nevertheless, today modal analysis allows treating real problems in large power systems. With the improving performance of modern computers, the extensive computational time has become less significant in the last years. Therefore, in our study small-signal stability assessment bases on the prediction of eigenvalues. However, for online small-signal stability studies, the direct calculation of eigenvalues is not applicable not only because of the computation time, but primarily because of the unavailability of a complete set of system parameters and up-to-date load flow information.

III. GENERATION OF PATTERN FOR NN

To generate training data for the NN, different load flow conditions are considered. These conditions are generated by real power transmissions between two selected areas. To achieve this power exchange, the total generation in one area is increased while the total power in the other area is decreased. When the total generation in one area is changed,

the power difference is distributed equally among all the generators. Also, the number of generators in the power plants is adapted depending on the required power.

The different load flow scenarios result in generating 3,296 patterns for NN training. The dominant eigenvalues for all cases are shown in Figure 5. The slant lines in the figure mark constant damping at 0% to 20%. As seen in the figure, most of the cases are for well-damped conditions, but in some cases the eigenvalues shift to the low damping region and can cause system instability.
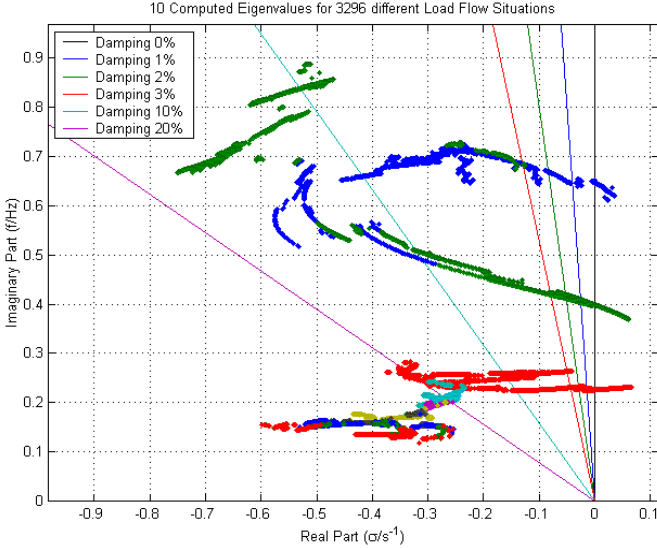

Figure 5: Computed Eigenvalues of the PST 16-Machine Test System for 3,296 different load flow situations

IV. FEATURE SELECTION

Features are as a rule physical quantities containing the necessary information for use as NN input. Large-scale power systems include many features such as transmission line flows, generated powers and demands, etc. The possible feature set is usually too large for any effective NN training [5]. Therefore, feature extraction or selection techniques must be used. Thereby, the objective is to reduce the number of features to a smaller number by remaining the most important information contents.

The feature selection method used in this study is called Multi Step Selection technique (MSS). MSS is based on the Principal Component Analysis (PCA) and the k-Means clustering algorithm.

Principal Components (PC) describe the features in an orthogonal space. Usually a few PC are sufficient for characterizing all features. This can be decided based on the variances, which are the eigenvalues of the feature correlation matrix. However, PC are features without physical meaning, which is the general drawback of feature extraction methods. On the other hand, feature selection techniques remain original feature vectors. It is evident that in this case more features are required because the original features contain only partial information and beside this in a mixed form.

In this paper, PCA was used for selecting original features based on new feature vectors reduced dimensionality. The PC are calculated according the equation

$$\boldsymbol{F}_O \approx \boldsymbol{F}_{PC} \, \boldsymbol{T}^T \qquad (1)$$

where

$\boldsymbol{F}_O$ contains original feature vectors

$\boldsymbol{F}_{PC}$ contains selected most important PC feature vectors

$\boldsymbol{T}^T$ transposed eigenvector matrix to select eigenvalues of the covariance matrix $\boldsymbol{C} = \boldsymbol{F}_O^T \, \boldsymbol{F}_O$

According to Factor Analysis (FA), the matrix $\boldsymbol{T}^T$ can be interpreted as Loadings Matrix of the selected PC as factors. The columns of $\boldsymbol{T}^T$ contain the loadings of the original feature vectors to all selected PC. Note that in this relation the PC are not normalized with their standard deviations and thus the individual importance of each PC are considered. Now, the idea is to use the columns of $\boldsymbol{T}^T$ instead of the high dimensional original feature vectors $\boldsymbol{F}_O$ for clustering. In fact, the columns of $\boldsymbol{T}^T$ are equivalent to those of $\boldsymbol{F}_O$ but with a much lower dimension. Therefore, the used k-Means clustering algorithm shows with $\boldsymbol{T}^T$ a better performance and accuracy as applied to the original features directly. This is why both techniques, principal component analysis and clustering, are used in combination. When the clustering is completed, one feature will be selected from each cluster [5]. However, it should be emphasized that for NN training the corresponding original features were used.

The MSS technique is necessary because of the large number of possible feature in power systems. In this study, the original feature set was split into 3 homogeneous subsets including power features (real power, reactive power), voltage features, and the corresponding voltage angle features. Then, the feature selection method is applied to each subset. The selected features are then combined to form a new group, from which the final features are selected applying the same method again. Finally, 50 of the original features remain as NN input variables.

V. NN BASED APPROACH

The proposed stability assessment method requires that the observation area in the complex eigenvalue plain is defined first. Since the task of this study is the small-signal security assessment, the observation region is defined as the area, where inter-area eigenvalues typically occur. This can be seen in Figure 5. Hence, the frequency range of the observation area is 0.2 Hz to 0.75 Hz. The damping range is 4% to –2%. The observation area is then divided into smaller regions, which are shown in Figure 6 surrounded by dotted lines.
The basic idea is now to activate these regions depending on whether there is an eigenvalue within a region or not. The NN is used to train not the specific eigenvalue position but the activation of each of the regions is shown in Figure 6.
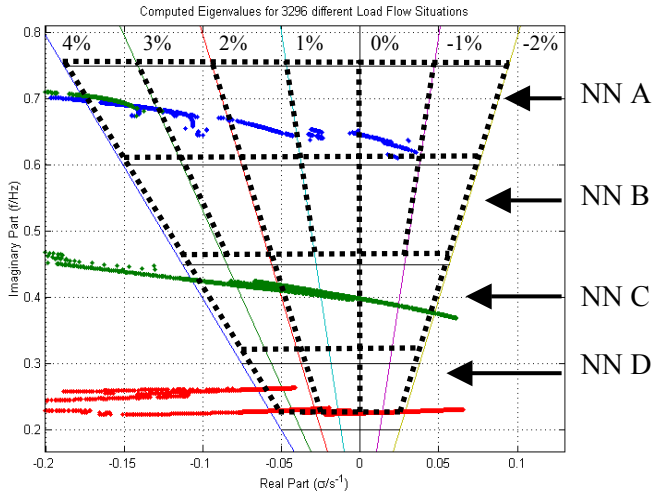
Figure 6: Computed Eigenvalues of the PST 16-Machine Test System for 3,296 different load flow situations and Regions of the observation Area

A region is activated when an eigenvalue is located inside this region. Because the positions of the regions are defined first, one can derive the system stability after NN training by observing the activated regions. If no region is activated, the system is stable. In case of a weakly damped system or instability, one or more regions will be activated and the situation is indicated clearly.

TABLE IV
REGION DISTRIBUTION TABLE FOR THE ENTIRE OBSERVATION AREA

NN	NN Output #	Frequency Range	Damping Range	Stable / Unstable
A	1	0.60 – 0.75 Hz	4 ... 3 %	S
	2		3 ... 2 %	S
	3		2 ... 1 %	S
	4		1 ... 0 %	S
	5		0 … -1 %	US
	6		-1 … -2 %	US
B	1	0.45 – 0.60 Hz	4 ... 3 %	S
	2		3 ... 2 %	S
	3		2 ... 1 %	S
	4		1 ... 0 %	S
	5		0 ... 1 %	US
	6		-1 ... -2 %	US
C	1	0.30 – 0.45 Hz	4 ... 2 %	S
	2		2 ... 0 %	S
	3		0 ... -2 %	US
D	1	0.20 – 0.30 Hz	4 ... 2 %	S
	2		2 ... 0 %	S
	3		0 ... -2 %	US

The regions are defined in Table IV. To increase the accuracy of the classification, one NN is used for all regions within the same frequency range. Hence, 4 independent NN are used. Notice that the regions are not distributed equally over the entire area. This is done because NN is not a high precision tool and cannot be accurate in narrow zones.

After the regions are defined, they need to be activated according to the positions of the eigenvalues. Thus, a distance between the eigenvalue and the center of a given region is used to compute activation for this region. The eigenvalue is defined by its frequency f_{ev} and damping ratio ζ_{ev}. The center of a region is its geometrical center. The distance between a given region and a given eigenvalue is computed as follows:

$$dist_f = 2 \cdot \frac{|f_{ev} - f_c|}{|f_{max} - f_{min}|} \quad (2) \qquad dist_\zeta = 2 \cdot \frac{|\zeta_{ev} - \zeta_c|}{|\zeta_{max} - \zeta_{min}|} \quad (3)$$

where $dist_f$ and $dist_\zeta$ are the distances in the direction of the frequency and the damping axes, respectively.

The distance used for the region activation is given by

$$dist = max(dist_f, dist_\zeta) \quad (4)$$

Based on this distance, the activation value a for the region is

$$a = \begin{cases} 1 - 0.5 \cdot dist & 0 \le dist \le 2 \\ 0 & dist > 2 \end{cases} \quad (5)$$

This is done for all computed eigenvalues resulting from one pattern. The final activation value act of the region is the maximum activation of all eigenvalues regarding this region

$$act = max(a)|_{EV} \quad (6)$$

If an eigenvalue is located exactly on the border of a region, the distance $dist$ given by (4) equals 1. Thus, the activation act of this region obtains the value 0.5 according to (5). This is the minimum activation for an eigenvalue within a region and thus this becomes the classification margin.

VI. NEURAL NETWORK RESULTS

The region activations are computed for all patterns. The data are then normalized and the NN is trained. The number of training patterns was 2,966 and the number of testing patterns was 330.

For classification purpose the NN outputs representing the activation values of regions are transformed to binary values. If the activation exceeds the value of 0.5 the region is deemed to be activated, otherwise not activated. For activated regions the existence of one or more eigenvalues within this region is predicted. The determination of the correct eigenvalue locations is not possible in this approach. Therefore, the required accuracy has to be considered by partitioning the complex plain into regions. However, for practical use it is sufficient to know whether or not an eigenvalue exists in a predefined region.

The results of the NN testing were compared with the actual system simulation. To evaluate the results, two types of errors can be defined: false dismissal and false alarm. For each of the 4 NN, the false dismissal and the false alarm errors have been calculated according to equation (7)

$$E[\%] = 100 \cdot \frac{number\ of\ false\ dismissals\ or\ false\ alarms}{number\ of\ pattern \times number\ of\ NN\ outputs} \quad (7)$$

The results are tabulated in Table V. The errors are close to zero percent and show a high accuracy of the stability prediction. From Figure 6 follows that eigenvalues are never located inside the region, which corresponds to NN B. Therefore, the errors resulting from NN B are always zero.

NN	False Dismissal		False Alarm	
	Training	Testing	Training	Testing
A	0.06 %	0.10 %	0.08 %	0.05 %
B	0.00 %	0.00 %	0.00 %	0.00 %
C	0.11 %	0.10 %	0.00 %	0.00 %
D	0.06 %	0.10 %	0.03 %	0.00 %

As an error evaluation after NN training, the false dismissal and the false alarm errors for NN A are shown in Figures 7 and 8, respectively. The six bars indicate the individual errors for each of the six predicted regions from NN A shown in Figure 6.
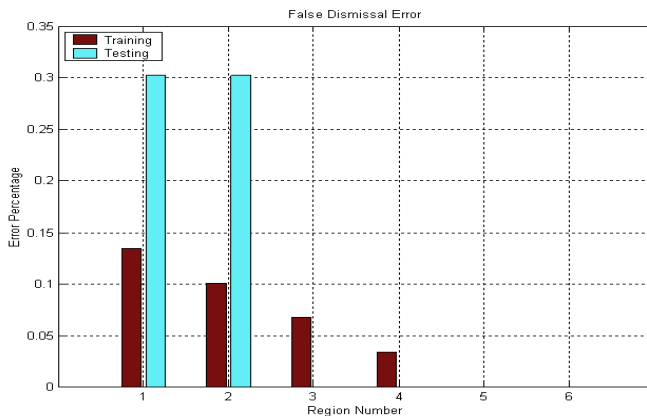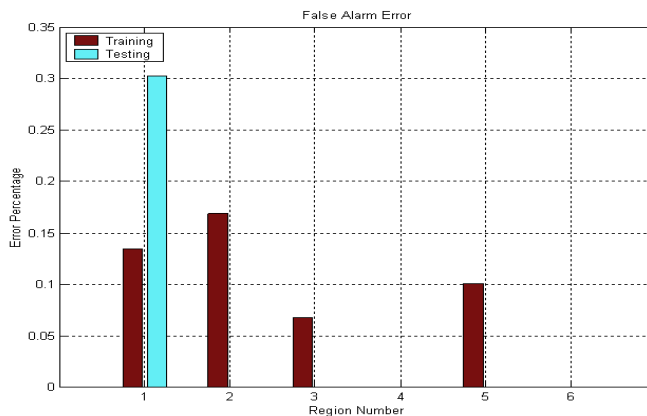

Figure 7: False Dismissal Error for NN A

Figure 8: False Alarm Error for NN A

VII. CONCLUSION

This paper introduced a new method based on neural networks for eigenvalue prediction of critical stability modes. Instead of tracking the exact position of eigenvalues, the proposed method focuses on user defined regions. The regions can be defined at any location within the complex space and are typically located at the area of insufficient damping where inter-area eigenvalues occur. The method predicts the activation of regions by the eigenvalues, which depends on the nearness of eigenvalues to the region center. The advantage of this technique is a high flexibility. Thus, the power system stability can be predicted independently of the number of dominant eigenvalues. Moreover, the computational time is reduced and the accuracy of the NN enhanced. The results obtained by this approach show low errors and high accuracy for stability classification of power systems.

VIII. REFERENCES

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IX. BIOGRAPHIES

Simon P. Teeuwsen (1976) is presently PhD student in the Department of Electrical Power Systems at the University of Duisburg/Germany. He started his studies at the University of Duisburg in 1995. In 2000, he went as exchange student to the Unversity of Washington, Seattle, where he performed his Diploma Thesis. After his return to Germany in 2001, he received his Dipl.-Ing. degree at the University of Duisburg. He is a member of VDE and VDI.

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