

Fast Eigenvalue Assessment for Large Interconnected Powers Systems

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Abstract--This paper deals with methods for fast eigenvalue prediction in large interconnected power systems. The methods can be used for on-line oscillatory stability assessment. Special interest is focused on the prediction of critical inter-area oscillatory modes. Instead of eigenvalue computation using the complete power system model, the proposed approach is based on computational intelligence such as neural networks and decision trees. Computational intelligence methods need only a small set of selected system information. These methods do not require the entire system model and therefore, they are highly applicable in Europe's liberalized and competitive energy market.

Index Terms--Oscillatory Stability Assessment, Interconnected Power Systems, Eigenvalue Computation and Prediction, Computational Intelligence Methods, On-Line Tool

I. INTRODUCTION

With the deregulation of the European electric power market, a competitive situation for the market participants arose. Long-distance power transfers from regions with surplus generation are taking place to meet the demand in other regions, whereas economical aspects are playing a dominant roll. However, the variation of the load flow over a wide range may lead to dangerous situations, in which the small-signal stability is lost and inter-area oscillations, affecting the whole interconnected power system, occur. Such oscillations in the frequency range of 0.15-0.3 Hz have been recorded in the European interconnected power system many times. Figures 1 and 2 show two examples. It is to be seen from Figure 1, that the generators in Spain and France on the one side and those in Poland and Hungary on the other, are swinging against each other, with Germany participating on the frequency swings only marginally. However, the oscillating power over the interconnections in Germany is high, because Germany is located between the swinging network parts. Figure 2 shows a slow damped system behavior following the loss of active power generation in Spain. A first analysis of the frequency curve results in the assumption that the behavior is dominated by more than one inter-area mode because of the beat effects observable in the records. The

phenomenon was investigated in many simulation studies carried out in Germany and other European countries [1]-[5]. For this purpose, a dynamic model of the entire system has been created consisting of hundreds of generators, thousands of lines and nodes. Measurements were used for verification of the model. Two techniques have been applied for the analysis, namely time domain simulation and the application of the modal analysis for the entire European interconnected power system.

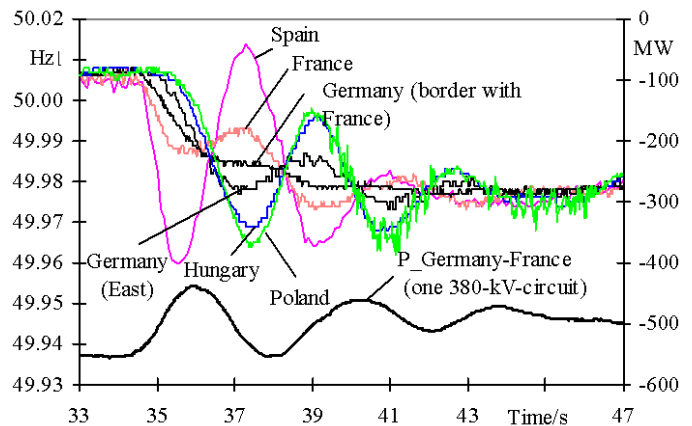


Fig. 1 Behavior of the European Electric Power System following Loss of 900 MW Generation Power ¹⁾

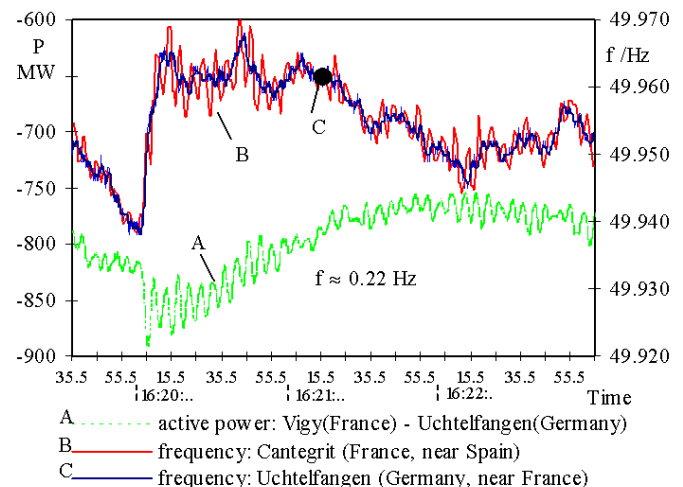


Fig. 2 Inter-area Oscillations after 487 MW Load Rejection in Spain¹⁾

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¹⁾ The measurements were made available for presentation by the German electric power company RWE Essen

Because the recorded oscillations occurred during increased power transfers in the network, one of the objectives was to investigate the impact of long distance power transfers on the damping of inter-area oscillations. Various studies have shown that the limits for transfers are determined by oscillatory stability rather than by the transfer capability of lines. Therefore, for a secure system operation it is necessary to assess the impact of transfers and thus different load flow scenarios on the oscillatory stability before the transfers are realized. However, for on-line application, the available analysis and simulation methods are not practicable due to their complexity and the computational requirements. Furthermore, the dispatchers have to make decisions quickly and usually do not have the expertise for detailed small-signal stability analysis. Figure 3 shows the basic idea.

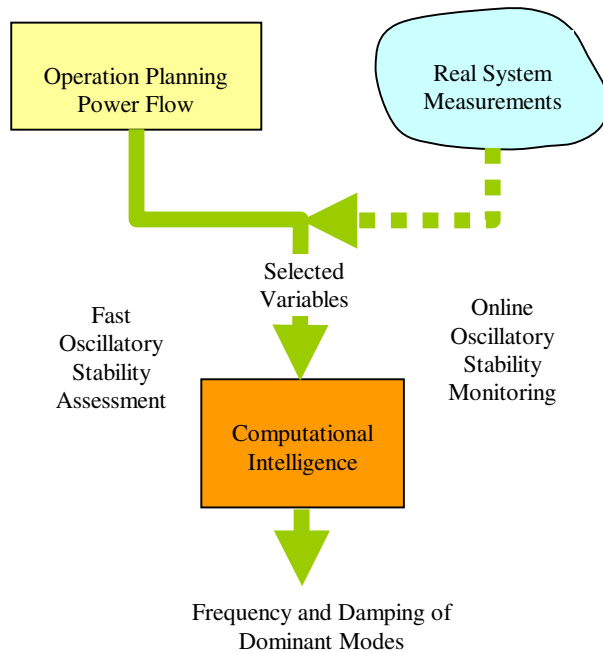


Fig. 3 Application of fast Eigenvalue Assessment

In the short-term operation planning the proposed method can help to assess the effect of different power flow scenarios on the oscillatory stability. For this, only selected variables resulting from power flow calculations are required. In on-line mode the system can also be used for stability monitoring provided that the variables are measured and exchanged by the utilities. However, the number of variables must be kept small because of the measuring and transmission requirements. Besides, in the competitive electricity market utilities are usually not interested in exchange of detailed information.

The selection of the input variables is one of the main challenges of the proposed method. Different aspects have to be considered: information content, redundancy, robustness,

availability and other issues. This task cannot be done based on engineering knowledge and judgment only. Rather, mathematical feature selection methods developed in the field of Computational Intelligence (CI) are required. The issues of feature selection concerning this work are discussed in [3].

II. INVESTIGATED POWER SYSTEM

The power system investigated in this study is the extended UCTE/CENTREL high voltage European network, which also includes the East-European and Balkan states. It consists of approximately 500 generators, several thousand lines and nodes, hundreds of transformers, etc. The generators are described by 5th order models, whereas for controllers different user-defined models are used. The system is prepared for dynamic investigations in the time range of seconds to a few minutes. Figure 4 shows comparisons between measurements and simulations results used for verification purpose.

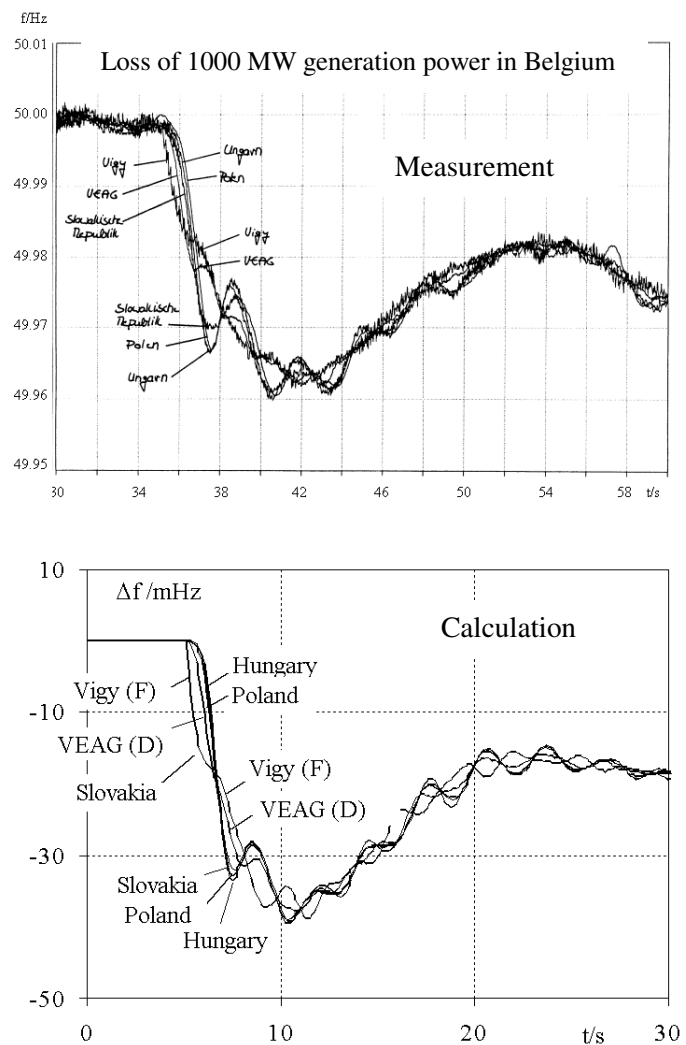


Fig. 4 Comparison of Measurement and Simulation Results

Figure 5 contains the dominant eigenvalues for 2500 different load-flow situations. It is calculated by varying the

real power exchange between different network areas, which corresponds to different utilities. By increasing the power generation in one area, the necessary number of generation units was taken into operation. At the same time in the power receiving area, switching off units reduced the generation.

Generally, the load-flow scenarios were adjusted based on practical experience. From Figure 5 follows that all three eigenvalues may experience changes up to unstable values. Depending on which real power transactions are realized in the power system, the eigenvalues may remain in the stable operation region or they may shift significantly to unstable locations. Furthermore, the impact of transactions on the eigenvalues is strongly non-linear. Obviously, it depends on several factors and cannot be described analytically.

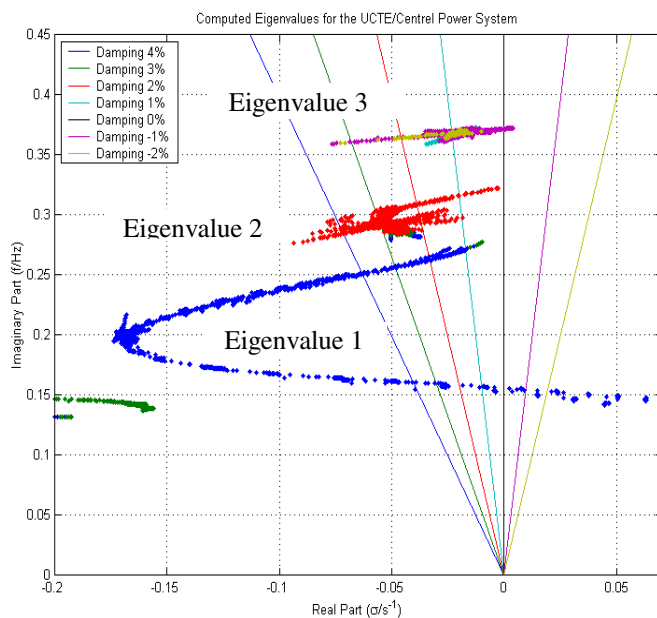


Fig. 5 Calculated Inter-area Eigenvalues for 2500 Load Flow Scenarios in the European Power System

An overview of the system inherent dynamic characteristic provides the mode shapes depicted in the Figures 6a-c. These mode shapes represent the dominant 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 the arrow directions 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 (Eigenvalue 1) in the base case is beyond expectation. However, it can change with the operating point in a wide range as shown in Figure 5. Eigenvalues 2 and 3 are varying in a smaller range. However, for some load flow scenarios they are very close to the stability limit.

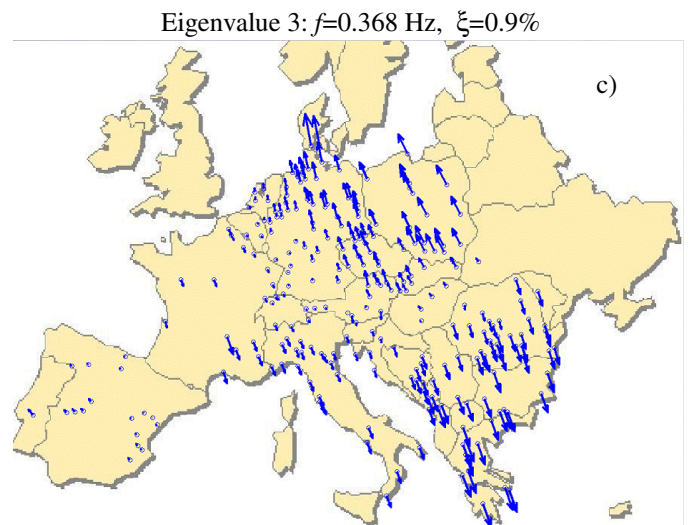
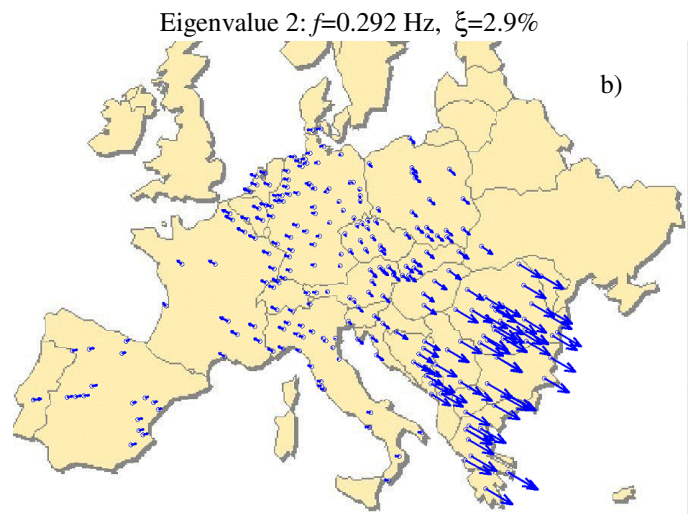
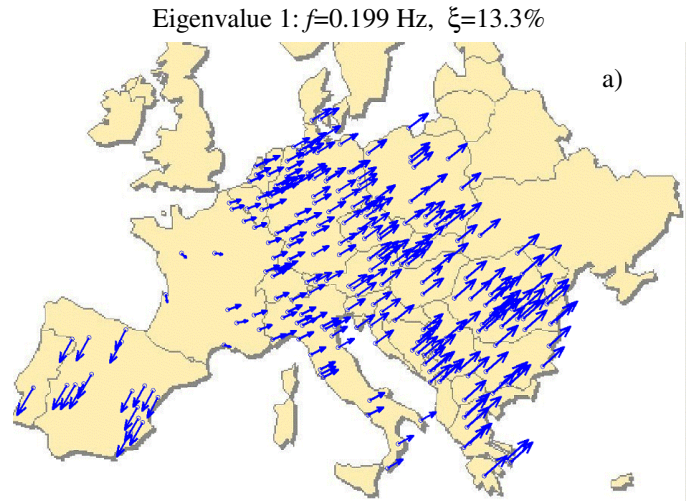


Fig. 6 Modeshapes to the Dominant Inter-area Modes. Eigenvalues are calculated for one certain Power Flow Situation

III. CI-BASED EIGENVALUE CALCULATION

CI methods are used to model input-output relationships based on a small set of input data, which correspond to selected variables of the power system. The outputs are directly related to the stability problem. Typical CI methods

are Neural Networks (NN), Neuro Fuzzy methods (NF), and Decision Trees (DT). These methods are learned on training patterns and show good performance in interpolation.

The coordinates of eigenvalues can be calculated with Neural Networks directly. Once a multilayer feed-forward NN is properly trained, it is able to approximate highly non-linear functions. When used for OSA, a multilayer feed-forward NN can be designed to predict eigenvalue locations directly. In this case, the NN outputs are the coordinates of dominant eigenvalues. The direct eigenvalue prediction by NN is shown in Figure 7 and will be discussed in the next section in detail.

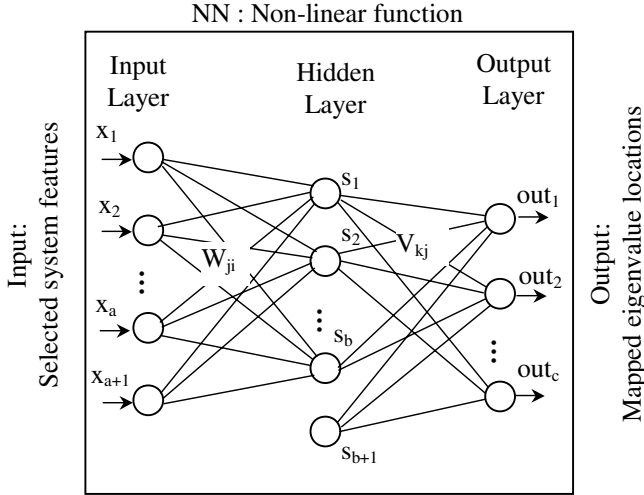


Fig. 7 NN-based Eigenvalue Prediction

Neuro Fuzzy methods are based on Fuzzy Logic systems using rules and membership functions to describe input-output relationships. However, since one might have no exact knowledge about the rules in advance, the NF systems are trained similarly to NNs by a training algorithm in order to find the rules. Since both the NN and the NF methods are based on training, they may require long training times depending on the given problem. The most common NF method used is the Adaptive NN based Fuzzy Inference System (ANFIS). In OSA, an ANFIS can be used to estimate minimum-damping coefficients of dominant eigenvalues.

In contrast to trained systems, the Decision Tree method is based on a learning or growing process, which ends once the full DT is set up. Therefore, the DT method is much faster to apply to given data. The DT method is rule based and splits the data into subsets depending on their characteristics. DTs can be grown for both classification and regression. In classification, the DT can be used to classify the power system state into stable situations with sufficient damping and unstable situations with insufficient damping. This is shown in Figure 8. When implemented as regression tree, the DT method can be used similarly to an ANFIS to estimate minimum-damping coefficients.

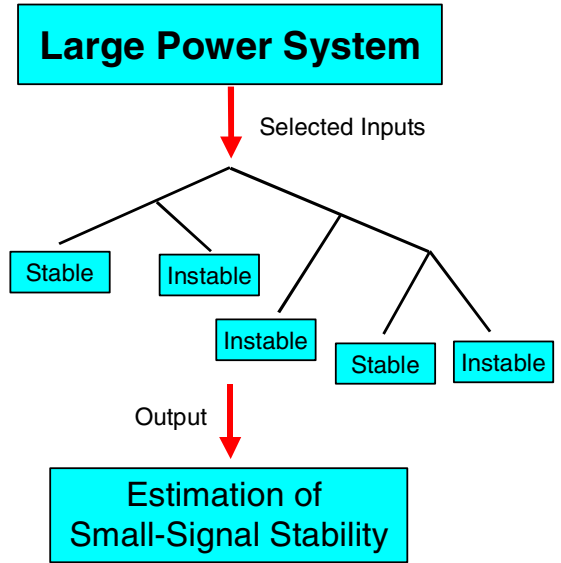


Fig. 8 DT-based Stability Estimation

An expert with detailed knowledge about the power system performs the CI training off-line before the CI method is implemented as an on-line tool. To ensure reliable operation during changing operating conditions, the OSA tool must be updated frequently to learn new system states.

IV. EIGENVALUE MAPPING

A. Direct Eigenvalue Calculation

The method of direct eigenvalue calculation has been proved in [4] and [5] and is applicable with some restrictions: the locus of different eigenvalues may not overlap each other and furthermore, the number of eigenvalues must remain always constant. These follow from the fact that eigenvalues are assigned directly to NN or DT outputs. The computed eigenvalues of the European interconnected power system UCTE/CENTREL under various load flow situations are shown in Figure 9. The figure shows two dominant eigenvalues with damping around and below 3%. A third eigenvalue with damping above 10% becomes dominant only for certain load flow conditions. The computed eigenvalues are marked with x, the eigenvalues predicted by the NN are circled. The direct eigenvalue prediction is highly accurate, but it lacks the dependency of a fixed number of eigenvalues to predict since it is directly related to the eigenvalue coordinates.

Large power systems experience more than one (or two) dominant eigenvalues and the number of dominant eigenvalues may vary for different load flow situations. Therefore, the eigenvalue mapping should be performed rather by eigenvalue region prediction, which is highly flexible regarding the number of dominant eigenvalues and their positions.

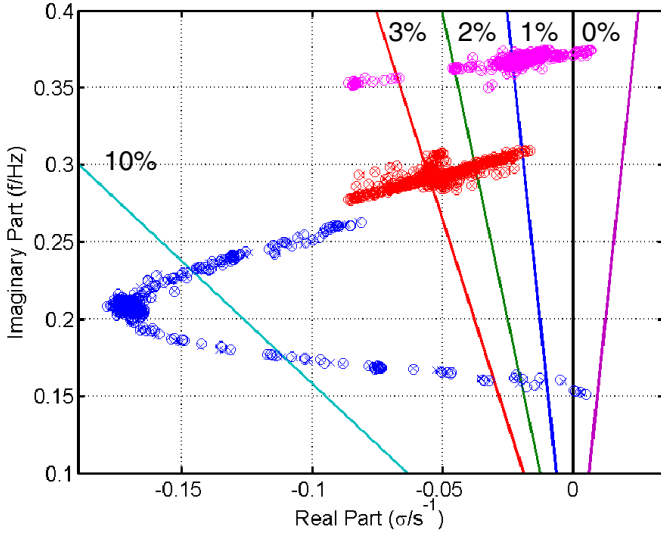


Fig. 9 Comparison of Eigenvalues of the European Power System UCTE/CENTREL under various Load Flow Conditions. The accurate Eigenvalues are marked with x, the Eigenvalues predicted by the NN are circled.

B. Eigenvalue Region Prediction

The eigenvalue region prediction method requires that the observation area in the complex eigenvalue space be 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 constant step width. This is done for the given application 5 times for 5 different frequencies f . The sampling steps used are as follows:

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

The observation area of insufficient damping is shown in Figure 10. The sample points are marked by circles. In this application different NN are assigned to the selected 5 frequency ranges.

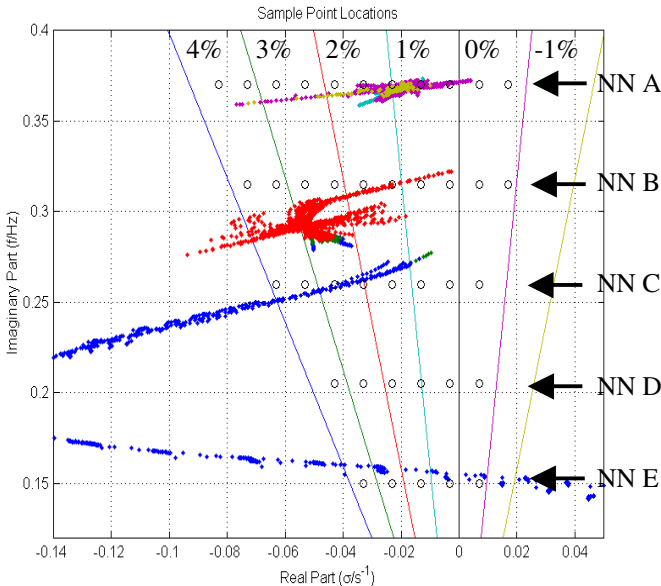


Fig. 10 Partitioning and Sampling of Eigenvalue Plain

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 part 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 possible distance 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 Figure 11.

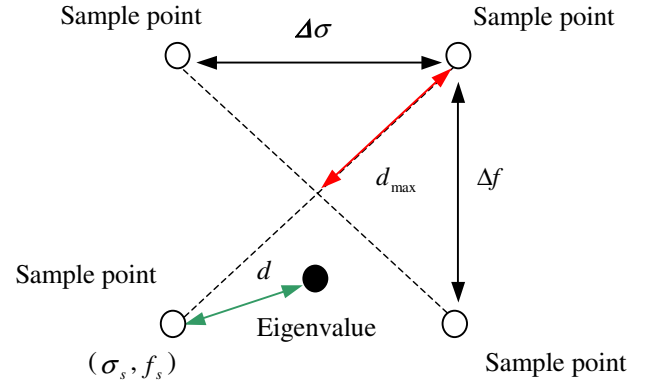


Fig. 11 Definition of the Maximum Distance d_{\max}

According to Figure 10 and Equation (1), the maximum distance can be computed as

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

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

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

This activation a is computed for a given sample point considering 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:

$$act \geq 0.5 \quad d \leq d_{\max} \quad (5)$$

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. Therefore, some experience is necessary to apply the proposed method to particular power systems. The sample point activations were computed for the eigenvalues of the 2500 calculated load-flow scenarios in UCTE power system. Then the data set was 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 retained 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 Figure 12a. 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. 12b).

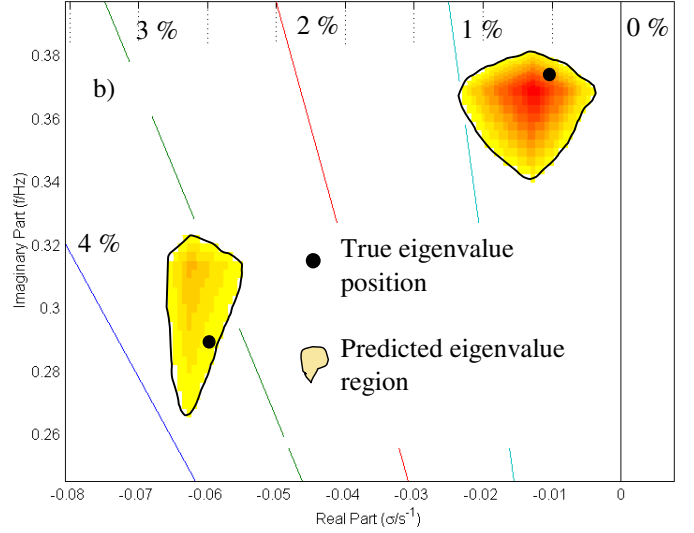
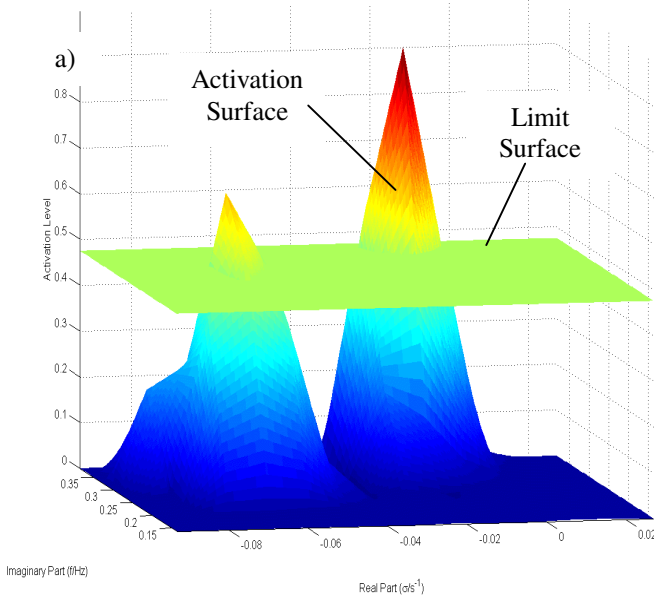


Fig. 12 (a) Activation Surface constructed by Sample Point Interpolation and Limit Surface, (b) View from above: Predicted Regions in the Complex Space

If the NN is trained properly, the true eigenvalue position will be within this predicted region (as shown in Figure 12b). 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 as 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 are calculated according to Equation (6). Table I contains the results for the investigated system.

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

TABLE I
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 these predictions are not utilizable. The eigenvalues were always located near to the predicted region. By using a slightly modified activation function it is possible to reduce the error rate. In doing so, 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. Figure 13 shows the definition of region widths $\Delta \xi_{reg}$ and Δf_{reg} , respectively.

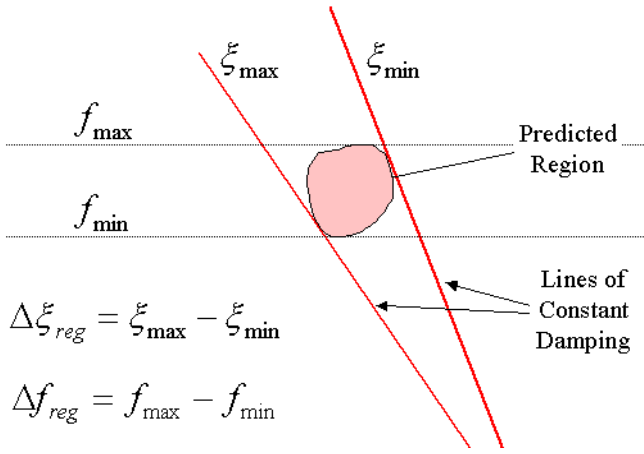


Fig. 13 Definition of the Width of a Predicted Region in Damping ($\Delta\xi_{reg}$) and Frequency (Δf_{reg})

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

TABLE II
WIDTH OF PREDICTED EIGENVALUE REGIONS

Region Width	Training		Testing	
	Mean	STD	Mean	STD
$\Delta\xi_{reg}$	1.038 %	0.430 %	1.035 %	0.429 %
Δf_{reg}	0.055 Hz	0.023 Hz	0.055 Hz	0.024 Hz

Assuming that the eigenvalues will always be expected in the center of the predicted region, the method provides an average accuracy for damping of $\pm 0.52\%$ and for frequency of ± 0.023 Hz. In summary, by varying the activation function the accuracy could be increased at the expense of error rate and vice versa. Therefore a trade-off might be necessary according to the actual requirements.

V. CONCLUSIONS

The recent and future power system expansions, the competitive environment in the liberalized power market, and the continuously increasing wind power generation affect the stability situation in the European power system UCTE/CENTREL. Transmission System Operators have to manage more and different critical situations than in the past. Therefore, they need fast and flexible on-line assessment tools.

This study proposes the implementation of Computational Intelligence methods for fast on-line OSA. The CI methods are based on a small number of inputs only, which is an important issue in a liberalized power market. Moreover, they are fast and accurate.

Both the direct eigenvalue prediction and the eigenvalue region prediction are applicable tools for OSA. However, since the direct eigenvalue prediction is limited to few

eigenvalues, the eigenvalue region prediction method is preferred.

However, accurate results can also be obtained when different CI methods are implemented such as Neuro Fuzzy Systems and Decision Trees.

VI. REFERENCES

- [1] U. Bachmann, I. Erlich and E. Grebe, "Analysis of interarea oscillations in the European electric power system in synchronous parallel operation with the Central-European networks", IEEE PowerTech, Budapest, 1999
- [2] H. Breulmann, E. Grebe, et al., "Analysis and Damping of Inter-Area Oscillations in the UCTE/CENTREL Power System", CIGRE 38-113, Session 2000
- [3] S.P. Teeuwesen, I. Erlich, U. Bachmann, "Small-Signal Stability Assessment of the European Power System based on Advanced Neural Network Method", IFAC 2003, Seoul, Korea, September, 2003
- [4] S.P. Teeuwesen, A. Fischer, I. Erlich, M.A. El-Sharkawi, "Assessment of the Small Signal Stability of the European Interconnected Electric Power System Using Neural Networks", LESCOPE 2001, Halifax, Canada, June 2001
- [5] S.P. Teeuwesen, I. Erlich, M.A. El-Sharkawi, "Feature Reduction for Neural Network based Small-Signal Stability Assessment", PSCC 2002, Sevilla, Spain, June 2002

VII. BIOGRAPHIES



Simon P. Teeuwesen (1976) is presently PhD student in the Department of Electrical Power Systems at the University of Duisburg-Essen/Germany. He started his studies at the University of Duisburg in 1995. In 2000, he went as exchange student to the University 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, VDI, and IEEE.



Istvan Erlich (1953) received his Dipl.-Ing. degree in electrical engineering from the University of Dresden/Germany in 1976. After his studies, he worked in Hungary in the field of electrical distribution networks. From 1979 to 1991, he joined the Department of Electrical Power Systems of the University of Dresden again, where he received his PhD degree in 1983. In the period of 1991 to 1998, he worked with the consulting company EAB in Berlin and the Fraunhofer Institute IITB Dresden respectively. During this time, he also had a teaching assignment at the University of Dresden. Since 1998, he is Professor and head of the Institute of Electrical Power Systems at the University of Duisburg-Essen/Germany. His major scientific interest is focused on power system stability and control, modelling and simulation of power system dynamics including intelligent system applications. He is a member of VDE and IEEE.



Mohammed A. El-Sharkawi received the B.Sc. degree in electrical engineering in 1971 from Cairo High Institute of Technology, Egypt, and the M.A.Sc. and Ph.D. degrees in electrical engineering from the University of British Columbia, Vancouver, B.C., Canada, in 1977 and 1980, respectively. In 1980, he joined the University of Washington, Seattle, as a Faculty Member. He served as the Chairman of Graduate Studies and Research and is presently a Professor of Electrical Engineering. He is the Vice President for Technical Activities of the Neural Networks Society. He organized and taught several international tutorials on intelligent systems applications, power quality and power systems, and he organized and chaired numerous sessions in IEEE and other international conferences. He is a member of the editorial board and Associate Editor of several journals, including the IEEE TRANSACTIONS ON NEURAL NETWORKS.