

Robust Oscillatory Stability Assessment for large Interconnected Power Systems

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Abstract--This paper deals with robust dynamic security assessment for large interconnected power systems. Special interest is focused on the prediction of critical inter-area oscillatory modes of power systems based on neural networks. After selection of inputs for the neural network and proper training, the stability condition of the power system can be predicted with high accuracy. Hereby, the neural network outputs are assigned to activations of sampling points in the complex plain depending on the distances to the eigenvalues. This method depends highly on the reliability of the measured input data. Missing or bad input data will automatically lead to false prediction results. This paper proposes different methods, which improve the prediction robustness by detecting bad data inputs and outliers. In a second step, input signals identified as bad data inputs will be restored to their correct value.

Index Terms--Oscillatory Stability, Interconnected Power Systems, Dynamic Security Assessment, Neural Networks, Robustness, Outliers, Bad Data Detection and Restoration

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 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 [1], [2]. The deregulation of electricity markets in Europe aggravated the situation once more due to the increasing number of long distance power transmissions. The network is becoming more stressed also by the transmission of wind power. The installed capacity of wind generators achieved in Germany already about 12 GW. New wind farms with several hundred MW power will be connected directly to the high voltage grid, for which, however, this is not designed. Considerable changes in the load flow are expected also due to the decision of the German government to close down nuclear power plants during the next few years.

In fact, the European Power System is designed rather as a backup system to maintain power supply in case of power plant outages. The system is operated by several independent transmission utilities, joint by a large meshed high voltage grid. Because of the increasing long distance transmissions, the system steers closer to the stability limits. Thus, the operators need computational real time tools for controlling system stability. Of main interest in the European Power System is hereby the oscillatory stability assessment (OSA). The use of on-line tools is even more complicated because TSOs exchange only restricted information. Each TSO controls a particular part of the power system, but the exchange of data between different parts is limited to a small number because of the high competition between the utilities. However, the classical small-signal stability computation requires the entire system model and is time consuming for large power systems. Therefore, this paper suggests using Neural Networks (NN) for a fast on-line OSA based only on a small set of data.

Real time stability assessment has to be designed as a robust tool that is not influenced by time of the day, the season, the topology and missing or bad data inputs. Therefore, this paper focuses on the robustness issues of the proposed OSA. The basic approach will be explained shortly because it is already published in other papers [3] and [4].

II. 16-MACHINE DYNAMIC TEST SYSTEM

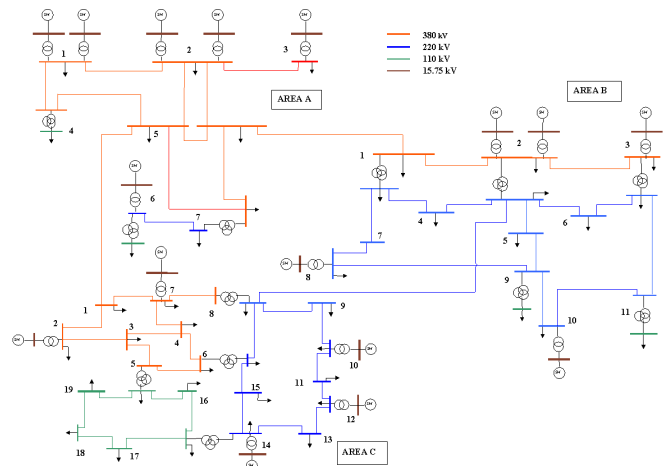


Fig. 1 One-Line Diagram of the PST 16-Machine Test System

The PST16 network (Figure 1) used in this study is a 400/220 kV 16-machine test system. It allows to study different kinds of stability problems especially inter-area

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oscillations and has been developed based on characteristic parameters of the European power system [5].

Since the operating point in real power systems changes continuously, 5 different operating conditions are considered. These operating conditions include high and low load situations like in winter and in summer, and change of the networks' topology when transmission lines are switched (Table I).

TABLE I
APPLIED OPERATING CONDITIONS

#	Name	Description
1	Winter	Base Case, Generation and Load at 100 %
2	Spring	Generation and Load decreased to 80 %
3	Summer	Generation and Load decreased to 60 %
4	Winter S1	One Circuit of A to B Tie Line switched off
5	Winter S2	One Circuit of B to C Tie Line switched off

To generate training data for the NN, various load flow scenarios under the 5 operating conditions shown in Table I are considered. These scenarios are generated by real power exchange between 2 areas. The different load flow scenarios result in generating 5,360 patterns for NN training.

III. APPROACH FOR PREDICTING CRITICAL MODES BY NN

Large power systems include many system variables, called features, such as transmission line flows, generated powers and demands. Therefore, the feature set is too large for any effective OSA method and creates the bottleneck problem for NN training [6]. For this reason, feature selection is performed once in the beginning. In the following OSA method, the initially selected features are used. The selection method is based on the principal component analysis (PCA) and the k-Means cluster algorithm [4]. In the first step, the PCA is applied to all features to reduce the data set. In the second step, the reduced data set is clustered by the k-Means algorithm. Because of the similarity between features within a cluster, one can be selected and the others can be treated as redundant information. In this study, a set of 50 features were selected and used as NN input.

The proposed OSA method consists of three steps

- Filtering and restoration of data
- Classification of critical and non-critical scenarios
- Eigenvalue mapping for critical scenarios

The focus of this paper is directed on the first topic, which ensures that only a set of consistent data can proceed the NN. The second and third step represents the core of the method. However it has been discussed in former papers and therefore, it will be described here to the extent necessary for understanding the procedure. The three steps for robust on-line OSA are shown in Figure 2.

Once the input features have passed the filter, pre-classification is performed as second step to decide if the presented pattern belongs to a sufficient damped load flow scenario or not. In this study, the decision boundary for sufficient and insufficient damping is at 4%. When a pattern

includes no eigenvalues with corresponding damping coefficients below 4%, the load flow of this pattern is considered as sufficient damped. When at least one of the modes is damped below 4%, the load flow is considered as insufficient damped. Only those patterns, which include insufficient damped modes, are used to train eigenvalue mapping by the NN in the third step. In this way, this NN is focused on critical load flow scenarios, which allows to produce more accurate results.

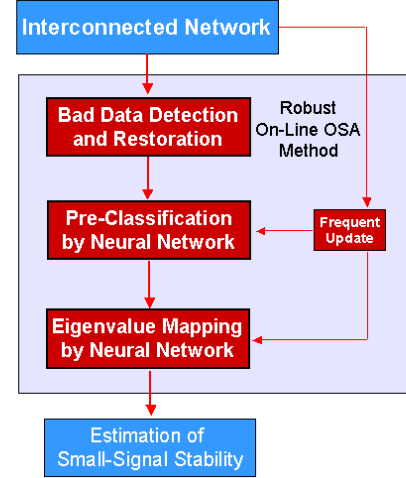


Fig. 2 Robust On-Line OSA Method using Neural Networks

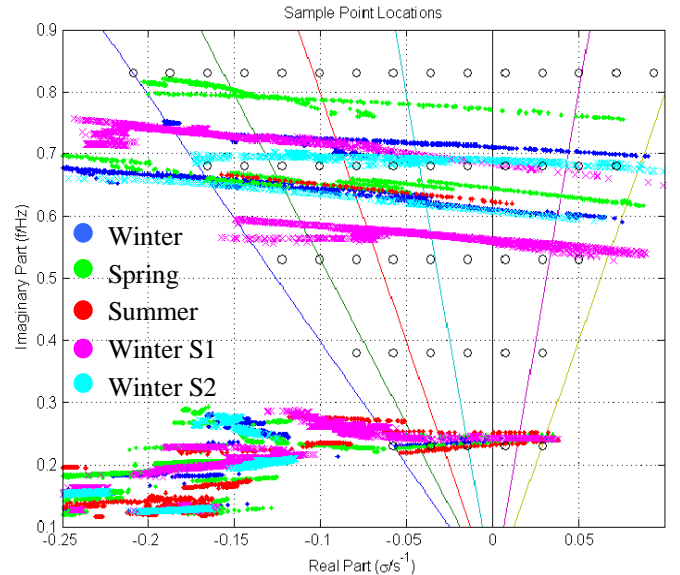


Fig. 3 Computed Eigenvalues of the PST 16-Machine Test System for Insufficiently Damped Load Flow Scenarios and Sample Point Locations in the Observation Area

The eigenvalue mapping is performed as proposed in [3] and [4]. It requires that the observation area in the complex eigenvalue space is defined first. It is located in the region of insufficient damping in the range between 4% and -2%. Then, this area is sampled along the real axis (σ) between 4% and -2%. This is done 5 times for 5 different frequencies f . The sampled observation area of insufficient damping is shown in Figure 3, where the sample points are marked by circles. The sampling results in a set of 47 sample points. 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 closer the distance between an eigenvalue and a sample point, the higher the activation for this sample point.

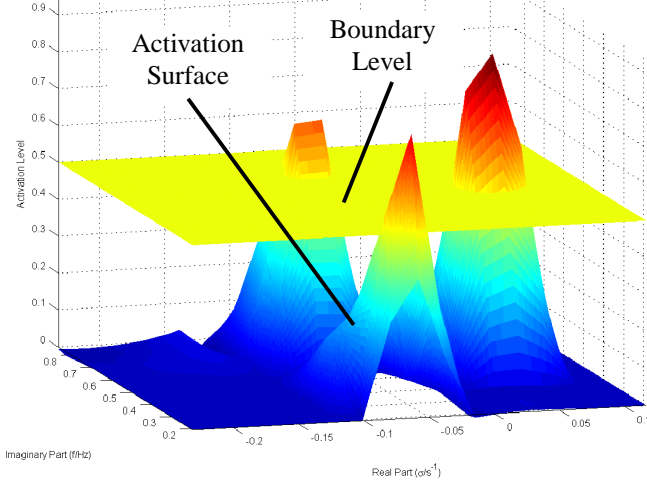


Fig. 4 Activation Surface constructed by Sample Point Interpolation and Boundary Level

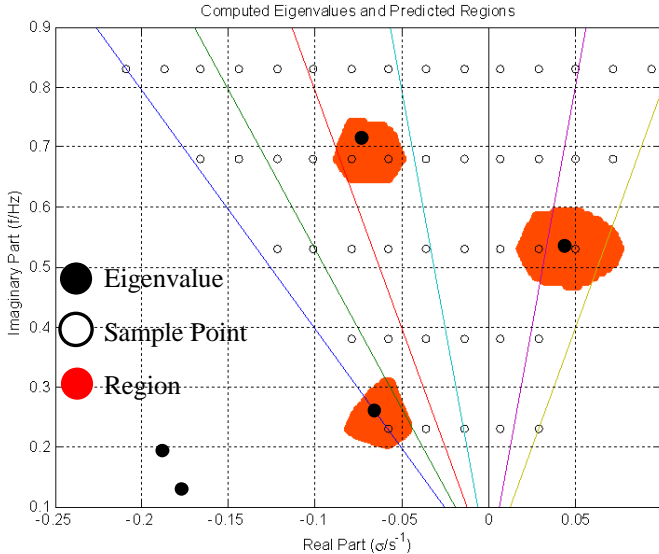


Fig. 5 Complex Eigenvalue Space with Predicted Regions and Real Positions of corresponding Eigenvalues

The sample point activations are computed for all patterns. The data are then normalized and shuffled randomly before the 5 NN are trained independently. Once the NN are trained properly, the NN results need to be transformed from activation level into eigenvalue locations. This transformation is done using the sample point activations. For all patterns, the activation values given from the sample points are used to setup an activation surface, which is used to construct a region in which the real eigenvalue is located. The activation surface is constructed by linear interpolation between all rows and columns of sample points shown in Figure 3. The surface at the constant level of 0.5 is called boundary level. It results from the minimum activation, which is necessary to detect an eigenvalue in the complex space. However, the intersection of the activation surface and the boundary level leads to a region,

which is called predicted region. For one pattern from the data set, the activation surface and the boundary level is shown in Figure 4. Figure 5 shows the view from above onto the boundary level. Thus, the predicted region in the complex eigenvalue space can be determined.

By using the proposed NN based OSA method, a fast prediction of the eigenvalues is possible, provided that the method is robust in terms of the network situation. In fact, when the operating point of a given power system changes, the corresponding eigenvalues may shift significantly. Changes in the network topology, the load situation, and the voltage level will affect the position of the eigenvalues and therefore the stability situation in the power system. Therefore, robustness can be obtained by NN training with patterns including such cases. This is done using the operating conditions and load flow scenarios described in section 2. In the studied power system all scenarios have been considered by only one set of NN. That means, the designed OSA tool could be used over the whole year period at any operating conditions. However, it depends on the network and possible topological scenarios. Hence, if necessary, it is recommended to train separate NN for different situations like seasons or topology.

IV. BAD DATA DETECTION AND OUTLIER RESTORATION

Most of the NN input information is obtained from the control center and therefore from the state estimator, which ensures verified data. However, there is still a risk for bad data when the data are transferred from external control centers to the TSO running the OSA. Furthermore, there might be some special NN input features, which will not pass the state estimator, i.e. particular generator data. State estimation methods have been improved for a long time and they are able to correct bad data measurements. But in fact, they require the entire system topology because they base on load flow equations. But usually, none of the TSOs has detailed knowledge of the entire power system topology up-to-date for online OSA. For these reasons, alternative methods need to be applied for bad data detection and restoration, which do not base on the system topology and the load flow equations.

A. Similarity Analysis and Check of Limits

The easiest method to find outliers is the comparison to the known limits of the data. Limits for particular measurements are known and can be found in the data set very fast. Therefore, any new pattern is verified first based on known general limits. However, outlier features can be located within the range, even when they are bad or with error since they don't meet load flow conditions of the particular case. Only when the pattern set as a whole is investigated, the outlier can be detected. The similarity analysis bases on the idea to build a subset of patterns from the feature matrix, whereby the patterns in the subset are similar to a new given one. Then, the new pattern is compared feature by feature to the subset patterns. Features, which show a high error, might contain bad data. The subset can be selected manually, i.e. all patterns for

each Monday, or it can be selected using an algorithm like described in this paper. When a new pattern is presented to the detection algorithm, a subset of similar patterns from the feature matrix is built using the correlation coefficients. In the following, the new pattern is compared to the subset. Inlier factors show the deviation of each feature within the subset and outlier factors indicate the deviation of each feature between subset and the new pattern. A feature is flagged as outlier when its outlier factor exceeds the corresponding inlier factor. The proposed method works very accurate when the presented pattern contains few outliers resulting from small and medium errors. The lack of the method is the search for similar patterns in the entire feature matrix. For presented patterns containing many outliers or very high errors, the algorithm cannot find the corresponding patterns in the matrix.

B. Principal Component Residuals

The theory of the principal component residuals is well-known and described many times in literature, i.e. [7] and [8]. It bases on the PCA method, which is a projection of the features onto the axes of the orthogonal principal coordinate system. The standardized data matrix \mathbf{Z} of size $p \times n$ includes p patterns and n original features. Its covariance matrix is called $\mathbf{\Sigma}$. When PCA is performed, the result is the matrix \mathbf{T} of size $n \times n$ including the eigenvectors of the covariance matrix $\mathbf{\Sigma}$. Usually the largest eigenvalues and the corresponding eigenvectors are of interest as they represent the matrix \mathbf{Z} with sufficient accuracy. For bad data detection, however, the smallest principal components will be investigated due to the expectation of large values in case of bad data. The projections onto the smallest principal component coordinates are computed by

$$\mathbf{Y} = (\mathbf{Z} - \bar{\mathbf{Z}}) \cdot \mathbf{T}_r \quad (1)$$

where \mathbf{T}_r is a $n \times r$ matrix including the eigenvectors of \mathbf{T} , which correspond to the smallest eigenvalues of the covariance matrix $\mathbf{\Sigma}$ and $\bar{\mathbf{Z}}$ is a matrix including the mean values of \mathbf{Z} , which is zero for the normalized case. The $p \times r$ matrix \mathbf{Y} contains the principal component residuals, which are relevant for studying the deviation of an observation from a fitted linear subspace. When a pattern of the feature matrix corresponds highly to the transformation, it will be projected on the main largest principal axes only and the projections onto the last few principal axes should be nearly zero. When a row of \mathbf{Y} shows values far from zero, the pattern corresponding to this row does not match the principal axes and thus it can be treated as an outlier pattern.

If the principal components are calculated of a large consistent set of feature vectors, the corresponding matrix \mathbf{T}_r can be used for checking new-presented patterns for their affiliation to the data set. Bad data or errors can be recognized on the principal axes much easier as in the original coordinates.

This technique is fast, highly reliable and even small outliers can be detected. However, when the pattern is

detected as an outlier pattern, there is still no information, which features are affected and if there is a single or multiple outlier.

To show the ability of the similarity analysis and the principal component residuals in detecting bad data, both methods are applied for the same load flow condition. The comparison is shown in Table II for one particular load flow scenario at the Winter and the Summer operating condition. The data are presented once as correct data, once with bad voltage data (correct + 0.5%) at one bus and once with bad power data (correct + 10%) on one line. The criterion for the detection is the maximum of the residuals for the last 3 components in case of the principal component residuals analysis and in case of the similarity analysis the maximum ratio of the outlier factors by the inlier factors. The table shows a noticeable increase in the applied criteria in case of bad data, compared to the correct data case. The increase allows to distinguish easily between correct and bad data.

TABLE II
COMPARISON OF CORRECT AND BAD DATA FOR
WINTER AND SUMMER LOAD FLOW SITUATIONS

	Data description	Maximum of last 3 Residuals	Maximum of Outlier/Inlier
Winter Situation	Correct Data	0.41	1.00
	Bad Voltage Data 412.39 instead of 410.34 kV	43.30	114.65
	Bad Power Data 851.16 instead of 773.78 MW	1.22	18.31
Summer Situation	Correct Data	0.76	0.82
	Bad Voltage Data 415.99 instead of 413.92 kV	43.47	26.00
	Bad Power Data 564.37 instead of 513.06 MW	13.99	27.93

C. NN Auto Encoder

The auto encoder network is a well-known type of NN and discussed in detail in [9]. This NN, shown in Figure 6, replicates the input vector at the output. In other words, the NN is trained to obtain identical input and output.

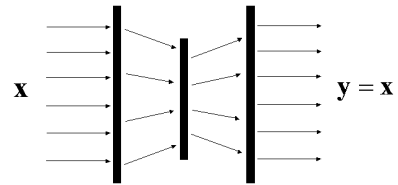


Fig. 6 NN Auto Encoder

The error between input and output vector will be low for any trained load flow condition. When a new pattern contains bad data, the features of this pattern do not belong to a feasible load flow condition and the error will be high when presented to the NN auto encoder. Therefore, abnormal differences between inputs and outputs of the auto encoder indicate pattern greatly suspicious to contain bad data. The auto encoder is highly sensitive to outlier pattern. However, it is not possible to determine the feature from the new pattern, which contains the bad data. Since all features inside the NN

are cross connected, a high auto encoder error at feature i does not result necessarily from bad data at feature i . Therefore, the NN auto encoder can only be used, like principal component residuals too, to detect outlier patterns, but not outlier features.

D. Multidimensional Feature Forecasting by NN

Another method, which is able to find outlier features uses feature forecasting to produce expected values, which have to meet by correct measurements. This method for nonlinear, multidimensional feature forecasting bases on NN. Hereby, a multilayer feed-forward NN is trained with the last history data of all selected features. To keep the size of the network in a dimension where it can be trained easily, the last 3-6 history data are used. Figure 7 shows the basic idea for n input features and k history data.

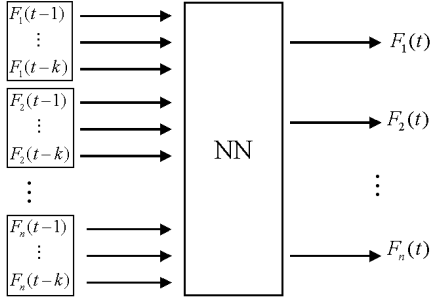


Fig. 7 Basic Scheme for Nonlinear, Multidimensional Feature Forecasting using NN with n Input Features and k History Values

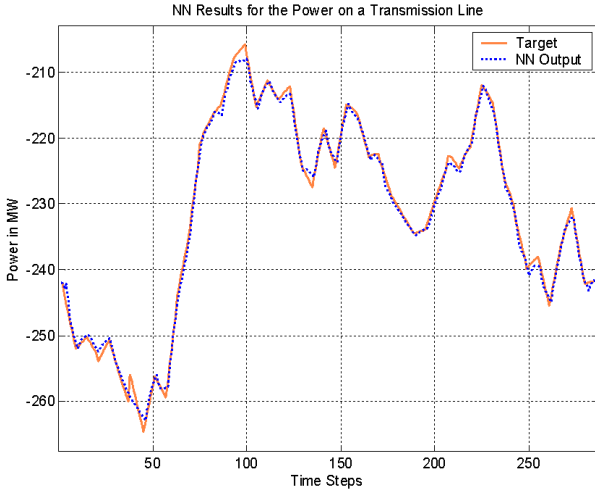


Fig. 8 Results of the Multidimensional Feature Forecasting by NN over 1 Day. Power on a Transmission Line

The NN is trained with time series data from the database, which is assumed to be consistent. When NN is used on-line, the NN outputs are compared to the measured features and those, showing differences beyond a certain limit, are flagged as outlier. The advantage of this method results from its multidimensional characteristic. As well the history of all features (time series) as the load flow conditions are considered and thus the NN is able to predict the correct reference value for check the measurements. Figure 8 shows NN results of feature forecasting for one feature (real power on a transmission line) over one day. The NN training was carried out with a time series over 6 days. The NN inputs are

4 history data (weighted average values) of all 50 selected features.

V. OUTLIER RESTORATION

Once a new input pattern recognized as outlier pattern and the particular bad features are selected, the bad data have to be restored to make it proper for OSA. This is possible using the same NN auto encoder network as described in the previous section. Hereby, the NN auto encoder is involved into an optimization loop where it describes the power-flow-conform relationship between the features. A sequential quadratic optimization, which is the most favorable algorithm for continuous problems, is utilized to adjust the elements of the feature vector. The algorithm restores the bad data elements by minimizing the error of the NN auto encoder. Usually it can be assumed that most of the original measurements are correct and thus these variables can kept constant. Hence, only some suspicious inputs need to be changed by the optimization. The restoration of bad features is succeeded when the difference between the input and output vectors of the auto encoder is small. The optimization diagram is shown in Figure 9.

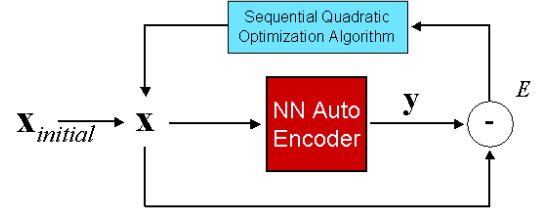


Fig. 9 Feature Restoration by Optimization using NN Auto Encoder

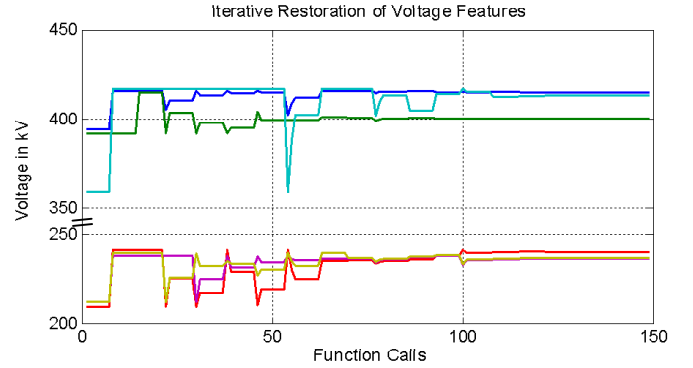


Fig. 10 Progress of Feature Restoration for 6 Voltage Features

To test the ability of the optimization algorithm when restoring the missing input data, 6 voltage features are determined as “missing” and set to 0. Starting from 0 as initial value, the optimization will restore the original values within a few milliseconds and with high precision. Figure 10 shows the progress of restoration of selected voltages depending on the number of auto encoder function calls during the optimization process. The total number of iterations is 19, which is much smaller than the total number of function calls since the optimization calls the cost function several times during each iteration step. The comparison between original and restored feature values is listed in Table III. As can be seen, the restoration is very accurate.

TABLE III
COMPARISON OF 6 ORIGINAL AND RESTORED VOLTAGE FEATURES IN KV

#	Original	Restored	Difference
1	414.99	415.07	+ 0.02 %
2	400.02	400.02	+ 0.00 %
3	239.99	240.30	+ 0.13 %
4	414.99	413.08	- 0.46 %
5	236.03	236.44	+ 0.17 %
6	236.48	236.88	+ 0.17 %

The example shown before is representative for the optimization based restoration carried out by the authors. Because the NN auto encoder is trained with various load flow scenarios, it will always find a solution, which meets a feasible load flow condition, when the reminding fixed variables are enough to represent this load flow situation. However, it requires that the input feature vector contains redundancy not only for a few variables, but for the whole vector. This issue can be considered by the selection of features based on the clustering technique as the clusters contain independent groups, which have to be represented with redundancy in final choice. For a few missing features, the algorithm will always find the correct solution. In the investigated test network, even for 50% (!) missing inputs the algorithm was able to find a solution, which was still close enough to the real scenario to use for OSA.

VI. CONCLUSION

A robust OSA can be carried out based on properly designed and trained NN. The proposed method for predicting critical inter-area modes allows to consider different load flow conditions resulting from seasonal and topological changes. Thereby, the activation of sampling points by possible eigenvalues located nearby is predicted. Thus the method becomes independent from the number of critical modes. Furthermore, different NN can be used each of them assigned to a particular section of the complex eigenvalue plain. Thus, the NN will be able to consider widely warring load flow scenarios.

Robust assessment requires reliable input data. The paper discusses different methods for detection erroneous features. The most powerful methods are the principal component residuals based method and the NN auto encoder. These methods will recognize a pattern even in case of small errors. The disadvantage is that both methods cannot detect the element in the feature vector, which is the suspicious outlier. However, the multidimensional feature forecasting by NN is highly applicable because the feature prediction shows low errors and high accuracy. Comparing predicted and measured features, the elements including bad data can be identified easily. Once the outliers are detected, they can be restored by optimization, which utilizes the NN auto encoder. Essential for the success of the OSA is an amount of sufficient redundancy in the selected features to allow bad data detection and restoration. This is guaranteed when the feature selection method is applied based on clustering method.

VII. 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. Teeuwsen, I. Erlich, M.A. El-Sharkawi, "Small-Signal Stability Assessment based on Advanced Neural Network Methods", IEEE PES General Meeting, Toronto, Canada, July, 2003
- [4] S.P. Teeuwsen, 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
- [5] S.P. Teeuwsen, I. Erlich, M.A. El-Sharkawi, "Neural Network based Classification Method for Small-Signal Stability Assessment", IEEE PowerTech, Bologna, Italy, June, 2003
- [6] S.P. Teeuwsen, I. Erlich, M.A. El-Sharkawi, "Feature Reduction for Neural Network based Small-Signal Stability Assessment", PSCC 2002, Sevilla, Spain, June 2002
- [7] R. Gnanadesikan, Methods for Statistical Data Analysis of Multivariate Observations, Wiley, New York, 1997
- [8] D.M. Hawkins, Identification of Outliers, Chapman and Hall, London, 1980
- [9] R.D. Reed and R.J. Marks, II, Neural Smthing, MIT Press, Cambridge, Mass.,1999

VIII. BIOGRAPHIES



Simon P. Teeuwsen (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

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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

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