

Fast Assessment of Small-Signal Oscillatory Stability in Large Interconnected Power Systems

I. Erlich, A. Fischer

Abstract -- This paper deals with suitable approaches for fast assessment of oscillatory stability of large interconnected power systems within power system operation. Beside voltage stability and transient stability, oscillatory stability has to be assessed, too. It can be shown, that parallel eigenvalue computation using a parallel variant of Arnoldi method can reduce the time necessary for eigenvalue computation of large power systems. Furthermore, it is shown that methods of Computational Intelligence can relieve the fast assessment of oscillatory stability. Based on a set of precalculated transit scenarios, both method of k^{th} Nearest Neighborhood and Decision Trees help to perform the decision making of the transmission system operator. All methods will be tested and evaluated with a detailed dynamic model of the European interconnected power system.

Index Terms -- Small-Signal Stability, Decision Trees, Dynamic Security Assessment, Interarea-Eigenvalues, Nearest Neighborhood, Oscillatory Stability, Parallel Eigenvalue Computation

I. INTRODUCTION

WITH the deregulation of the European electric power market a competitive situation for the market participants arose. Long-distance power transits from regions with a surplus of generation are taking place to meet the demand in other regions, whereas economical aspects are playing a dominant roll. The variation of the load flow in 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. Furthermore, the synchronous parallel operation of the Western European Power System UCTE with the Eastern part CENTREL since 1995, aggravated the oscillatory stability situation, too.

The liberalization has changed the traditional role of the system operator, which is now an entity not owning any generation, charged with the responsibility of maintaining quality and reliability of electric power supply. In the European electric power market, the system operator is mostly the local transmission system owner, too and named transmission system operator TSO. Beside other tasks like market operations, settlements and operation data management, each TSO of an interconnected power subsystem has the responsibility for power system operation in his area, which include the daily and hourly operation

planning and real-time control of the restructured generation-transmission system maintaining static and dynamic system security and reliability. In order to accomplish his tasks, operators use efficient static and dynamic security tools. Methods for voltage and transient stability assessment have been intensively investigated and developed in the past. However, the small signal stability of large strongly meshed power systems is an emerging problem of recent years. Corresponding methods are not available yet.

Furthermore, oscillatory stability assessment itself is aggravated because of two major reasons. Firstly, oscillatory stability cannot be rated on the base of local information. It normally requires a full and realistic dynamic model of the whole interconnected power system. Therefore, the exchange of information between utilities gains in importance. On the other hand, this is increasingly hindered by many of the independent power producers behaving restrictively hiding their data. Secondly, the existing de facto standard methods and tools for small-signal stability are not able to perform security analysis in the claimed response time required for online use [2].

Modal analysis is the state-of-the-art method to assess the damping of predominant modes. It is commonly used in the system planning, particularly for design and tuning of control systems. At the TSO side, evident real power margins over cross-border lines and corresponding stability reserves have to be presented quickly and in a manner, which is close to human reasoning, rather than eigenvalues. Furthermore, weakly damped modes have to be traced under N-1 contingency conditions for actual and planned load flow situation. Learning from transient stability assessment, for the fast assessment of oscillatory stability two supplementary approaches are followed within the work for this paper :

- Efficient parallel eigenvalue computation improving performance of modal analysis
- Supplementary use of appropriate methods of Computational Intelligence

This work was supported in part by the Deutsche Forschungsgemeinschaft DFG, Bonn.

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The mutual use of both methods is based on continuously online-enhancement of a database containing possible system states, transit scenarios, etc. and the corresponding small signal stability characteristics. They can be created using a parallel variant of the modified Arnoldi method. It is based on the partitioning of the system equations, which can be computed in parallel and therewith faster.

Based on the minimum distance of selected features describing the power system steady states, the most similar dynamic state in the database can be identified. This method, called k^{th} Nearest Neighborhood method provides a quick evaluating of load flow data or EMS data from the state estimator regarding oscillatory stability. Additionally, Decision Trees help to identify crucial cross-border line loadings in cases when a power transit is limited by small-signal stability.

II. PARALLEL ARNOLDI METHOD APPLIED TO LARGE POWER SYSTEMS

Methods for selective eigenvalue computation of large scale power systems are well established in the power system dynamic analysis [1]-[4]. They can be classified in sequential methods and subspace methods. The latter one comprises the methods of Subspace Iterations, Arnoldi method and Lanczos method. In [6], results of parallel eigenvalue computation of power systems using Subspace Iteration have been presented. The approach in this work is characterized by the parallel computation of n eigenvalues on $2n$ CPUs (in [6] $n=1..4$) whereas a fix number of nodes always is assigned to the computation of each eigenvalue.

In the following a solution using the parallel Arnoldi algorithm [5] is presented. In this method the number of computed eigenvalues does not depend on the number of available CPUs.

A. Brief Description of the Portioning Problem

The original Arnoldi method is based on a reduction technique, in which the system matrix is reduced to an upper Hessenberg matrix by the recurrence [1]

$$h_{i+1,i} \mathbf{v}_{i+1} = \mathbf{A} \mathbf{v}_i - \sum_{j=1}^i h_{ji} \mathbf{v}_j \quad i = 1..k \quad (2.1)$$

where

\mathbf{v}_1 an arbitrary arnoldi starting vector

$h_{ji} = \mathbf{v}_j^H \mathbf{A} \mathbf{v}_i$

$h_{i+1,i}$ scaling factor

k order of the Hessenberg matrix

The Arnoldi vectors \mathbf{v}_i , $i = 1..k$ form the Matrix \mathbf{V} , which transforms the system matrix \mathbf{A} to the matrix \mathbf{H} , whose eigenvalues are almost identical with the interesting subset of \mathbf{A} . That means:

$$\mathbf{A} \mathbf{V} \approx \mathbf{V} \mathbf{H} \quad (2.2)$$

The parallel variant of the Arnoldi method [5] is based on a portioning of the transformation (2.2) :

$$\mathbf{A}_m \mathbf{V}_m \approx \mathbf{V} \mathbf{H} \quad \forall \quad m = 1..m_{\max} \quad (2.3a)$$

with

$$\mathbf{V}^T = [\mathbf{V}_1^T \quad \mathbf{V}_2^T \quad \Lambda \quad \mathbf{V}_{m-\max}^T]^T \quad (2.3b)$$

However, the system matrix \mathbf{A} in (2.1-2.3) is only provided implicitly. In order to keep the sparsity of the matrices, the linearized system equations are usually provided in the following form.

$$\Delta \dot{\mathbf{x}} = \mathbf{A}_D \Delta \mathbf{x} + \mathbf{B}_D \Delta \mathbf{u}_k \quad (2.4a)$$

$$\Delta \mathbf{i}_k = \mathbf{C}_D \Delta \mathbf{x} - \mathbf{Y}_D \Delta \mathbf{u}_k \quad (2.4b)$$

with

$$\Delta \mathbf{i}_k = \mathbf{Y}_N \Delta \mathbf{u}_k \quad (2.4c)$$

From (2.4a-c) follows, that the explicit system matrix can be calculated by

$$\mathbf{A} = \mathbf{A}_D + \mathbf{B}_D (\mathbf{Y}_N + \mathbf{Y}_D)^{-1} \mathbf{C}_D \quad (2.5)$$

Furthermore, this is not practicable because of the high computational effort necessary when applying shift-invert transformation to the matrix \mathbf{A} from (2.5) :

$$\mathbf{A}_T = (\mathbf{A} - \lambda_s \mathbf{E})^{-1} \quad (2.6)$$

Therefore, in [3] the implicit calculation of the matrix-vector Product $\mathbf{A}_T \mathbf{v}_i$ is done by solving the system

$$\begin{bmatrix} \mathbf{A}_D - \lambda_s \mathbf{E} & \mathbf{B}_D \\ \mathbf{C}_D & -(\mathbf{Y}_N + \mathbf{Y}_D) \end{bmatrix} \begin{bmatrix} \mathbf{u}_i \\ \mathbf{q}_i \end{bmatrix} = \begin{bmatrix} \mathbf{v}_i \\ \mathbf{0} \end{bmatrix} \quad (2.7)$$

where

λ_s complex shift point

\mathbf{q}_i an auxiliary vector for the i th iteration cycle

\mathbf{u}_i matrix-vector product $\mathbf{A}_T \mathbf{v}_i$ for the i th iteration

B. Parallel Algorithm

A portioning of the solution steps of (2.7) under consideration of the implicit form of \mathbf{A} in (2.4a-c) for parallel computation is realized by the algorithm depicted in Fig. 1. The algorithm can be divided into a preconditioning part and in the iteration loop part. The latter one comprises PARPACK [5], the implementation of the parallel variant of the Arnoldi method, and the product computation performed implicitly from (2.4a-c) with respect to (2.7). Basically, the performance of the Arnoldi iteration is mainly influenced by

- The closeness of the shift-point to the (assumed) eigenvalues in the complex plane, also correlating with the numbers of necessary iteration cycles
- The number of eigenvalues neighboring the shift-point

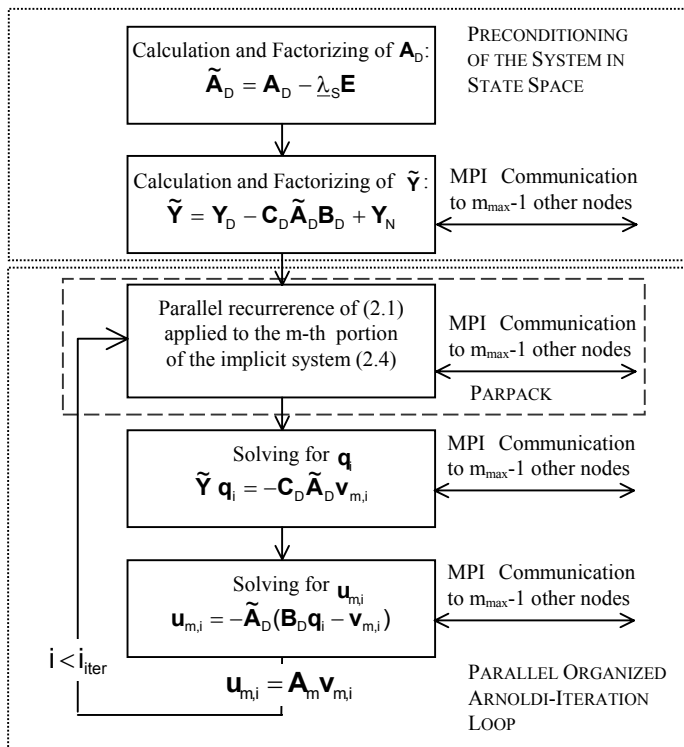


Fig. 1. Parallel eigenvalue computation

C. Hard- and Software Environment

The available hardware environment was 1) a personal computer with dual motherboard containing 2 Intel® P III CPUs at 800 MHz, and 2) a multiprocessor system Siemens PRIMERGY® N800 containing 8 Intel P III Xeon® CPUs at 900 MHz. On both systems the standard operating system Windows® 2000 was installed offering multithreading and multiprocessing capabilities.

D. Numerical Examples

In order to rate the capabilities of the parallel eigenvalue computation, at first a detailed dynamic model of the whole European interconnected power system has been used. It consists of 496 generators described by 5th order models, partially equipped with AVR and governor models. It contains 2098 transmission lines, several static loads modeled under consideration of their voltage dependencies, 2- and 3-coil transformer, HVDC elements, power supplies, reactors and shunt capacitors. For comparison purposes, two smaller power system models containing 136 generators, and 36 generators have been used, respectively (see Table I).

TABLE I
CONSIDERED TEST SYSTEMS

Configuration	System 1	System 2	System 3
No. of generators	496	136	36
No. of buses	2016	1033	72
No. of lines	2098	686	96
No. of states	5562	2898	180

E. Results

The evaluation of the performance of a parallel algorithm is generally done using the Efficiency E and the Speed-up S_p .

The Speed-up S_p is defined as the speed gain by the parallel implementation compared with the single processor version. Efficiency is the ratio of S_p and the number of processors. It can reach values between 0 and 1. Fig. 2 and Fig. 3 show the Efficiency and the number of Arnoldi Iterations needed for the calculation of 10 up to 100 eigenvalues for all three test system of Table I. Fig. 2 relates to Hardware Environment 1 (Dual CPU Motherboard), and Fig. 3 to Environment 2 (Siemens PRIMERGY® N800 with 8 CPUs). For power system models of System 1 and System 2, Efficiency increases with the number of desired eigenvalues and reaches up to E=96.1 % (System 1 and Hardware Environment 1) pretending n=100 eigenvalues (Fig. 2).

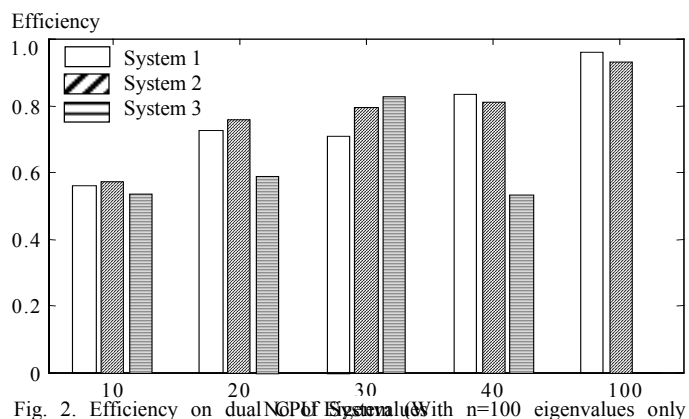


Fig. 2. Efficiency on dual CPU System 1 (With n=100 eigenvalues only System 1 and 2 have been tested)

With the Siemens PRIMERGY® N800 Hardware Environment, maximum values of Efficiency up to E=77.9 % have been reached (n=30 Eigenvalues and m=3 CPU units, System 1), see Fig. 3. Hereby, the number of CPUs used was varied in a range from m=1 up to m=8. Furthermore, in Fig. 3 only maximum Efficiency values corresponding with a specified number of CPUs are depicted.

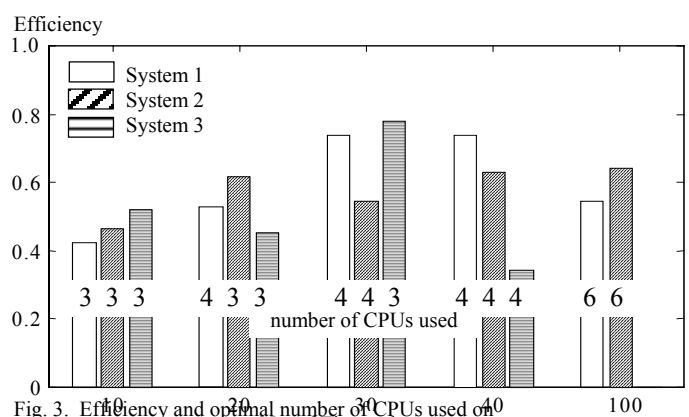


Fig. 3. Efficiency and optimal number of CPUs used on Siemens PRIMERGY® N800 (With n=100 eigenvalues only System 1 and 2 have been tested)

Additionally, the following can be noted:

- The optimal number of CPUs units m_{opt} is defined by both a minimum of computation time and a maximum of Efficiency. It strongly depends also from the number of desired eigenvalues and the order of the transforming Hessenberg matrix, respectively.
- With a suboptimal number of CPUs larger than the optimal number, the performance is only negligible higher or equal, but the efficiency decreases significantly.

III. APPLICATION OF METHODS OF COMPUTATIONAL INTELLIGENCE TO OSCILLATORY STABILITY ASSESSMENT

Methods of Computational Intelligence can relieve the assessment of oscillatory stability rather than replace analytical tools and methods. Furthermore, they provide adaptivity, fault tolerance and help to assist human reasoning. In our work the method of the k^{th} Nearest Neighborhood and Decision Trees were used. They can be combined supplementary with modal analysis in order to extract relevant information for a further enhancement of computational efficiency, an improvement of interpretability and a better management of uncertainties. The common prerequisite for their application is the presence of a sufficient number of pre-calculated input and target data generated by modal analysis.

A. Learning Data Preparation

A very important step preparing the application of methods of computational intelligence to oscillatory stability assessment is the convenient selection of attributes for potential online use. Therefore, it is necessary to select appropriate features available from energy management system. Generally, the following features seem to be appropriate:

- Generated real power of each Power Producer
- Generated reactive power of each Power Producer
- Weighted generator voltages of each Power Producer
- Transborder real power between TSO subsystems
- Transborder reactive power between TSO subsystems
- Transmitted real power over selected lines and interfaces
- Transmitted reactive power over selected lines and interfaces
- Topological Information

For evaluating the scenarios the damping ratio

$$D_i = \frac{-\sigma_i}{\sqrt{\sigma_i^2 + \omega_i^2}} \quad (3.1)$$

with

σ_i real part of the i th Eigenvalue

ω_i imaginary part of the i th Eigenvalue

is used.

In order to provide a sufficient amount of learning data, 5452 different load flow scenarios of System 1 have been generated. Therefore, power generation has been reduced in an importing area, while generation was increased by the same amount in the exporting area. Using modal analysis, for each load flow situation 10 Eigenvalues have been calculated,

Fig. 4.

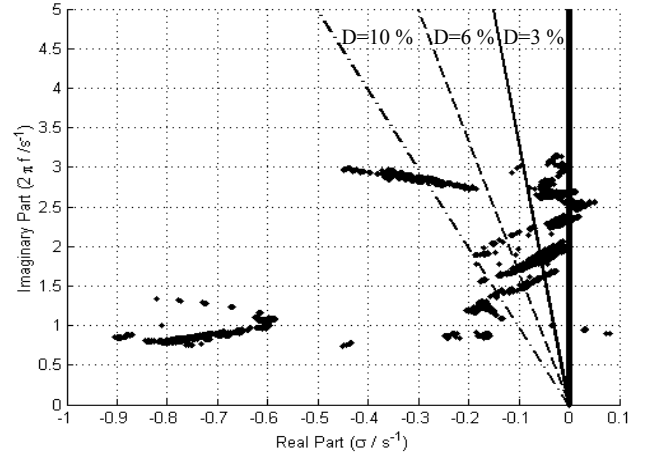


Fig. 4. Changes of 10 local and inter-area eigenvalues of the UCTE/CENTREL dynamic model under the impact of 5452 load flow scenarios (System 1)

B. Nearest Neighborhood Method

The application of k^{th} Nearest Neighborhood Technique is based on the minimum of a distance measure in the attribute space :

$$d_{min} = \min\{d_{ij}\} \quad (3.2)$$

where

d_{ij} distance between the two dynamic states i and j

When the amount of learning sets grows to infinite, the distance between object i and j is reduced to zero. A distance measure can be defined in several manners. In this study the standardized Euclidean distance was used:

$$d_{ij} = \sqrt{(\mathbf{f}_i - \mathbf{f}_j)^T \mathbf{D}^{-1} (\mathbf{f}_i - \mathbf{f}_j)} \quad (3.3)$$

where

$\mathbf{f}_i, \mathbf{f}_j$ attribute or feature vectors of the dynamic states i and j

\mathbf{D} diagonal matrix with diagonal elements containing variances of the i th attribute of all objects

If the distance d_{min} is lower as an defined upper bound ε , the oscillatory behavior of the power system can be assumed to be similar, characterized by the eigenvalue spectrum:

$$d_{ij} < \varepsilon \Rightarrow \lambda_{k,i} \approx \lambda_{k,j}, k = 1..n \quad (3.4)$$

Fig. 5 shows the variation of the exchanged transborder real power for 5452 investigated transit scenarios within the European interconnected power system. Fig. 6 shows the corresponding 3 neighboring eigenvalues for a selected sample test load flow scenario associated with a minimum distance measure in the transborder real power profile of Fig.5. A neighborhood of the transborder real power exchange profile strongly correlates with the neighborhood of the corresponding interarea eigenvalue. The scenarios were calculated for the detailed dynamic model of the interconnected UCTE/CENTREL power system (System 1).

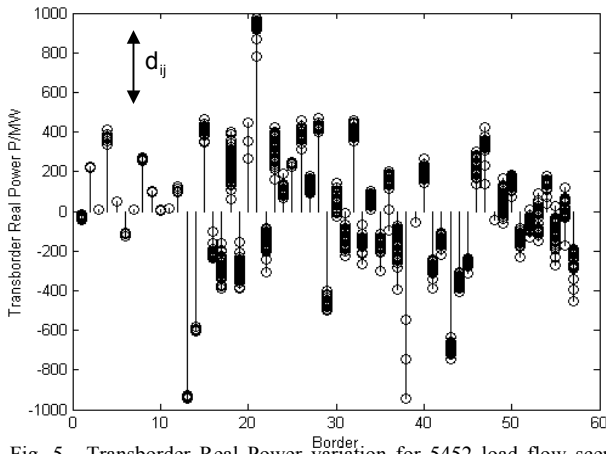


Fig. 5. Transborder Real Power variation for 5452 load flow scenarios of System 1

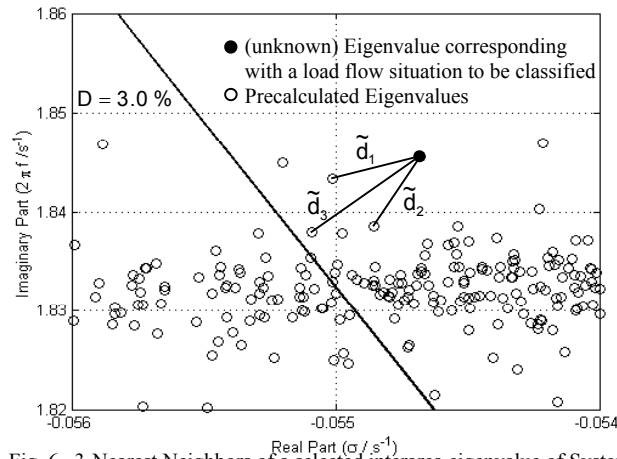


Fig. 6. 3-Nearest Neighbors of a selected interarea eigenvalue of System 1

The method of k^{th} Nearest Neighbor is a very simple approach. Its robustness and accuracy strongly depends on the number of pre-calculated scenarios. However, the main advantage of this method is that a detailed dynamic model not immediately needed for the assessment of oscillatory stability.

C. Decision Trees

The method of Decision Trees [8,9] allows the selection of features and the corresponding characteristic values for classification purpose. It has been applied to the evaluation of power system dynamic states using power flow information. The decision rules are generated systematically for the most appropriate features. Numerical criterion is a common measure for the information gain able to identify relevant and non-relevant features as well as to define the corresponding threshold level for a test in the Decision Tree nodes. The measure characterizing the common information gain can be defined in several ways. We have used the following measure:

$$M(X, Y) = \frac{2H(X; Y)}{H(X) + H(Y)} \quad (3.5)$$

with the information quantity provided by

$$H(X; Y) = H(X) - H(X|Y) \quad (3.6)$$

$H(X)$ denotes the entropy of X . It is defined by

$$H(X) = \sum_{x \in A_x} P(x) \log \frac{1}{P(x)} \quad (3.7)$$

with

$P(x)$ occurrence of the feature x .

Furthermore, $H(X|Y)$ is defined as the mean posterior entropy :

$$H(X|Y) = \sum_{y \in A_y} P(y) \left[\sum_{x \in A_x} P(x|y) \log \frac{1}{P(x|y)} \right] \quad (3.8)$$

$P(y)$ occurrence of the feature y

$P(x|y)$ conditional occurrence of the feature x

The measure M for each feature and its possible values will be calculated separately for each decision node (Fig. 7b). The maximum of the measure M characterizes the best suitable test for node splitting, comprising feature and value, respectively (Fig. 7a).

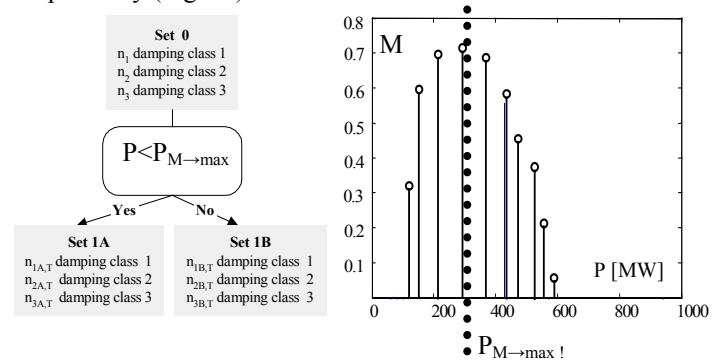


Fig. 7a,b. Node splitting based on maximum score measure M

A classification of oscillatory behavior of a power system the damping classes shown in Table III are suitable. In the detailed dynamic model of the European power system system (System 1), $n=2000$ different transit scenarios have been classified regarding the damping of an interarea mode with $\underline{\lambda} = -0.053 + j1.834$ 1/s (Fig. 8). As feature vector, the summarized transborder real power exchange between all TSO subsystem has been selected. All transit scenarios have been classified into the two damping classes "critical" and "sufficient". All terminating leaves contain only one damping class ($H=0$), the number of splitting nodes was $n=104$.

TABLE III
CLASSIFICATION OF THE DAMPING OF INTER-AREA MODES

Damping [%]	Damping Classes	Explanation and possible Actions
> 10	ideal	ideal damped mode
6 - 10	normal	normal damped mode; no direct call for action; corrective actions possible but not required
3 - 6	sufficient	sufficient damped mode, exact verification of several stages of the impact of planned or possible dynamic states to the small-signal security; corrective actions possible
0 - 3	critical	critical damped mode; corrective actions required
< 0	instable	instable; partial separation of the interconnected grid, Aimed and system-wide coordinated rejection of individual producer or consumer-units

Because the identified features and their values corresponding with a maximum of M (3.5) have been selected first, the transborder real power exchange over these interfaces have to be monitored more intensively as the others.

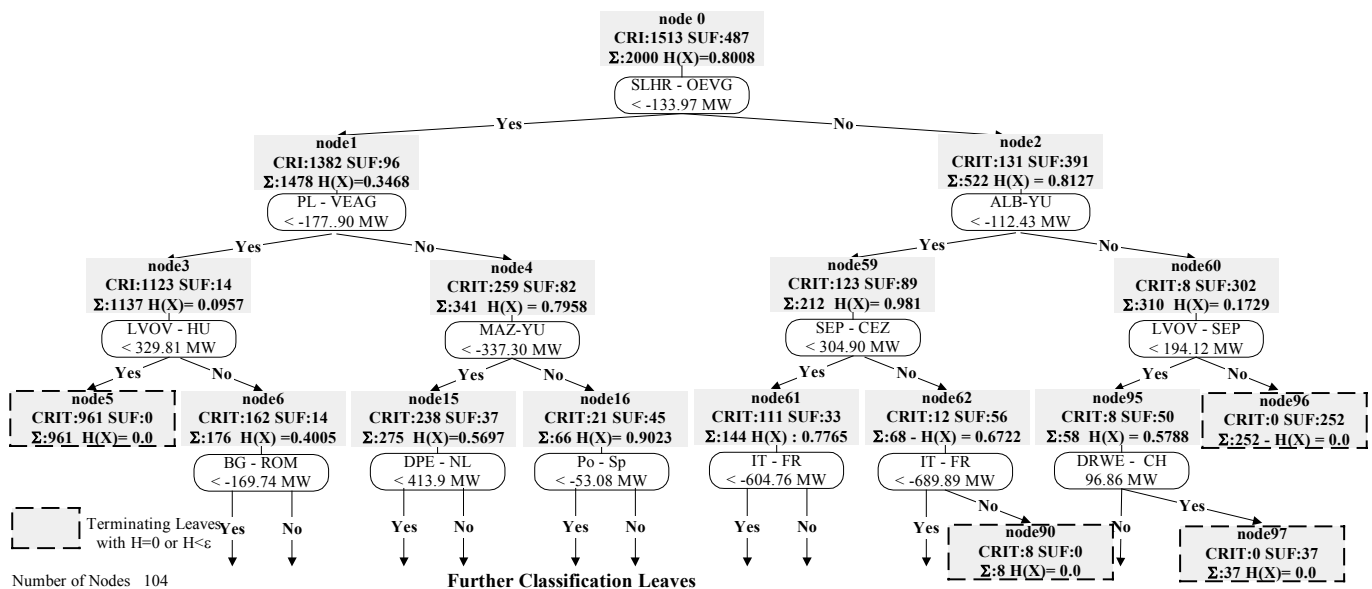


Fig. 8 : Upper part of a Decision Tree identifying most significant transborder interfaces and critical power exchanges in System 1 considering the variation of the damping of the interarea eigenvalue with $\lambda = -0.053 + j1.834$ 1/s (basecase load flow)

Furthermore, well defined transborder real power limits are identified. Thus, exact limits and operation conditions can be formulated necessary for the decision making of the TSO.

IV. CONCLUSIONS

For operational prospective dynamic security assessment, particularly oscillatory stability assessment, modal analysis using parallel processing can help to reduce the response time. Therefore, the parallel Arnoldi algorithm has been adapted and investigated within three test systems. One of them is a realistic dynamic model of the European interconnected power system UCTE/CENTREL. A significant reduction of the computational time for eigenvalue computation was obtained using two different parallel hardware environments. The Speed-up and Efficiency values reached qualify the parallel algorithm for a fast small signal stability assessment. The mutual use of methods of Computational Intelligence, the k^{th} Nearest Neighborhood and the Decision Tree methods, enable a fast assessment of the oscillatory stability within power system control.

V. ACKNOWLEDGMENT

The authors gratefully acknowledge Fujitsu-Siemens company in Paderborn, Dept. Performance and Benchmarks tests, for their cooperation and for the PRIMERGY© N800 multiprocessor system which was made available.

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VII. BIOGRAPHIES



István 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 had also 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/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 member of IEEE and VDE.



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