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Stability Assessment of Electric Power Systems using Growing Neural Gas and Self-Organizing Maps

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Abstract. Liberalized competitive electrical energy markets need tools for real-time stability assessment to link the technical with the market issues. Analytical tools are available but time-consuming. Alternatively, knowledge based systems speed up the stability assessment but most of them need extensive and assessed training data. Unsupervised learning methods like Growing Neural Gas or Self-Organizing Maps use training situations and the information of stability separately. Doing this, the calculation of training data is less time consuming. The use of the two methods within a fully automated tool for stability assessment is discussed in this paper. Aspects of self-learning, quality of the assessment and application to real power systems are considered.

1 Introduction

The operation of electrical transmission systems has to be more flexible under competition. An optimal use of the operating fund 'network' can be achieved by running the system closer to the stability limit. If economical requirements can be realized technically, it is essential to check the distance to the stability limit. Particularly the trading of transmission capacity for wheeling contracts needs a tool which checks the stability of the system in real-time.

Conventional methods for stability assessment are well known [1]. The transient stability can be determined by dynamical simulations. Thermal and voltage limits result from load flow calculations just as voltage stability bases on load flow equations. If we assess all different kinds of stability we need a lot of computational effort. The fastest applied analytical tools need more than about 30 minutes to determine the stability of a large real transmission system. Simplifying assumptions are one possibility to reduce the calculation time. This results in a loss of accuracy.

An alternative method is the mapping of preprocessed stability situations on a decision tree [2] or an artificial neural network [3]. Both divides or ranks input situations in critical and non critical ones basing on relation characteristics of single input resp. measurement values. The supervised learning methods are trained by the use of excessive training data sets. Decision trees are established for the classification of situations according to stable or unstable states. But the calculation of training data sets is impractical for complex systems if the distance to the stability limit is the desired output information and not only the statement of stable or unstable. To avoid this problem, the following approach uses unsupervised learning methods like self-organizing maps (SOM) [4] and growing neural gas (GNG) [5], which separate the clustering of situations from the stability assessment of these situations. First results using SOM for voltage stability are presented in [6][7][8]. The results of GNG are presented here for the first time.

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Section 2 gives more details on conventional stability assessment. The advanced methods using SOM and GNG are explained and validated in section 3. These methods are applied in a fully automated and autonomous component for stability assessment in section 4.

2 Stability Assessment

Stability assessment is a broad field from classification of contingencies or situations to the calculation of the distance to the stability limit in different senses of stability. More than the classification of an actual situation in stable or unstable, the distance towards the stability limit shows how robust the system is against changes of operation variables. The following describes a conventional way of security assessment for the latter.

At first a load flow calculation determines if an actual base case fulfills the thermal and voltage limits and if the system is voltage stable. A dynamic simulation assesses the transient stability for several contingencies. Which contingencies have to be considered has to be determined separately. If we modify an operation variable of the system stepwise, e.g. the load, we can execute this procedure until one of the limits is reached. An optimization process for finding the limit can also be used. Fig. 1 shows this with the two left bars (arrow a) for voltage stability and b) for transient stability). Doing this, we need several load flow calculations and dynamical simulations.

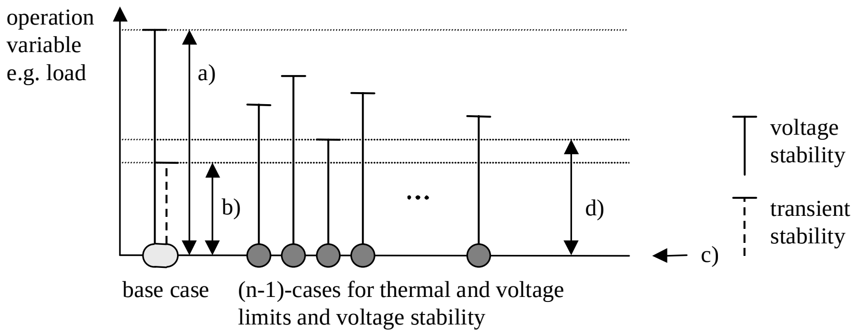

Fig. 1: Different kinds of stability assessment

Additionally, selected (n-1)-cases have to be assessed (cases c)). The cases which have to be considered can be selected according to the reliability. The situation with the lowest stability defines the actual stability value (arrow d)). If the transient stability limit is lower, b) is the actual value. This value can be expressed by using the unit of the modified operation variable, e.g. MW for the load and will be called *LI*.

The described procedure or parts of it are applicable if a calculation time of at least 30 minutes is sufficient. For faster results we can reduce the calculation time by using supervised learning methods like artificial neural networks or decision trees. For these applications we need assessed training data for several situations. But using the stability assessment as mentioned above we can only pre-calculate four situations per hour. The generation of several hundreds of situations is impractical. Therefore applications with supervised learning techniques are mostly restricted to the classification in critical or non-critical situations [1][2][3].

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3 Advanced Methods for Stability Assessment

Unsupervised learning methods are used in order to guarantee a fast stability assessment and a good representation of the state space. These methods find characteristic groups and structures in the input data space. Measurement values which are available in energy management systems represent the input space. After training, the stability values (section 2) are calculated separately only for the limited number of groups which have been determined by the unsupervised method. More than simple clustering methods, SOM and GNG represent the neighboring structure of the state space. This information can be used for the arrangement of an actual state within all possible situations. The following presents the principles and the application of SOM and GNG. After that, their ability for stability assessment will be compared with the help of a real power system example.

3.1 Self-Organizing Map

A SOM maps a high dimensional input space to a low dimensional output space [4]. Fig. 2 shows the structure of the SOM and the example of a two-dimensional section of an input space $\boldsymbol{x}$ with two different clusters. The state information y of the clusters is colored pale and dark. The mapping of the SOM is done by feature vectors $\boldsymbol{w}_j$ in a way that their mean distances to the training vectors are minimizes. The feature vectors are structured in a neighborhood grid. If the grid is two-dimensional, the SOM offers the possibility for the visualization of its mapping [7][8].

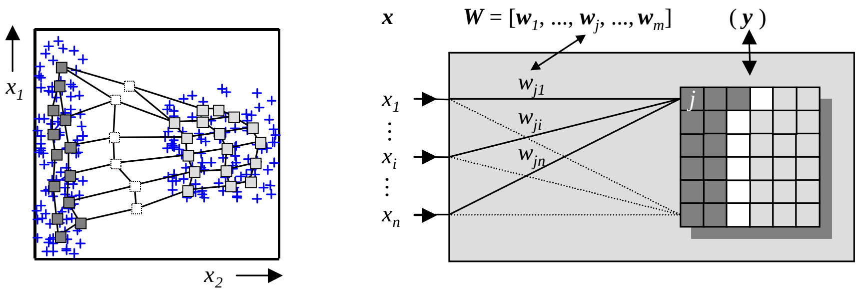

Fig. 2: Structure of a SOM with the example of a two-dimensional section of a state space

3.2 Growing Neural Gas

The GNG was proposed by Fritzke [5]. Similar to the SOM, feature vectors $\boldsymbol{w}_j$ are distributed in an input space of training data. In contrast to the SOM, the neighboring structure will also be defined in the training process. Connections c_{vw} can be set or deleted between states s_v and s_w and their feature vectors $\boldsymbol{w}_v$ and $\boldsymbol{w}_w$. These connections represent the topological structure of the data space. Fig. 3 shows the structure of the GNG and an example.

The advantage of growing neural gas is that the number of feature vectors and connections is not fixed. They will be adapted in a continuous process. An adaptation to a changing input data space can be realized easily. The principle accuracy of the input space representation is greater because of a higher degree of freedom in comparison to the SOM. On the other hand, the visualization of the results is not possible.

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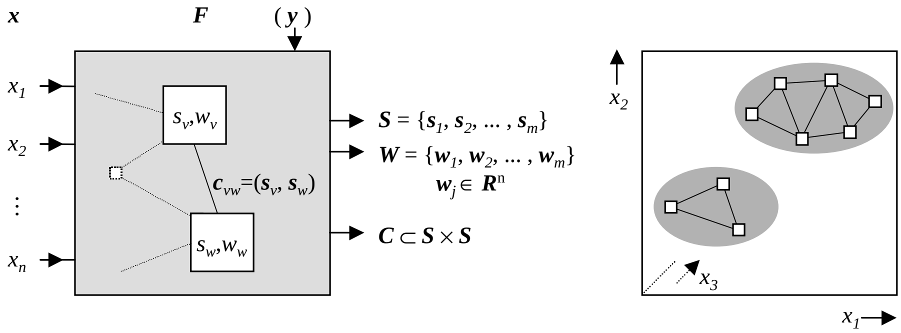

Fig. 3: Structure of the GNG and an example of connected feature vectors in an input space

3.3 Validation of Conformity

Both methods are tested for the validation of conformity for the stability assessment. of a real German 134-bus power system with 21 generators at 8 generation busses. The training data set is made of 3000 different state vectors representing normal and contingency situations given by generator outages. The load level is distributed randomly between an upper and a lower limit. The generation pattern is defined randomly in order to include all possible states of the power system. As the result of a correlation analysis the active and reactive power of the generation units and the active power of four selected loads are chosen as the 20 components of input vectors. The values of the components are normalized within the interval [0,1], because this guarantees equal weights for each component. After the training of SOM or GNG the stability value for each feature vector is determined as the maximum possible load increase *LI*.

The conformity of the mapping of pre-calculated values of *LI* to several test vectors is shown in figure 4. In the left part the extreme range of the Error E_{ext} defined as the difference between the analytically calculated value LI_{cal} and the value simulated by SOM LI_{SOM} or GNG LI_{GNG} is shown over the number of states of SOM or GNG. Each trained SOM shows different areas for different contingency cases. The error behaves for both methods nearly similar.

For a special SOM with 18x18 states a more detailed look on its error is shown in the right part of figure 4. The simulated value LI_{SOM} for 3000 test vectors is represented ordered by magnitude. According to these values the analytically calculated values LI_{cal} and their range of deviation is given. The error *E* of the mapping is also drawn separately. The error *E* increases according to *LI*. The extreme values with an error of - 16.5 % and + 17.3 % are single test vectors which are represented not sufficiently. Nearby the stability boundary resp. for small values of LI the accuracy of the mapping is better, which is a desired result. Additionally, a frequency distribution of the error *E* of this SOM is represented. The standard deviation of this frequency distribution is σ_{SOM} = 3.2 % of *LI*.

All in all, a GNG is as good as a SOM for the assessment of stability. The degree of freedom of the GNG for the representation of higher dimensions can not be transposed into minor errors. But on the other hand, the two dimensional representation of the SOM can be used for visualization of the system state. The maximum dimension of the SOM resp. the number of states is restricted by the time for the pre-calculation of the stability information. For practical applications a SOM with 18x18 states is a good compromise. The error of the mapping enables the operation of the power system down to a minimum of LI_{SOM} = 5 %. In this case the calculated values would be between LI_{cal} = 0 % and 10 %.

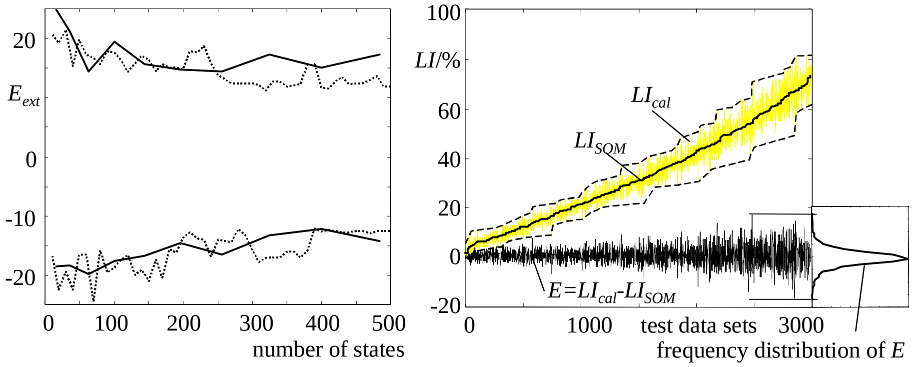

Fig. 4: Mapping error of SOM and GNG

4 Automated and Autonomous Component

The use of the proposed methods in control centers has to be realized as a fully automated and autonomous component. Fig. 5 shows the structure of such a stability tool according to necessary data.

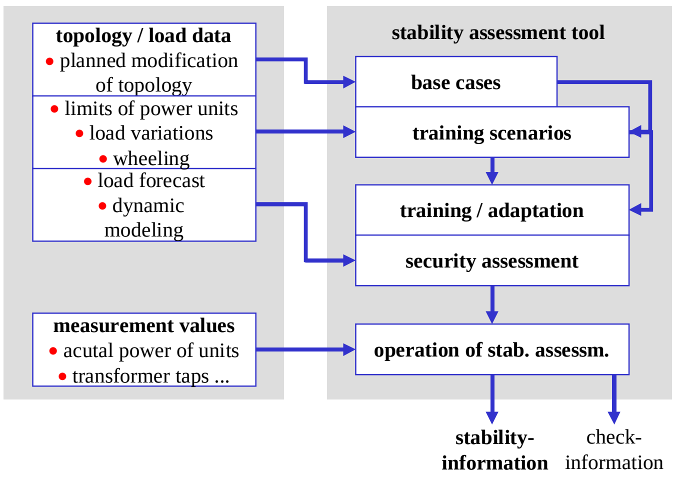

Fig. 5: Structure and data access of an automated component for stability assessment

The base cases are the normal operation situations of the system. Different planned topologies can be considered. From these base cases training scenarios are derived automatically by modifying load levels, generation pattern and wheeling. These situations are clustered with the proposed unsupervised methods. After that, the stability of the finite number of received clusters of situations must be assessed using

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conventional methods. Now, the stability assessment tool is ready for operation with incoming measurement values. The assessment time comes to only a few seconds. If the assessment fails because of a situation outside the training data, a check information warns. If the base cases change, the training scenarios are updated automatically and the self-organizing map or the neural gas have to be adapted.

It has to be mentioned that the stability assessment is valid for first contingencies in the sense of (n-1)-security only. Cascading contingencies are not covered, if they are far outside the training data.

5 Conclusions

In order to enable a real-time stability assessment and to avoid a time consuming generation of assessed training data the application of SOM and GNG is proposed. With these methods the mapping of the training data structure and their assessment is separated. The comparison of both methods shows that the error behaves nearly similar and the two dimensional mapping of the SOM is sufficient for this problem. Also the SOM can be used for visualization. For a SOM with 18x18 states the standard deviation of the error is 3.2 % and the accuracy allows an operation nearby the stability boundary down to 5 % of *LI*.

To automate the proposed method for stability assessment a concept for a fully automated tool for control centers is discussed. The next step in this project is the assignment of pre-calculated stabilizing measures to clusters of situations defined by the SOM or the GNG.

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