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ARTIFICIAL INTELLIGENCE APPLIED TO ON-LINE TRANSIENT STABILITY ASSESSMENT OF ELECTRIC POWER SYSTEMS

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Summary. A novel approach to fast transient stability assessment of power systems is presented. It consists of inductive inference which allows the construction of decision rules derived from off-line simulation data. The proposed procedure derives from ID3 by Quinlan, appropriately modified so as to handle a large number of continuous variables. The decision rules are expressed in terms of static, controllable variables. This makes the method able to solve both on-line transient stability analysis and preventive control problems.

1. INTRODUCTION

The on-line transient stability assessment of electric power systems is an extremely problematic, still open question.

The conventional approach consists in assessing the system's robustness to withstand credible large disturbances; and even if nowadays Liapunov's direct criteria have matured enough to become truly effective, they still remain off-line methodologies [1,2]. The need for conceptually different on-line approaches, along with an in-depth qualitative understanding of the system's behaviour is strongly felt.

In this paper, such an on-line approach is presented. It consists in using Inductive Inference (II) [3, 4] (which is the Artificial Intelligence (AI) approach to pattern recognition) to construct classification rules inferred from large bodies of preclassified off-line simulation data.

The proposed procedure derives from ID3 by Quinlan [5], appropriately modified so as to handle the large number of continuous variables characterizing power system operating conditions.

Our research effort has been oriented towards the development of an appropriate quantization procedure as well as the design of a more flexible control strategy using some heuristic domain-dependent knowledge.

After completion of the learning stage, the obtained rules can be used by a knowledge based system for transient stability analysis. Furthermore, simplified versions of these rules can be used to acquire qualitative understanding of the system's behaviour.

2. INDUCTIVE INFERENCE APPLIED TO TRANSIENT STABILITY [6]

2.1. Classification problem

We define our classification problem in the case of a fixed topology and a given disturbance (or fault).

Let C^+ be the class of sufficiently robust operating points (the robustness of the power system with respect to a given disturbance is currently measured by the corresponding critical clearing time of this fault, and C^- the remaining states.

Given a preclassified learning set E ($E = E^+ \cup E^-$; $E^- = E \cap C^-$; $E^+ = E \cap C^+$) and given a representation language (e.g. first order predicate calculus) which is used to express any knowledge about the learning states, the task of inductive inference is to build a final classification rule, simple and reliable to the extent possible. This in turn will be used to predict the class-membership of any operating point, i.e. to decide whether the system is stable or not with respect to the occurrence of a particular fault.

This particular class definition enables us to formulate naturally some heuristic knowledge to guide the learning system. Moreover, the obtained rules will carry information specific enough to permit the operator to be aware, during the on-line assessment, of the actual robustness of his power system with regard to transient stability.

The learning states are preclassified by means of a classical time domain (step-by-step) transient stability analysis program. Therefore, there is no inherent limitation about the dynamic models used to simulate the power system.

2.2. Attributes

The learning states are characterized by a fixed number of attributes (or variables) which can be selected by the learning system to formulate a decision rule. In the case of the application of our methodology to real life power systems, these should of course be chosen with the help of experts like operators or system operation and planning engineers who know the weak points of their system.

Overall, the resulting choice must be a good compromize between storage requirements of the learning set (which may be very demanding in the case of large systems), and information whose loss can prevent the obtained rules from being sufficiently reliable.

In the absence of this experts' knowledge and in order to preserve generality, we propose the following list of attributes :

Attributes related to the system as a whole :
- total active and reactive load power;
- mean, minimum and maximum node voltage.

*Attributes related to the various regions * :*
- total active and reactive generated and load power;
- active power exchanges with the different neighbouring regions;
- mean, minimum and maximum node voltages in this region.

Attributes related to generator nodes :
- active power and initial acceleration for each machine.

One could of course argue that one of the classical independent sets of state variables like $(P/V;P/Q)$ or (V/θ) would have been sufficient, but except for generator nodes and possibly for very important load nodes, the sole nodal variables are not determinant.

* The power system can be decomposed in a reduced number of regions which are composed of electrically close nodes (connected by rather short lines), while the "tie-lines" between these regions are rather long lines.

Rather, it is their conjunctive action which can modify the robustness of the system; this explains why we have chosen more global, lumped values. Moreover, by avoiding storage of irrelevant information, this choice allows us to combine reasonable representativity and admissible storage requirements for the learning set.

On the other hand, one could propose to use more directly involved attributes such as Liapunov functions for instance, but we think that it should be possible to build decision rules without using such information. In that case, all the attributes will be static, directly or indirectly controllable variables. This in turn allows the use of the resulting rules in a preventive control environment and their physical interpretation will be facilitated.

Finally, let us point out that this choice remains strongly independent of the topology. A new set of attributes must be defined only in the case of very broad changes like several line trippings or generator outages.

3. BRIEF DESCRIPTION OF THE PROPOSED METHOD

3.1. Modified ID3 [6]

The procedure consists in selecting, by using the criterion explained in [6], an attribute a_i and an optimal quantization threshold $v_{i\,opt}$ in order to generate the following partition of the initial learning set :

$$E = E_1 \cup E_2 \ ;$$

$$E_1 = \{e \in E \mid a_i(e) \leq v_{i\,opt}\} \ ; \ E_2 = \{e \in E \mid a_i(e) > v_{i\,opt}\} \ .$$

The procedure is then applied recursively to the non-terminal subsets of this partition. A set is terminal if all its states belong exclusively to C^+ or C^- or better if its entropy is lower than a certain threshold value *. This generates a tree (Fig.1), each node of which corresponds to a subset of its parent node. The root node corresponds to the initial learning set; the terminal or leaf nodes correspond to samples belonging "almost" exclusively to C^+ or C^- .

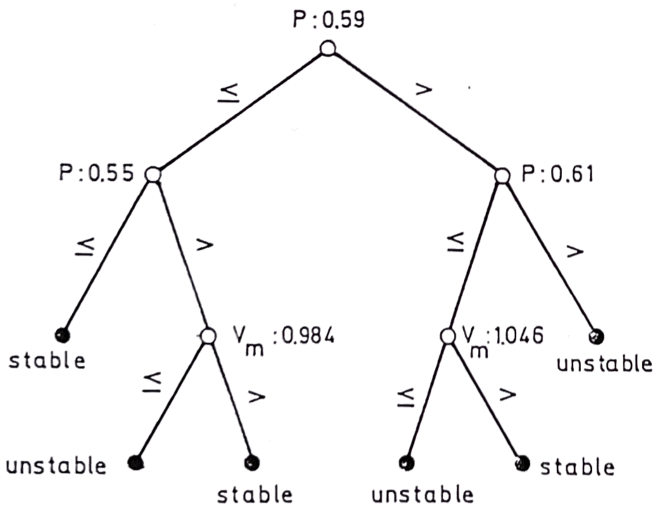

FIG. 1 Decision tree obtained for the one-machine-infinite-bus system studied in [6]. P is the active power in p.u. produced by the machine and V_m is the magnitude of the machine node voltage in p.u.

* The entropy of any subset A of E is defined as

$$-[p_+(A)\log_2 p_+(A) + p_-(A)\log_2 p_-(A)]$$

where $p_+(A) = \#A^+/\#A$ and $p_-(A) = \#A^-/\#A$; $A^+ = A \cap C^+$ and $A^- = A \cap C^-$ and $\#S$ is the number of elements in the set S .

The criterion used for selecting and quantifying an attribute at each non-terminal node of the tree uses some heuristic knowledge and entropy calculations. It has been designed in order to reduce at each step, to the extent possible, the entropy of the descendent nodes while preventing unreliable choices. In the case of abnormal growing of the tree backtracking can be caused in order to reconsider previous choices.

3.2. Overall approach

The complete system consists of two different modules cooperating to build a reliable decision tree :

1) The modified version of ID3; given a learning set this module builds several decision trees.
2) A test module generating a test set in order to decide whether one of the preceding rules is reliable enough. If not, new learning states are added to make the learning set more representative and the most reliable rule is passed to the preceding module as initial hypothesis to generate in turn new rules.

The new states which are added to the learning set are misclassifications and the learning set is becoming more representative, without growing too much, in an iterative fashion.

4. CONCLUSION

In this short paper, we have led the foundations of a new on-line approach to transient stability assessment, where the classification criteria are formulated in terms of static, more or less controllable, variables. The information they carry can therefore be used for analysis as well as for preventive control purposes. This is one of the originalities of our method as compared to other recently proposed ones. Another interesting feature is that these easily understandable rules express the system's transient stability behavior for a wide range of operating conditions, and can be used to inform the operator about the salient characteristics of his system.

The application of the proposed method to the simple one-machine-infinite-bus system [6] has shown that the quantification procedure behaves well. In the very near future we intend to apply the discussed method to a more realistic medium-sized power system.

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