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Decision Trees applied to on-line Transient Stability Assessment of Power Systems

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Abstract. Decision rules provided by an inductive inference method are examined for the purpose of their on-line use in transient stability analysis and preventive control of power systems. To this, the stability region, expressed in terms of the relevant static, prefault parameters of the system, automatically identified by the decision rules, is considered at first. Stability margins are then proposed, measuring the distance to instability, i.e. the degree of the system robustness to face a major disturbance. Methods to act on these margins in order to reinforce stability, if necessary, are further suggested. The stability measures and their use are illustrated via simulation results obtained on the basis of a realistic example.

1 Introduction

In the field of transient stability, the presently available methods are unsuitable for on-line analysis and even more for control tasks (whatever on-line or off-line) [1]. Indeed, complementary in their achievements, the existing two types of (time domain and direct) methods, are by nature mere off-line analysis tools; an exception to these is the recently proposed, direct type method of Ref. [2] which however is designed on the basis of very simplified system modelling.

The desire to assess a system's capability to withstand fortuitous large disturbances on the sole basis of its actual operating condition, as well as to provide on-line operator aids for corrective actions, whenever necessary, led us recently to a conceptually different type of approach. Elaborated within an artificial intelligence framework, it proceeds in two steps. A first, off-line step, where suitable "decision rules" are constructed; these are relationships expressing in an as simple as possible way the stability characteristics of a system in terms of some relevant static attributes of its actual operating condition. A second step where these rules are suitably exploited for the purpose of both on-line analysis and control tasks.

The former off-line problem, has been considered in Refs. [3,4,5]. An inductive inference (II) method has been developed to construct decision rules in the form of trees, i.e. of a hierarchical organization where the relevant static attributes of a system "decide" explicitly on its stability behaviour. Although not mature yet, the proposed II method has already provided very interesting, promising, results.

This paper aims to tackle the abovementioned on-line problem. More specifically, it aims to prospect approaches able to extract and exploit the information contained in the decision trees. Section 2 defines the general notions related to the transient stability problem and the methodology proposed for its solution. It introduces also the essential characteristics of the decision trees upon which the present study is based. In Section 3 the notions of scalar and multi-dimensional distances, to stability and instability are defined and a method for their efficient computation is illustrated on a simple example. In Section 4 the first simulation results based on a realistic power system are given and their physical interpretation is discussed. A first application of the distance measures to the analysis and preventive control of a power system is illustrated on the basis of these results.

2 Problem formulation

The II method proposed in [5] provides a framework for building automatically, on the basis of a large number of transient stability simulations, decision trees (DT) which can be used efficiently on-line, in order to classify the current operating point (OP) into one of a number of stability classes. The purpose of this paper is to discuss an alternative way to assess the stability. It consists in calculating distances, on the basis of the preceding DTs, and is expected to provide more refined information on the robustness of the system and to be able to suggest remedial control actions needed to enhance the latter.

In this section we define the types of DTs which are considered in our approach and the elementary transient stability assessment (TSA) problems for which they are used.

2.1 Decision trees

A DT (see Fig. 1) is a hierarchical structure, composed of *test* nodes and *leaves*. It is used to deduce an unknown property of an object on the basis of its known, easily observable attributes. At each test node, beginning at the top node of the tree, the value of an attribute is tested, and according to the outcome of the test, the object is directed to a successor of the current node. The process stops when a leaf is reached, where appropriate information is stored to assess the value of the unknown property. The important characteristics of a DT are :

i. the set of all objects to which it is applicable;

ii. the type of attributes it can handle and the way it handles this information (via tests at the intermediate nodes);

iii. the type of unknown properties it can deduce (i.e. the information stored at the leaves of the tree).

The types of DTs we are concerned with in this paper, are rather simple, and are defined according to these criteria [5] by :

i. the static OPs of a given power system;

ii. continuous, real, attributes (simple algebraic combinations of the state variables of the OP), analysed at the intermediate nodes of the DT via dichotomic tests of the form :

$$a(OP) \leq v_{th} \ ? \qquad (1)$$

where $a(OP)$ denotes the value of an attribute of the OP and v_{th} a proper threshold value [5]; consequently each test node has exactly two successors, corresponding to the two outcomes of a test (1);

iii. the unknown property is a discrete classification of the OPs into stability classes (e.g. Stable, Fairly Stable, Unstable).

Note that, while this type of DTs is powerful enough to cope with the practical TSA problem, the inductive inference method and the distance calculations can both be extended to handle a much larger class of problems.

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Each node of the DT, corresponds to a subset of OPs. The top-node corresponds to the set of *all* possible OPs, as defined by the operating constraints of the power system. The set corresponding to some node is defined by the constraints introduced by its predecessor test nodes. The leaves of the tree correspond to the most refined subsets. This is further ilustrated in the next section. For convenience, we denote the nodes by a number (say n) and the corresponding subset by E_n.

2.2 Elementary TSA problem

A DT corresponds to a given contingency and a fixed topology of the system. The severity of the fault can be assessed via numerical simulations and the power system be classified into one of a (small) number of stability classes. On the basis of a large number of preanalysed OPs, the II method builds a DT, able to classify, on the basis of appropriately chosen attributes, any OP, seen or unseen, into one of these classes. The overall TSA problem is defined with respect to a list of contigencies each one of which must be analysed on-line.

For the sake of simplicity, we consider in the sequel only the two-class problem (Stable vs. Unstable). Moreover, these classes are defined with respect to the critical clearing time (CCT) of the fault. The CCT is the conventional (continuous) measure of the robustness of a system to face a given fault; it is the maximum time duration of the fault such that the system is able to recover its synchronism. The stability classes are defined with respect to a threshold value τ of the CCT in the following way :

$$\begin{aligned} UNSTABLE(OP) &\Leftrightarrow CCT(OP) \leq \tau \\ STABLE(OP) &\Leftrightarrow CCT(OP) > \tau \end{aligned}$$

Remark. The continuous information contained in the CCT is lost by the II procedure, which uses only the *class* of the learning states to built the DT. Thus the DT does not depend on the precise values of the CCTs of the learning states. An interesting outcome of our research is that, at least in the quite simple cases investigated sofar, this information can be recovered via the distance calculations, as illustrated in Section 4.

3 Distances

The objective of this section is to define several kinds of distances which can be used to exploit the information contained in a DT and refine the discrete classification provided by it.

3.1 Definitions

Let us define :

- the weighted norm of order k of an object as :

$$\| o \|_k \triangleq \sqrt[k]{\sum_{i=1}^{p} \left| \frac{a_i(o)}{w_i} \right|^k} \tag{2}$$

where the w_i are appropriate weighting factors ;

- the multi-dimensional distance between two objects as :

$$\begin{aligned} D(o_1, o_2) &\triangleq (a_1(o_2) - a_1(o_1), \ldots, a_p(o_2) - a_p(o_1)) \\ &= (\Delta a_1, \ldots, \Delta a_p) \end{aligned} \tag{3}$$

- the weighted scalar distance of order k as :

$$d_k(o_1, o_2) \triangleq \| D(o_1, o_2) \|_k \tag{4}$$

- the scalar distance between an object o and a set E :

$$\delta_k(o, E) \triangleq \inf\{d_k(o, o') \mid o' \in E\} \tag{5}$$

The multi-dimensional distance corresponding to (5) is denoted by $\Delta_k(o, E)$. It is the shortest incremental attribute vector, such that the object characterized by the attributes of o incremented by this vector belongs to the set E.

Remark. According to Eq. (4), the multi-dimensional distance between a set and an object depends generally on the specification of a norm. Thus, the values of k and the weighting factors will determine its physical interpretation. As illustrated below, however, if the constraints defining E have a very simple form it is actualy *independent* of the norm and its computation is straightforward.

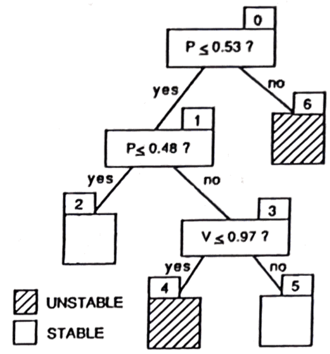

Figure 1: DT for a one-machine-infinite-bus system [3,4].

3.2 Distance from an object to a goal class

In the context of TSA, we will be interested in the computation of the distance, in terms of the attribute values, between the actual OP of the power system and the boundary between the different stability classes. To clarify our meaning, we will consider the example of Section 2 in order to explain and illustrate at the same time the derivation and interpretation of the distances. We are first going to introduce an alternative representation for the classes which is easily derived from a DT and is well suited to the calculation of distances.

Constraint formulation for a class. Let us first consider the stable class of the DT of Fig. 1. An OP is considered Stable iff it is directed to $Leaf_2$ or $Leaf_5$. In order to be directed to one of these, it must satisfy the contraints introduced by the tests at the intermediate nodes of the DT. For example, in order to be directed to the $Leaf_2$ it must satisfy the test at nodes 1 and 2, which corresponds to the logical statement :

$$[OP \in E_2] \Leftrightarrow [0 \leq P \leq 0.48] \wedge [0.9 \leq V \leq 1.1] \tag{6}$$

where we have added, for the sake of uniformity, the constraints $[0 \leq P \leq 1]$ and $[0.9 \leq V \leq 1.1]$ which hold for all the OPs. The constraints relative to $Leaf_5$ are obtained in the same way, and the Stable class is described by :

$$\begin{aligned} \text{STABLE(OP)} &\Leftrightarrow \text{Leaf}_2 \vee \text{Leaf}_5 \\ &\Leftrightarrow \{[0 \leq P \leq 0.48] \wedge [0.9 \leq V \leq 1.1]\} \vee \\ &\qquad \{[0.48 < P \leq 0.53] \wedge [0.97 < V \leq 1.1]\} \end{aligned}$$

The corresponding formula for the Unstable class is :

$$\begin{aligned} \text{UNSTABLE(OP)} &\Leftrightarrow \text{Leaf}_4 \vee \text{Leaf}_6 \\ &\Leftrightarrow \{[0.48 < P \leq 0.53] \wedge [0.9 \leq V \leq 0.97]\} \vee \\ &\qquad \{[0.53 < P \leq 1] \wedge [0.9 \leq V \leq 1.1]\} \end{aligned}$$

The stable and unstable regions are represented geometrically in Fig. 2, in the (P, V) plane.

Distance computation. Due to the simple form of the constraints of type (6) defining a leaf, it is in fact almost trivial to compute the multi-dimensional distance from an OP to it, which in this particular case is independent of the chosen norm. The constraints of a leaf define a hypercube in the attribute space and the optimization of Eq. (5) can be achieved seperately for the elementary contraints on each attribute. E.g., the distance from the stable $OP = (P = 0.3; V = 1.03)$ to the unstable $Leaf_4$

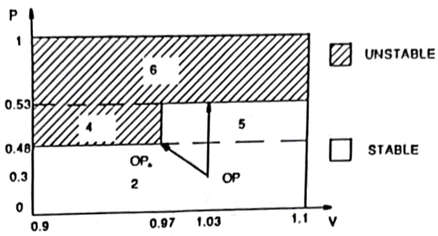

Figure 2: stability regions.

is optimized by $OP_* = (P = 0.48; V = 0.97)$ (see Fig.2) and

$$\Delta_k(OP, E_4) = (\Delta P = 0.18, \Delta V = -0.06).$$

The distance to the $Leaf_6$ is (see Fig. 2)

$$\Delta_k(OP, E_6) = (\Delta P = 0.23, \Delta V = 0).$$

The preceding procedure provides the distance from an object o to any leaf of the DT. A class is defined as the union of its leaves, and could thus be characterized by as many multi-dimensional and scalar distances as it has leaves. If a unique scalar distance is required, it will be chosen, according to formula (5), as the minimal among these and the unique multi-dimensional distance is the multi-dimensional distance to the corresponding leaf. It is important to note that this unique multi-dimensional distance *will* generally depend on the order k and the weighting factors w_i, since the values of the scalar distances to the different leaves depend on them, and also the *nearest* leaf to the object.

In the case of our example, if we define the norm by

$$\| \Delta OP \| = | \Delta P | + | 5 \Delta V |$$

then $d(OP, E_4) = 0.18 + 0.3 = 0.48$ and $d(OP, E_6) = 0.23$ and the multidimensional and scalar distance to the unstable class are those obtained for $Leaf_6$.

Conclusion. The preceding procedure is straightforward and can be used on-line in order to calculate the distances between an object and the different classes. The scalar distances correspond to the notion of margin with respect to a class and can be used in order to measure the degree of stability in a continuous way. The multi-dimensional distances indicate the *direction* of the closest boundary of the corresponding class are similar to sensivity coefficients.

4 Simulation results

We have analysed the behaviour of the above defined distances on the basis of a realistic power system, which is an old version of the Greek system, composed of 14 generators, 92 busses and 112 lines. The stability problem we investigate is relative to a three-phase short-circuit at the generator bus # 34. The operating points are classified in two classes, with respect to a threshold value of 0.32 seconds of the CCT. The decision tree for this fault is represented in Fig. 3. P is the active power generated at bus 34; V_1 and V_2 are the voltages at bus 34 and at the nearby bus 84.

The explicit representation of the two stability classes is :

STABLE $\Leftrightarrow$ $\text{Leaf}_3 \vee \text{Leaf}_6 \vee \text{Leaf}_9 \vee \text{Leaf}_{12}$ $\Leftrightarrow$
$\{[0 \le P \le 514] \wedge [0.9 \le V_1 \le 0.985] \wedge [0.9 \le V_2 \le 1.15]\} \vee$
$\{[0 \le P \le 554] \wedge [0.985 < V_1 \le 1.15] \wedge [0.9 \le V_2 \le 1.15]\} \vee$
$\{[554 < P \le 614] \wedge [0.985 < V_1 \le 1.068] \wedge [0.9 \le V_2 \le 1.068]\} \vee$
$\{[554 < P \le 599] \wedge [1.068 < V_1 \le 1.15] \wedge [0.9 \le V_2 \le 1.15]\}$

UNSTABLE $\Leftrightarrow$ $\text{Leaf}_4 \vee \text{Leaf}_{10} \vee \text{Leaf}_{13} \vee \text{Leaf}_{14}$ $\Leftrightarrow$
$\{[514 < P \le 614] \wedge [0.9 \le V_1 \le 0.985] \wedge [0.9 \le V_2 \le 1.15]\} \vee$
$\{[554 < P \le 614] \wedge [0.985 < V_1 \le 1.068 \wedge [1.068 < V_2 \le 1.15]\} \vee$
$\{[599 < P \le 614] \wedge [1.068 < V_1 \le 1.15] \wedge [0.9 \le V_2 \le 1.15]\} \vee$
$\{[614 < P \le 750] \wedge [0.9 \le V_1 \le 1.15] \wedge [0.9 \le V_2 \le 1.15]\}$

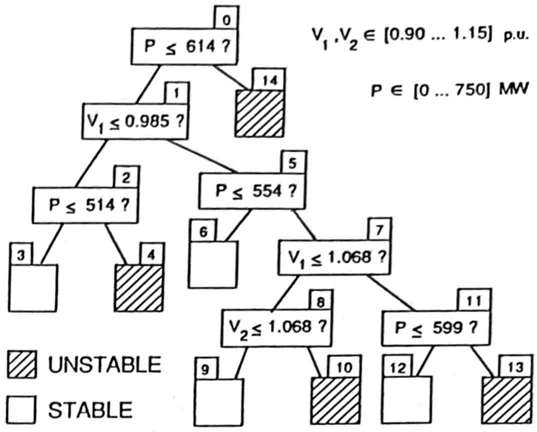

Figure 3: DT for the Greek 14-machine system [5].

The most general form of the scalar distance is :

$$\| \Delta OP \|_k = \sqrt[k]{\left| \frac{\Delta P}{w_P} \right|^k + \left| \frac{\Delta V_1}{w_{V_1}} \right|^k + \left| \frac{\Delta V_2}{w_{V_2}} \right|^k} \quad (7)$$

Since the attributes V_1 and V_2 are of the same type and have the same intervals, it is natural to fix $w_{V_1} = w_{V_2} = w_V$. Moreover, one of the remaining two weighting factors can be arbitrarily fixed (only the relative weighting is important); we fix $w_v = 0.25$.

We have investigated to types of norms; the weighted sum of absolute deviations ($k = 1$) :

$$\| \Delta OP \|_1 = \left| \frac{\Delta P}{w_P} \right| + \left| \frac{\Delta V_1}{w_V} \right| + \left| \frac{\Delta V_2}{w_V} \right| \quad (8)$$

and the weighted euclidean norm ($k = 2$) :

$$\| \Delta OP \|_2 = \sqrt{\left| \frac{\Delta P}{w_P} \right|^2 + \left| \frac{\Delta V_1}{w_V} \right|^2 + \left| \frac{\Delta V_2}{w_V} \right|^2} \quad (9)$$

122 stable OPs have been analysed in the following way :

1. For each OP, the multi-dimensional distances to the four unstable leaves are calculated, once for all, since they are independent of the selected norm.
2. A norm is chosen, i.e. a value for w_P and k .
3. For each OP, the norms of the four multi-dimensional distances to the unstable leaves are calculated , and the lowest one is selected as the distance to the unstable class.

The procedure has been repeated for different values of w_P, ranging from 7500 MW to 10 MW. For each such value, we have calculated the mean μ and standard deviation σ of d_1 (resp. d_2), over the 122 OPs labelled stable. Moreover, in order to assess its physical interpretation and quality, we have estimated the correlation between d_1 (resp. d_2) and the CCT, through the following following coefficient :

$$\rho(d, CCT) \triangleq \sum_{122\ OPs} \frac{(d - \mu_d)(CCT - \mu_{CCT})}{\sigma_d \sigma_{CCT}} \quad (10)$$

The value of ρ belongs to $[-1 \dots 1]$ and is interpreted in the following way :

$$\rho = 0 \quad \Leftrightarrow \quad \text{no correlation between } CCT \text{ and } \rho$$
$$|\rho| = 1 \quad \Leftrightarrow \quad d = aCCT + b \quad \text{(total correlation)}$$

The results, summarized in Table 1, inspire the following comments :

- according to the correlation coefficient, d_1 appears to be, independently of the value of w_P, a better measure of the CCT than d_2;

- the higher the value of w_P, the lower the distances along the P-axis; consequently, among the 4 multi-dimensional distances to the unstable leaves, the one of minimal ΔV_1 and ΔV_2 will be chosen as the minimal distance to the unstable class; in other words, imposing a high value of w_P amounts to allowing variations of P only;
- for both distances the correlation coefficient depends significantly on the value of w_P, and takes its maximum value for intermediate values (near 100); the corrsponding value of ρ ($\simeq 1$) indicates a strong correlation between the distance to the unstable class and the value of the CCT;
- for w_P spanning from 7500 to 750, the mean and standard deviations are rigorously proportional to w_P; the P variations are considered by the norm as much smaller than the V variations and the information contained in the voltages is never taken into account. The value of $\rho = 0.895$ is interpreted as the information about the CCT contained in P. The maximum value of 0.955 measures the total information contained in the three attributes.

Table 1

k	w_P	μ_d	σ_d	ρ
1	7500	.008	.005	.895
2	7500	.008	.005	.895
1	750	.085	.053	.895
2	750	.085	.053	.895
1	300	.201	.126	.945
2	300	.168	.093	.909
1	100	.386	.260	.955
2	100	.306	.183	.927
1	50	.508	.370	.929
2	50	.412	.261	.903
1	10	1.35	1.45	.785
2	10	1.22	1.30	.752

Table 2

Leaf	ΔP	ΔV_1	d_1
4	0	-.065	.26
10	4	0	.04*
13	49	.018	.56
14	64	0	.64

Table 3

Leaf	ΔP	ΔV_1	d_1
4	4	-.065	.30*
10	44	0	.44
13	89	.018	.96
14	104	0	1.04

ΔV_2 is equal to zero in all cases.

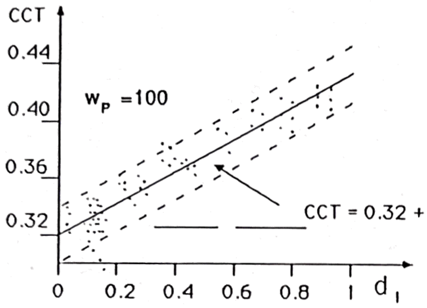

Figure 4: d_1 vs. CCT for 34 stable OPs.

4.1 Estimation of the CCT via d_1

Fig. 4 shows graphically the relationship between the distance d_1 with $w_P = 100$ and the CCT of a subset of 34 stable OPs. The points are admittedly very well grouped around a straight line

$$CCT = 0.32 + 0.115 d_1. \tag{11}$$

which confirms the high value (0.955) of ρ. Since the optimal distance has been selected on the basis of stable OPs of the power system only, we restrict ourselves to the analysis of a stable OP. Let us consider :

$$OP_1 = (P = 550; V_1 = 1.05; V_2 = 1.107)$$

Table 2 gives the calculated distance to the unstable leaves.

The nearest one is $Leaf_{10}$ and the scalar distance to the unstable region is 0.04. Using formula (11) we estimate the value of the CCT to be 0.329 s (the actual value, calculated by simulation is 0.331). According to the multi-dimensional distance to $Leaf_{10}$, we can enhance the stability of the system by modifying the value of P, in the opposite direction, i.e. by reducing the active power produced by the generator # 34. For instance, if we decrement P by 40 MW, the new OP obtained is

$$OP_2 = (P = 510; V_1 = 1.05; V_2 = 1.107)$$

Table 3 summarizes the distances of the latter to the unstable leaves. The nearest one is now $Leaf_4$, and the distance to the unstable class has increased to 0.30, which according to Eq. 11 corresponds to a CCT of 0.360 s. The actual value has been calculated as above and is found to be 0.362 s.

All these results confirm the validity and efficiency of the on-line use of DTs for transient stability enhancement.

5 Conclusions

Admittedly the on-line use of a collection of DTs, in order to assess the systems robustness and provide preventive control actions is a very broad topic. Its final solution will depend a great deal on the actual reliability and complexity of the DTs and require the consideration of external information, concerning for instance economy - feasability constraints or load prediction patterns.

Although at a prospective stage, the investigations reported here provide for the first time, means for defining (and computing efficiently) stability margins and "sensivity" coefficients, in terms of the *static* parameters of the power system. Among their numerous applications, the estimation and control of the CCT discussed in this paper, illustrates the promizing features of the approach. Its flexibility should allow its application to other practical problems related to security analysis and control of power systems.

Finally, while explained on the basis of simple examples, the overall proposed methodology is in principle applicable to a very broad class of TSA problems, including sophisticated dynamic modelling.

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6 References

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