AN ARTIFICIAL INTELLIGENCE APPROACH TO TRANSIENT STABILITY ASSESSMENT

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ABSTRACT

An Artificial Intelligence approach to on-line transient stability assessment is briefly discussed, and some crucial requirements for this algorithm are identified. Solutions to these are proposed. Some new attributes are suggested so as to reflect machine dynamics and changes in the network. Also a new representative Learning Set algorithm has been developed.

1.0 INTRODUCTION

Transient stability assessment. examines, whether on occurrence of a large disturbance, the power system is capable of surviving the ensuing transient and will move into an acceptable steady-state condition. Large disturbances are loss of loads, significant changes in the network such as short circuits, particularly three phase short circuits at the generator bus.

There are three approaches to the transient stability assessment problem. The conventional numerical integration method [1] discretizes the machine swing equations to obtain the evolution with time of the machine rotor angles. This method is tedious, and not suitable in an on-line environment. The Pattern Recognition method [2] is based on developing on-line tools for transient stability assessment. based on information gathered off-line. The difficulty in selection of features and development of the Learning Set have limited its application in an on-line environment. More recently, Direct methods [3] are being used for this problem. These involve application of the Lyapunov stability theory of non-linear systems to the transient stability problem. Even though these methods are accurate, they are computationally tedious, and thus unsuitable in an on-line environment.

This paper examines a recently proposed method for transient. stability assessment [4] namely, Inductive Inference Reasoning.

2.0 BACKGROUND

The Inductive Inference Reasoning method belongs to the domain of Artificial Intelligence, more specifically, Concept Learning from Examples [5,6]. To make the overall. transient stability assessment problem tractable, this approach decomposes it into elementary problems. An elementary transient stability assessment problem is defined with respect to a given network topology and contingency. For such an elementary problem, the Inductive Inference Reasoning method builds decision rules off-line, in the form of Decision Trees, using a large number of Examples (Learning Set). These are operating points whose stability class is known apriori. Each of these operating points is represented as a tuple of attributes which are variables of the power system, guessed to have a significant influence on the transient stability behaviour. On-line assessment involves traversing the Decision Tree for the given operating condition.

In [4], the attributes used to represent an operating point are simple pre-fault variables like bus voltages and active and reactive power injections. Decision Trees were constructed using threshold tests for these attributes. Even though the Inductive Inference Reasoning method chooses the best attribute among the given attributes, it is unable to determine whether a combination of these attributes would give better results. It is also intuitively understood that the quality of the Learning Set, with respect to representativeness of system hehaviour on occurrence of the contingency, has considerable effect on the reliability of the Decision Tree constructed. Hence, the choice of attributes and development of a representative Learning Set are very crucial for the Inductive Inference Reasoning method.

The contribution of this paper is twofold:

(i) Some new attributes have been suggested, which improve the reliability of the Decision Trees.

(ii) A new heuristic Learning Set algorithm has been developed.

3.0 SELECTION OF ATTRIBUTES

In this paper, the choice of candidate attributes is directed by the following heuristics:

* Transient stability behaviour is a strong function of the local variables. (that is, the variables which are electrically close to the fault location.)

* Transient stability behaviour cannot be completely understood by considering pre-fault or static variables. Dynamic variables like initial accelerations of machine- are representative as they inherently reflect machine dynamics and the changes in the network topology.

Chiefly two types of attributes have been considered.

Type-1:

(i) Simple pre-fault attributes like bus voltages, line flows, and mechanical power input to generators.

(ii) Heuristic pre-fault attributes like mean, minimal and maximal bus voltages; total active and reactive power load.

Type-2:

(i) Simple fault-on attributes like accelerations (γ) of machines at inceptions of fault; second derivatives of accelerations ($\ddot{\gamma}$) of machines.

(ii) Heuristic fault-on attributes like mean machine accelerations; $\max|\alpha_i|$, where α_i is the relative acceleration of machine i with respect to the reference machine.

The Decision Trees for each of the attributes types have been constructed and their reliability has been evaluated.

4.0 LEARNING SET GUNERATION

This is an important off-line task of the Inductive Inference Reasoning algorithm. The quality of the Learning Set determines the reliability of the Decision Tree for unseen cases. Two factors have been considered when building an initial Learning Set.

(i) Transient stability depends on the total system load level.

(ii) For any load level, transient stability behaviour differs with different distributions of loads and generations.

Learning Set Generation Algorithm involves the following steps:

(a) Arrive at the system load level limits, based on knowledge of the system clearing time. This involves estimating the base load level at which the critical clearing time is equal to the system clearing time and then considering load level values above and below it. (PG_{min} to PG_{max})

(b) Choose incremental step in system load ($\hat{}PG$).

(c) Identify loads nearest to the fault location.

(d) Identify critical machines and remaining machines cluster based on initial accelerations.

(e) From PG_{min} to PG_{max} with a step of $\hat{}PG$ define a system load level (= system generation for load-generation balance).

(f) For each system load level different distributions of generations and loads can be considered.

Generation distribution:

(i) Base Distribution: Load is distributed among generators in the same proportion as the base case.

(ii) Proportional Distribution: Load is distributed among generators in proportion of their ratings.

(iii) High Distribution: Large percentage of system load is assigned to the critical machines cluster.

(iv) Low Distribution: Low percentage of system load is assigned to critical machines cluster.

Load Distribution:

(i) Base Load: Active power loads are in the same proportion as in the base case. The ratio of reactive power to active power of loads are maintained the same as in the base case.

(ii) High Load: Loads near the faulted bus are assigned high values.

(iii) Low Load: Loads near faulted bus are assigned low values.

Hence, for each system load level, there are 12 possible distributions. A Learning Set may be generated by considering some of these distributions.

(g) The critical clearing times of all the above cases are calculated using the Extended Equal Area Criterion [7].

(h) The stability class of a case is obtained by the following rule:

IF system clearing time < critical clearing time of Case
Then Case is STABLE
Else Case is UNSTABLE.

5.0 SIMULATION RESULTS

The performance of the algorithm proposed for the transient stability assessment has been evaluated for the nine bus, three generator standard test system proposed by Western System Coordinating Council [8] The system diagram is given in Fig.1. A three

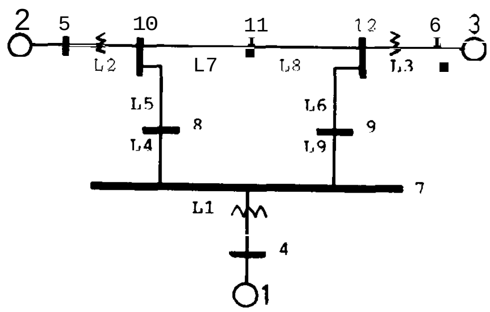

Fig.1 Test System

phase short circuit at bus 10 is assumed to have occurred. The system clears the fault in 0.22 seconds, with the post-fault network the same as the pre-fault one. For this system, pre-fault and fault-on attributes are selected. A Learning Set is generated which is further used in the Decision Tree construction. Cases, for which stability has to be determined, are then generated in the same way as the Learning Set. These cases are then applied to the Decision Tree to determine their stability class. The percentage misclassification of these cases gives the reliability of the Decision Tree.

(5.1) Selection of Attributes:

Type-1:

* Active power flow on line 4.
* Active power injections at buses 8, 10 and 11.
* Reactive power injections at buses 8,10 and 11.
* Total active power load.
* Total reactive power load.* Mean bus voltage.
* Maximum bus voltage.
* Minimum bus voltage.

Type-2:

* Accelerations of machines 1,2 and 3 at inception of fault.
* Second derivatives of accelerations of machines 1,2 and 3 at inception of fault.
• Mean acceleration of machines.
* Max| α_i |; machine 1 is taken as reference.

Type-3:

Combination of attributes of Type-1 and Type-2.

(5.2) Learning Set Generation:

* System load level range: 200 MW to 400 MW in steps of 5 MW.
* Generation distribution: Base case
* Load distribution:Base load, High Load and Low load.
* Voltages at generator buses: $V_1 = V_2 = V_3 = 1.025$

* Critical generator: 2.
Number of cases = 123
Number of stable cases = 65 (52.8%)
Number of unstable cases = 58 (47.15%)

(5.3) Decision Tree building:

The Decision Tree with Type-1 and Type-2 attributes are shown in Fig.2 and Fig.3 respectively.The Decision Tree for the combination of the two types of attributes (Type-3) is the same as that for the Type-1 attributes.

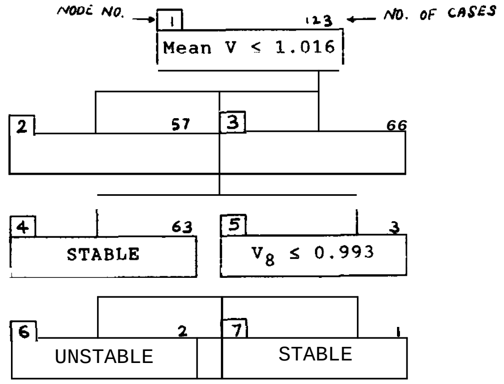

Fig.2 Decision Tree with Type-1 Attributes

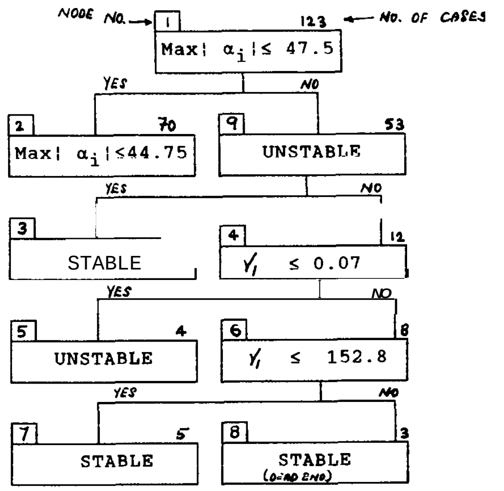

Fig.3 Decision Tree with Type-2 Attributes

(5.4) Generation of Unseen Cases:

* System load level range: 250 MW to 350 MW in steps of 7 MW.
* Generation distribution: Rase case
* Load distribution:Base load,High load and Low load.
* Voltages at generator buses: $V_4 = 1.04$; $V_5 = 1.03$; $V_6 = 1.01$

* Critical generator: 2.
Number of cases = 45
Number of stable cases = 26 (57.7%)
Number of unstable cases = 19 (42.2%)

(5.5) Performance Evaluation of Decision Tree

Reliability testing of Decision Tree is done by comparing the results against that obtained from a transient stability

Attribute Type	% Misclassification in	
	DT Building	Unseen Cases
Type-1	0.0	13.37
Type-2	0.81	2.22
Type-3	0.0	13.37

(5.6) Discussion

(i). The cases misclassified were found to have critical clearing times very close to the system clearing time.

The single case misclassified by the Decision Tree, generated using Type-7, attributes was also misclassified when Type-1 attributes were used. This indicates a definite improvement in performance when Type-2 attributes are used.

(iii). The reliability of the Decision Tree generated by Type-3 attributes was not better than Decision Tree generated using Type-1 or 2 attributes because at the root node and every other node a Type-1 attribute had higher scores than Type-2 attributes. This did not allow a Decision Tree to be generated using both kinds of attributes.

(iv) Out of the 19 Type-1 attributes provided, the algorithm chose on7y 3 attributes. The Decision Trees generated provides the following rules:

IF (Mean voltage > 1.016)
And (Total active power > 3.1)
And (Voltage at bus 8 > 0.993)
Or (Mean voltage > 1.016)
And (Total active power < 3.1)
THEN system is STABLE.

IF (Mean voltage < 1.016 !
Or (Mean voltage > 1.016)
And (Total active power > 3.1)
And (Voltage at bus 8 < 0.993)
THEN system is UNSTARLE.

6.0 CONCLUSTONS

The Inductive Inference Reasoning method for transient stability assessment was examined. A new heuristic Learning Set algorithm was developed and some new heuristic attributes were suggested. The percentage error of classification by the Decision Tree with the heuristic fault-on attributes was found to be lower than with pre-fault attributes. Its extension to other power system functions like steady-state security assessment needs to be explored.

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