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DECISION TREES METHODOLOGY IN POWER SYSTEMS

B. P. Singh

Abstract

Decision trees (DTs) and other areas of Artificial Intelligence (AI) techniques are often used in power system applications for more than 20 years. As a relatively research topic a need is felt to pay more attention to the understanding of basic DTs methodology, and its application to Electric Power Systems (EPSs). This paper presents a critical literature review on application of DTs methodology to EPSs already reported in important international conferences and in international journals.

Key-Words: Artificial Intelligence, Decision trees, Electrical power system, decision making, power system security assessment, transient stability, voltage security

1. Introduction

DTs belong to the Machine Learning (ML) or AI methods. DTs methodology offers an attractive perspective to the handling of Classification problems that have a small number of categories (e.g. stable vs. unstable). Successful operation applications include assessment, analysis, prediction, and estimation of various process variables which affect the efficient operation of the EPS, medical diagnosis, and fusion of sensor measurement and assessment of stability margin in EPSs etc.

All applications were reported in number of international conferences/journals. The present study covers the critical literature review of a wide range of DTs methodology to EPSs.

The paper has been organized as follows: section 2 give the methodology of DTs with the framework, various notations used, and induction of DTs. Section 3 is devoted to the critical literature review of application of DTs methodology to EPSs. Finally, conclusions are provided in section 4.

2. DTs Methodology

DTs is a classification data mining tool used to extract useful information contained in large data sets and so it can be used to help in Decision Making (DM) process. DTs in general are non-parametric inductive learning techniques, able to produce classifier in order to assess new, unseen situations or to uncover the mechanisms driving a problem [1] [2] [3].

2.1 What is DTs?

DT is a classifier in the form of a tree structure where each node is either: a Leaf Node (LN) indicates the value of the target attribute of examples, or a Decision Node (DN) specifies some test to be carried out on a single attribute value, with one branch and sub tree for each possible outcome of the test. DTs are used to classify an example by starting at the root of the tree and moving through it until a LN, which provides the classification of the instance.

2.2 Frame Work and Notation

DTs are structure on the basis of following sets: Universal Set (*US*) are a set of all objects of system interest, Learning Set (*LS*) is a sub set of such objects, which are pre-classified accordance to the goal partition, and consisting of a large number of Operating Points (Ops).

The *LS* is defined as:

$$LS = \{(V_1, C_1), (V_2, C_2) \dots (V_N, C_N)\} \tag{1}$$

Where C_K and V_K is defined as:

$$C_K = \{+, -\} \tag{2}$$

The component of vector

$$V_K = (V_{1K}, V_{2K}, \dots, V_{NK})^T \tag{3}$$

The components of vector V_K represent the values of the state S_K which is characterized by its N attributes:

$$S_K = [A_1 = V_{1K}] \text{ L } [A_2 = V_{2K}] \text{ L } \dots \text{ L } [A_N = V_{NK}] \tag{4}$$

Where the symbol Λ denotes the logical product (Conjunctions); these attributes A_i ($i = 1, 2, \dots, n$) are the pre-disturbance steady state variables and characterized each OPs.

The Test Set (*TS*) is defined by another number, *M*, of preclassified stases, obtained in a similar but independent way

$$TS = \{(V_{N+1}, C_{N+1}), (V_{N+2}, C_{N+2}) \dots (V_{N+\text{M}}, C_{N+\text{M}})\} \tag{5}$$

Thus, Knowledge Base (*KB*) is consists of *LS*, used for deriving the classifier structures and a *TS* used to evaluate the performance of DTs on new, unobserved OPs. Now, the decision is expand to a given node *N* and to perform this expansion relay on the information contained in the corresponding subset E_n of the *LS*. Thus information provided by a test *T* on the goal partition of E_n is given by

$$I(E_n, I) = H(E_n) - H(E_n/T) \tag{6}$$

Where $H(E_n)$ is the entropy of E_n and $H(E_n/T)$ is the mean condition entropy of E_n given the out comes of test *T*.

2.3 Induction of DTs

Select a priori relevant attribute called the Candidate Attributes (CAs). Starting at the top node of the tree, with the list of CAs and with the entire *LS* of pre classified states, analyze these states in order to select a test which achieves their 'optimal' splitting into two subsets, so that these subsets provide a maximum increase in classification purity. The selection proceeds in two steps:

(i) For each attribute says A_i its finds it Optimal Threshold Values (OTVs) V_i^* by scanning the values it assumes for all learning states: and defines a test: $A_i < Vi^*$

(ii) Among the different CAs, choose the best one A^* along with its optimal values V^{**} to split the node, according to the test $T : A^* < V^{**}$

In short, test *T* defining the Optimal Attribute (OAs) along with its OTVs. The selected *T* thus split *LS* into two subsets:

$$LS_1 = \{Vk\varepsilon\, LS|\, A^* < V^{**}\} \quad \text{and} \quad LS2 = \{Vk\varepsilon\, LS|\, A^* > V^{**}\} \qquad (7)$$

Corresponding to the two successor of the root.

The successors are then labelled terminal or non terminal on the basis of the stop splitting criterion, which stops splitting when it meet either a leaf or a dead end.

3. DECISION TREE METHODOLOGY IN POWER SYSTEM

The technology for building *KB* systems by inductive inference from examples has been demonstrated successfully in several practical applications in [2], which was focused on *ML* and on a family of learning systems that have been used to build *KB* systems.

A complete review of multistage Regression Analysis (RAs) was given in [4]. Some of the differences between the different multistage schemes were addressed in [5]. Emphasis on the Hierarchical Approach (HA), Hierarchical Classifiers (HCs) are a special type of multistage classifiers that allow rejection of class labels at intermediate stages. Later on, Decision Tree Classifier (DTCs) shows a great deal of potential in many patter recognition problems and used successfully in many areas such as radar signal classification, character recognition, remote sensing, medical diagnosis, expert systems, and speech recognition [6]. DTCs break down the complex *DM* process into a collection of simple decisions thus provided a solution that is easier to interpret by decision table conversion to optimal DTs [7], and sequential approaches [8]. DTs were able to produce classifiers in order to assess new, unseen situations or to uncover the mechanisms driving a problem [1] [2] [3] and potential use and drawbacks of DTCs were explained in [6].

With the advent of systems capable of making real time phasor measurements, the real-time assessment of the stability of a transient event in the EPS has become an important area of investigation. The real-time transient stability prediction can advance the field of protection and control. Many transient stability assessment techniques while simple in off-line applications are too complexes for real-time use. The first attempt to apply DTs methodology to transient stability assessment was initially proposed in [9]-[12], in which the information related to the transient stability was compressed and organized in the form of DTs with the twofold objective, first was to classify new, unseen states, and second was to uncover the salient parameters driving the transient stability phenomena [13] [14], the results obtained were quite promising and constructed DTs were produce nice features, with respect to accuracy and complexity. However, to make this method fully reliable and effective, author was extended his work to scrutinize the basic features of the Decision Tree Transient Stability (DTTS) method i.e. of the inductive inference method as applied to transient stability of EPSs [15].

A global view of the DTs methodology was presented in [16], to handle EPSs security assessment and its essential facts such as effectiveness and flexibility, approach was also tailored voltage security problem with the DTs approaches under two distinct facts, namely preventive – wise and emergency – wise and by means of two simulation studies, one carried out on the Brittany region of the EHV French system and the other on the academic type of example. These two studies explored feasibility aspects, highlight various features, and given comments that the proposed approaches have indeed potential for real world applications. Later on, Decision Tree Security Assessment (DTSA) method has been illustrated in [17] and suggests appropriate DTSA uses by (re)formulates old problems, identify new ones, and suggest appropriate strategies able to match them with the DTSA possibilities.

The DTTS method was revisited via a case study carried out on the French EHV power systems [18]. This case study aimed at investigating practical feasibility aspects such as data base generation, CAs, stability classes, etc, and features of the DTs at enhancing their reliability and broadening its applications domain.

In the same year another paper was published [19] which demonstrated the success of off-line constructed DTs which is then utilized on-line for predicting transient stability in real time. The testing test include fault of various durations on all the buses and all the transmission lines on the New England 39 bus system under heavy loading conditions. The method proposed in this paper shown the adequacy of a single DT for all fault locations, with classification accuracies as high as 97-98% and investigated the robustness to variation in the OPs using a test set of 40,800 faults from 50 randomly generated operating points with accuracy 95%.

DTs methodologies have been also introduced for the Oscillatory Stability Assessment (OSA) using Regression Trees (RTs) and Classification Trees (CTs) methods proposed in [20], which was focused on inter area oscillations of large scale interconnected EPSs and a new method for Eigen value prediction of critical stability modes of power system based on DTs. This paper shown only 10 inputs are sufficient for accurate OSA. Now, the implementation of DTs for online OSA was proposed in [21], in which Genetic Algorithm (GA) is used to find the best set of DT input feature based on the DT evalution with testing data and size of the feature set. This method was applied to the large interconnected European power system to demonstrate the application and high accuracy for the prediction result.

Security assessment is an important task in energy management system to determine the current state of the EPS control and to improve or enhance the security of the system. Over the year the steady state security assessment problem has been solved by simulation approach, probability approach, and pattern recognition approach. All this methods are unacceptable for on line implementation. Rule base expert systems have been developed to estimate line flows and bus voltages in effective manner [22]-[24]. Estimation of desire flows or voltages, it is needed to create a *KB* which contain all crucial rules for security assessment. This is a highly difficult task to extract the knowledge of experts. To overcome this difficulty, *ML* techniques such as Artificial Neural Network (ANN) and pattern recognition were used [25]-[26]. A rule oriented ML method called ID3 approach [27] was proposed to estimate line flows and bus voltages of a Taiwan power system which contain 170 buses and 207 lines under normal operation and post contingency situations.

The general DTs methodology were also proposed in [28] for the purpose of security assessment, prediction of robustness, and classification of operating states of an EPS as either secure/insecure using *MW* flows and voltages and the security level of the violation and the control actions by finding the location of OP when dropped at the top node of the DTs.

Similarly, paper [29], described a DTs methodology both for Dynamic Security Assessment (DSA) and load shedding scheme of a Greek mainland EPSs. Two DTs were used in this paper for DSA from the applications of proposed method on *OP* series from the system and to derived corrective control actions when the EPS is in danger in order to maintain the voltage stability under various loading conditions and *OS* in the presence of critical contingencies including outages of one or more generating units in the system. The loading margin is used to as a measure of system robustness at a given OPs. An EPS is considered voltage secure when a sufficient loading margin exists between initial *OP* (base point) and point of voltage instability. It is well known that series and shunt compensation substantially contribute to voltage stability, as they increase the system loading margin. A paper [30], proposed a DTs methodology for the specification of the effective location and rate of series compensation in order to increase EPS loading margin and alleviate EPS voltage instability. This methodology was applied to the Hellenic interconnected transmission system in normal operating condition and in (N-1) configurations and identifying the most sensitive lines and he proper rate of series compensation effectively.

DTs method was proposed in [31] to detect HIF using phase current, magnitudes of the second, third, and fifth harmonics, and the phase of the third harmonics.

DTs have also been used to predict/ forecast the values of various variables associated to the EPS and proposed in [32] to predict stochastic residual demand curves, estimation of daily load pattern of units, and prediction of values of reactors and capacitors of the Spanish EPS. This paper shows the great versatility and adequacy of DTs to be applied to different real applications, being very interpretable and suitable for probabilistic approaches as compare to the other forecasting techniques such as clustering techniques [33], time series [34], dynamic regression techniques [35], *NN* approaches [36], and input output hidden Markov models [37]. Predicting energy consumption also plays an important role in *DM* and planning for utility companies. In the past, RAs were mainly adopted to predict energy consumption [38] [39]. Other approaches such as *DT* and *NN* are found useful in developing predictive models in other fields [40] [41]. Due to the advancements in database management and improvements in computing speed have lead to new ways to conduct data analysis. A paper [42] illustrated how this concept can be used to predict electricity energy consumption in Hong Kong and compared a accuracy of *RA*, *DT*, and *NN* approaches for predicting electricity energy consumption in Hong Kong and it is found that the *DT* and *NN* models perform better than other model in the summer and winter.

DTs were also used for analysis purpose which is presented in [43], for medium and long term risk analysis in electricity markets. Risk analysis considered several source of uncertainty called risk factors consist of hydro inflows, fuel cost, system demand and CO_2 emission price in this paper and shown DTs methodology to gain information for wise *DM*, hedge against risk., identify the various variables that produce risk on the electricity price and in the operation profit and therefore help the electrical companies on the *DM*. the low cost and reliable EPS is achieved though modern interconnected EPSs. Now, it is desire to control the interconnected EPS by containing the impact of a disturbance to a particular region of the network, thus strategy called controlled islanding proposed in [44] to separate a several distributed power system into self handling islands that are characterized by minimum load –generation unbalance and slowly coherent generators. In 2006, a paper [40] was presented to detect cascading degradation of power system security at early stage using DTs. A 29-generator, 179 bus test system was used to simulate various kinds of contingencies that lead to stable and unstable scenarios. The simulated data were used to train ten different kinds of DTs off-line and the on-line performance of DTs is then evaluated as part of a controlled islanding strategy.

CONCLUSION

The major part of the work reported in [9]-[17] has been shown the suitability of the DTs methodology to EPSs.

The paper presents a critical review of the DTs methodology in EPSs. Due attention has also paid to recent applications such as transient stability, voltage security, oscillatory stability, steady state, and DSA, estimation of line flows and bus voltages predicting electrical energy consumption, and determination of optimal location and rate of series compensation etc. emphasis has been given to categorizing various DTs application to EPS reported in the literature that highlights their salient features.

Although it has sincerely attempted to present the most comprehensive set of references on application of DTs to EPSs, they would like to apologize for exclusion of many paper reported in many journals and conferences and hope that additional references will be advanced as discussion to this publication. It is envisaged that this paper will serve as a valuable resource to any future worker in this important area of research.

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B. P. Singh
Institute of Instrumentation Engineering
Kurukshetra University Kurukshetra
Haryana, INDIA
E-mail: bpsingh.kuk@gmail.com