"Interval Type-2 Fuzzy Logic Rule based Data mining for Steam Turbine Fault Analysis of a Power System Rotatory Machine Component"

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Abstract

Fuzzy decision tree or Soft Decision Tree (SDT) classifier using interval type-2 fuzzy logic rule based data mining for steam turbine fault analysis of a power system rotatory machine component is used not only for database analyses, but also for machine learning. The classification rules are based on standardized vibration frequency data for steam turbines and field experts' analyses of turbine vibration problems. The system can identify twenty types of standard steam turbine faults. The system was developed using 1500 simulated data sets. The data mining methods were then used to identify 20 explicit rules for the turbine faults. The results indicate that the fuzzy decision tree classifier using interval type-2 fuzzy logic rule based data mining can be effectively applied to diagnosis of rotating machinery by giving useful rules to interpret the data. The data mining and analysis was implemented between the fault information dimensions table and the relationship rule dimensions table. We made sure the causes of the fault and chose the priority solution for troubleshooting by generating candidates sets and filtering the candidate set and matching the fault. Fuzzy decision trees called soft decision trees (SDT) combines tree growing and pruning, to determine the structure of the soft decision tree, with refitting and back fitting, to improve its generalization capabilities. Moreover, a global model variance study shows a much lower variance for soft decision trees than for standard trees as a direct cause of the improved accuracy.

Keywords: Faults diagnosis, data mining, decision tree classifier (DTC); Soft Decision Tree (SDT), Interval Type-2 Fuzzy Logic Rules (IT2FLR).

I. Introduction

Beginning in around 1985, the goal of rotating machinery (here steam turbine) fault diagnostics was primarily to store the vibration spectra and to provide graphical tools so that the analyst could quickly access the data and determine what might be wrong with the machine. But as the data collection devices (originally spectrum analyzers) became smaller, faster, and more portable, the amount of data to be analyzed rapidly grew. The data acquisition system could soon store hundreds of spectra. As the data acquisition systems and measurement techniques improved, the analyst was faced with mountains of data. The overwhelming amount of data resulted in the new technique of data mining, which seeks to extract knowledge from huge volumes of data through numerical analysis of the data. Data mining is not only database analysis method, but also an important machine learning tool. This paper describes Fuzzy decision tree classifier using interval type-2 fuzzy logic rule based data mining for steam turbine fault analysis of a power system rotatory machine component. Many methods have been used for data mining, with the decision tree (DT) often shown to be the most valuable form of data mining. The most important feature of Decision Tree Classifier (DTC) is their capability to break down a complex decision-making process into a collection of simpler decisions, thus providing a solution which is often easier to interpret.

ISSN 2348 – 7968

Fault diagnosis is based on pattern identification and classification. The first step in steam turbine fault diagnostics is pattern identification from the measured data. The next step is to interpret what the patterns indicate about the machine, but proper interpretation requires some knowledge about the machine. Decision trees provide a good approach to supervised classification and prediction in artificial intelligence and statistical pattern recognition. Crupi et al. [2004] describe the use of neural networks to evaluate vibration signatures in rotating machinery and recognize the occurrence of faults. Decision trees can be more effectively applied to steam turbine fault diagnosis because the fault diagnosis requires not only pattern classification, but also rule extraction and knowledge interpretation.

In the spirit of solving our-days-needs of learning methods, this paper proposes a method called soft decision trees (SDT), i.e. a variant of classical decision tree inductive learning using interval type-2 fuzzy logic theory. Soft decision tree techniques have already been shown to be interpretable, efficient, problem independent and able to treat large scale applications. Interval type-2 fuzzy logic brings in an improvement in these aspects due to the elasticity of interval type-2 fuzzy sets formalism. The proposed method has been studied in detail and compared with alternative crisp methods and the results show a much improved prediction accuracy, explainable by a much reduced model variance. Also, more stability at the parameters level leads to better interpretability.

Steam Turbine Fault Diagnosis Study in Present Situation

Power system goes wrong in randomness, when each fault i.e. steam turbine fault has been taken places, it's changes in the scope of its parameters have a very strong randomness. There are more techniques and methods would be used in steam turbine fault analysis, for example: expert systems, causal maps, fuzzy sets, inductive learning, Artificial Neural Networks, wavelet transformation, Kalman Filters, etc…,In addition, the Chaos and Fractal Theories already begun to attract people's attention. The steam turbine operating conditions change, transient signal caused by fault is a non-stationary random process, and the data mining is to analysis the fault, which based on high-frequency transient state component of fault, and which to predict, determine and deal with the possible fault, so that we can set up the scheduling plan for reasonable and guarantee the security of electricity supply and improve operation efficiency.

Fault Mode

Steam turbine in the long-term operation and maintenance has accumulated rich experience and a lot of original information, and it is important for enterprises to change these experiences and information

Table.1. the Structure of Fault Mode Dimensions

ID	Fault properties	Description
1	Fault code	The fault of unique identifier
2	Fault Statistics code	Used for statistical analysis, the user can determine the statistical particle size.
3	Fault Level	Fault Level can be divided into mild fault, general fault, a serious fault and a fatal fault
4	Fault Parent code	The structure of fault mode organized by tree, and definite the logical relationship each other
5	Type of coding parts	Identification of the components correspond to the type of fault mode
6	Service Time	The fault corresponding to the general maintenance service time
7	Cause of fault	The essence reasons for fault
8	Fault appearance	The reasons of the fault corresponds to the appearance of common faults (Fault

		manifestation)

into knowledge. Fault mode is the genuine cause of the fault which is the appearance summarized when the products take place fault. Fault mode is the one of the main target of data mining, the appearance of fault are classified and cleaned up to form the fault mode is a valuable resource for enterprises. The user's description of fault is often the fault's appearance, and the fault appearance is only the outward manifestation of the issue of fault in many cases, the appearance of fault will correspond to the fault cause can be cleaned up and analyzed by the experience and relevant technical standards and come into a standard dimension table of the fault mode. A typical fault mode recorded content as shown in table 1. Among them, the items 1,2,4,7 are the key elements of the system and are the basic to deal with the fault information. The data of the fault mode dimension table initialization comes from the historical experience of enterprise data; Fault mode dimension table can be maintained by automatically and artificial maintenance, the main source of information is the user feedback of the new fault appearance.

II. Interval Type-2 Fuzzy Logic Rule Generation for Data Mining Based Fault Detection

Data mining rules

The knowledge characteristics of diagnosis field and the steam turbine fault mode analysis are provided by a variety of technical parameters or experience, it combined with interval type-2 fuzzy logic methods, production rules based on the uncertain knowledge reasoning were adopted, the general form of the rules as follows: Fuzzy Rules: IF P THEN Q, in which $P = P_1$ (C_1) AND / OR P_2 (C_2) ... $P_n(C_n)$,

P is fault appearance, it could be a simple fault appearance, and also, it could be a logical combination by a number of a simple fault appearance, for example,

$P = P_1(C_1)$ AND P_2 (C_2) OR P_3 (C_3)

For each fault appearance $P_1, P_2, ..., P_n$ can be assigned a corresponding confidence value $C_1, C_2, ..., C_n$, it is the percentage of the credibility of the fault appearance (probability of the fault appearance); Q is the real reason for the fault ,and it may be one or more conclusions. A large number of valuable knowledge would be found from fault information for production, management and for maintenance steam turbine and circuitry to use for reference, so that, the accuracy of fault diagnosis is improved and the time of fault remove is shorten. Data mining process in the fault information was shown in Fig 1.

The main objective of data mining is to use the correlation of the fault information in data warehouse in order to find the information which is hidden and divinable and understandably and valuable, and to find the model which is easy understand by people to describe the data in the data warehouse. The data was collected according to fault model which was cleaned up and a fairly standard, it is easy for enterprises to establish knowledge dimension table and the relationship rules dimension table, in the data warehouse can be found a large number of knowledge about equipment's performance, operation status, scheduling scheme, the cause of the fault, service decision, etc. It can generate many different fault conclusions; it is fit for multi-fault diagnosis of intelligent systems.

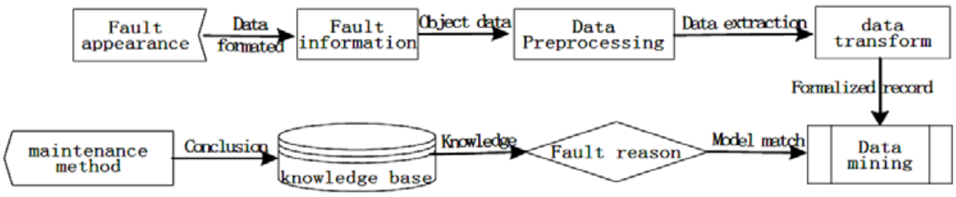


Fig.1 The data mining process of trouble information

First of all, the sequence of the fault dimension table was created in the data warehouse, the corresponding ID number was found according to these faults number, and the ID numbers were sorted. Then the output results of the Package1 were be converted into numeric, and it kept in the computer's memory as hexadecimal number. A "Test Model" was created by the rules of the dimension table records, and with the "Fault Model" match, then an ideal frequent item sets and candidate frequent item sets were generated.

We would be carried out with "Fault Model" and "Test Model" computing as the rules of data mining were given in previous, the frequent item sets 1 and frequent item sets 2 were generated. At last, traversing each records in the rules dimension table, repeat it, the frequent item sets 1 and frequent item sets 2 were generated. If the frequent item sets 1 is empty while it replaced by the contents of frequent item sets 2, while empty frequent item sets 2. Matching fault mode combines with the fuzzy inference rules to filter the dimension.

Interval Type-2 Fuzzy Logic Systems (IT2FLS)

Fuzzy Logic Systems (FLS) are known as the universal-approximators and have various applications in identification and control designs. A type-1 fuzzy system consists of four major parts: fuzzifier, rule base, inference engine and defuzzifier. A type-2 fuzzy system has a similar structure, but one of the major differences can be seen in the rule base part, where a type-2 rule base has antecedents and consequents using Type-2 Fuzzy Sets (T2FS). In a T2FS, we consider a Gaussian function with a known standard deviation, while the mean (m) varies between m1 and m2. Therefore, a uniform weighting is assumed to represent a footprint of uncertainty as shaded in Fig.2. Because of using such a uniform weighting, we name the T2FS as an Interval Type-2 Fuzzy Set (IT2FS). Utilizing a rule base which consists of IT2FSs, the output of the inference engine will also be a T2FS and hence we need a type-reducer to convert it to a type-1 fuzzy set before defuzzification can be carried out. Fig.3 shows the main structure of type-2 FLS.

By using singleton fuzzification, the singleton inputs are fed into the inference engine. Combining the fuzzy if-then rules, the inference engine maps the singleton input x = [x_1, x_2,…x_3] into a type-2 fuzzy set as the output. A typical form of an if-then rule can be written as:

$$R_i = if\ x_1\ is\ \tilde{F}_1^i\ and\ x_2\ is\ \tilde{F}_2^i\ and\ \ldots\ldots and\ x_k\ is\ \tilde{F}_k^i\ then\ \tilde{G}^i \qquad (1)$$

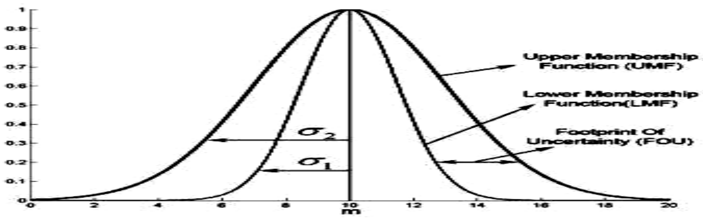


Fig. 2: Interval type 2 fuzzy set (IT2FS)

Where F_k are the antecedents (k = 1,2,…,n) and G^i is the consequent of the i^{th} rule. We use sup-star method as one of the various inference methods. The first step is to evaluate the firing set for i^{th} rule as following:

$$F^i(\underline{x}) = \prod_{i=1}^{n} \mu_{\tilde{F}_1}(x_1) \qquad (2)$$

As all of the F_k^s are IT2FSs, so $F^i(\underline{x})$ can be written as $F^i(\underline{x}) = \left[\underline{f}^i(\underline{x})\ \overline{f}^i(\underline{x})\right]$

Where:

$$\underline{f}^i(\underline{x}) = \prod_{i=1}^{n} \underline{\mu}_{\tilde{F}_i}(x_i) \qquad (3)$$

$$\overline{f}^i(\underline{x}) = \prod_{i=1}^{n} \overline{\mu}_{\tilde{F}_i}(x_i) \qquad (4)$$

The terms $\underline{\mu}_{\tilde{F}_i}$ and $\overline{\mu}_{\tilde{F}_i}$ are the lower and upper membership functions, respectively (Fig.2). In the next step, the firing set F_i(x) is combined with the i^{th} consequent using the product t-norm to produce the type-2 output fuzzy set. The type-2 output fuzzy sets are then fed into the type reduction part. The structure of type reducing part is combined with the defuzzification procedure, which uses Center of Sets (COS) method. First, the left and right centroids of each rule consequent are computed using Karnik-Mendel (KM) algorithm. Let's call them y_l and y_r respectively.

The firing sets $F^i(\underline{x}) = \left[\underline{f}^i(\underline{x})\,\overline{f}^i(\underline{x})\right]$ computed in the inference engine are combined with the left and right centroid of consequents and then the defuzzified output is evaluated by finding the solutions of following optimization problems:

$$y_l(\underline{x}) = \min_{\forall f^k \in \{\underline{f}^k, \overline{f}^k\}} \left(\sum_{i=1}^{M} y_l^i f^i(\underline{x}) \,/\, \sum_{i=1}^{M} f^i(\underline{x})\right) \quad (5)$$

$$y_r(\underline{x}) = max_{\forall f^k \in \{\underline{f}^k, \overline{f}^k\}} \left(\sum_{i=1}^{M} y_r^i f^i(\underline{x}) \,/\, \sum_{i=1}^{M} f^i(\underline{x})\right) \quad (6)$$

Define $f_l^k(\underline{x})$ and $f_r^k(\underline{x})$ as a functions which are used to solve (5) and (6) respectively and let

$$\xi_1^i(\underline{x}) = f_1^i(\underline{x}) / \sum_{i=1}^{M} f_1^i(\underline{x})$$

And

$$\xi_r^i(\underline{x}) = f_1^i(\underline{x}) / \sum_{i=1}^{M} f_r^i(\underline{x})$$

Then we can write (5) and (6) as:

$$y_l(\underline{x}) = \frac{\sum_{i=1}^{M} y_1^i f_1^i(\underline{x})}{\sum_{i=1}^{M} f_1^i(\underline{x})} = \sum_{i=1}^{M} y_1^i\, \xi_1^i(\underline{x}) = \theta_1{}^T \xi_l(\underline{x}) \quad (7)$$

$$y_r(\underline{x}) = \frac{\sum_{i=1}^{M} y_r^i f_r^i(\underline{x})}{\sum_{i=1}^{M} f_r^i(\underline{x})} = \sum_{i=1}^{M} y_r^i\, \xi_r^i(\underline{x}) = \theta_r{}^T \xi_r(\underline{x}) \quad (8)$$

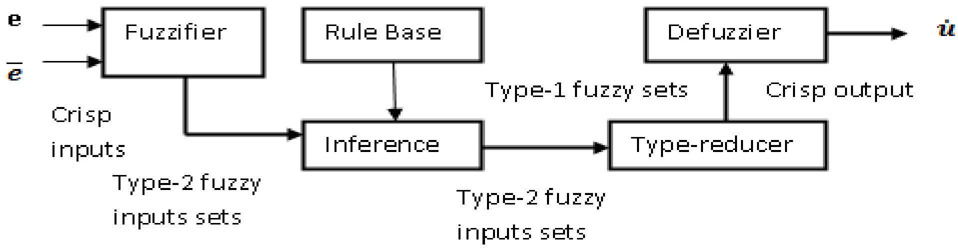


Fig.3: Main structure of interval type-2 FLS

Where

$$\xi_l(\underline{x}) = [\xi_l^1(\underline{x})\; \xi_l^2(\underline{x}) \ldots\ldots \xi_l^M(\underline{x})]$$

And $\xi_r(\underline{x}) = [\xi_r^1(\underline{x})\; \xi_r^2(\underline{x}) \ldots\ldots \xi_r^M(\underline{x})]$ are the fuzzy basis functions and

$$\theta_l(\underline{x}) = [y_l^1(\underline{x})\; y_l^2(\underline{x}) \ldots\ldots y_l^M(\underline{x})]$$

And $\theta_r(\underline{x}) = [y_r^1(\underline{x})\; y_r^2(\underline{x}) \ldots\ldots y_r^M(\underline{x})]$ are the adjustable parameters.

Finally, the crisp value is obtained by the defuzzification procedure as follows:

$$y(\underline{x}) = \frac{1}{2}[y_l(\underline{x}) + y_r(\underline{x})] = \frac{1}{2}[\theta_l^T \xi_l(\underline{x}) + \theta_r^T \xi_r(\underline{x})] = \frac{1}{2}\theta^T \xi(\underline{x}) \quad (9)$$

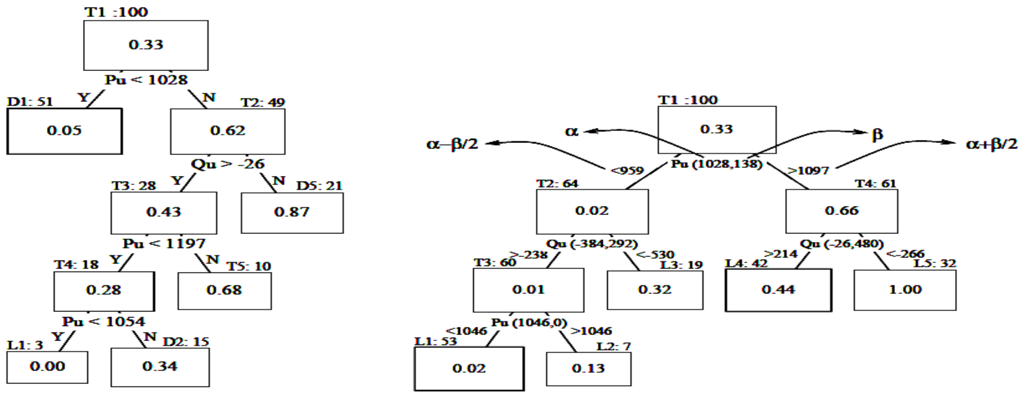
Where

$\theta = [\theta_l^T \theta_r^T]^T$ and $\xi = [\xi_l^T \xi_r^T]^T$

III. Soft Decision Tree Classifier (Interval Type-2 Fuzzy Logic based Decision Tree Classifier)

Soft decision trees versus crisp regression trees

We present intuitively the formal representation of a soft decision tree by explaining first the regression tree (RT) type of induction. Regression trees and soft decision trees (SDT) are extensions of the decision tree



(a). RT (b). SDT

Fig.4 Regression tree versus soft decision tree.

induction technique, predicting a numerical output, rather than a discrete class. Both trees may be used in regression problems given their output (numerical by definition), or in classification problems, by a priori de4ning symbolic classes on the numerical output. Fig.4 shows a crisp regression tree (left part (a)) and a soft decision tree (right part (b)). Both were built for a steam turbine fault diagnosis. The input space is here defined by an attribute characterizing the system

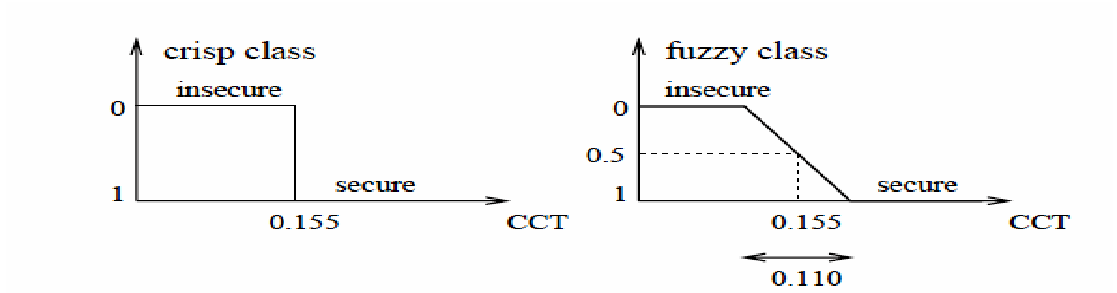


Fig.5 Example of a crisp class and a fuzzy class

state, denoted respectively by “P” fault appearance. The output is denoted by “Q” real cause of fault. We formulated it as an interval type-2 fuzzy class based on a parameter called critical clearing time (CCT) of the system state (see Fig.5). The trees predict the membership degree of instances to this interval type-2 fuzzy class. In a crisp decision (see Fig.5), the system could be considered “unhealthy” if the CCT is smaller than 155ms, “healthy” otherwise (classification problem). In a soft decision, there is a transition region of 110 ms (as we defined it) in which the system is neither”healthy” nor “unhealthy” (regression problem).

We may also express the result in a crisp way (see crisp class of Fig.5): since 0.87 ms corresponds to a CCT value smaller than 155 ms, the conclusion is that the class estimated by the regression tree is “unhealthy”. By translating the tree into a rule base, the rule extracted from the tree fired by our instance looks like:

Rule: If P is .87 ms then Q unhealthy

Soft decision tree

The two parameters defining it are: α, which is the location of the cut-point and corresponds to the split threshold in a test node of a decision or a regression tree, and β which is the width, the degree of spread that defines the transition region on the attribute chosen in that node. With such a

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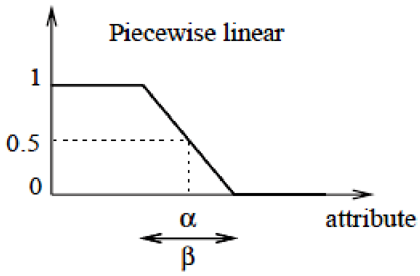
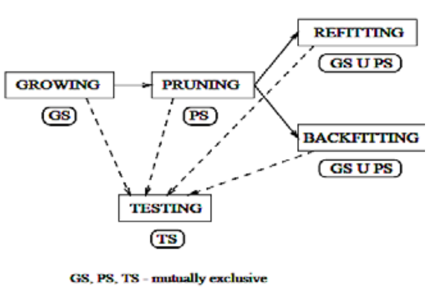


Fig.6 Example of discriminator function: piecewise linear.

Piecewise linear discriminator function, the local input space of a node is split (fuzzy partitioned) into two overlapping sub regions of objects. Some objects go only to the left successor, some only to the right one, and the objects in the overlap region go to both successors. The larger the transition region in a test node, the larger the overlap and the softer the decision in that node. In consequence, any given instance is in general propagated through the tree by multiple decision paths in parallel: in the simplest case through one path, in the most complex case, through all the paths. This given instance does not effectively belong to a node it passes through, but has a membership degree attached to that node. Thus, the node may be seen as a fuzzy set. Finally, the given instance reaches multiple terminal nodes and the output estimations given by all these terminal nodes are aggregated through some defuzzification scheme in order to obtain the final estimated membership degree to the target class.

Building a soft decision tree (SDT)

Fig.7 presents an overview of the complete procedure for building a soft decision tree (SDT). The process starts by growing a “sufficiently large” tree using a set of objects called growing set GS. Tree nodes are successively added in a top-down fashion, until stopping criteria are met. Then the grown tree is pruned in a bottom-up fashion to remove its irrelevant parts. At this stage, a cross validation technique is used which makes use of another set of objects, called the pruning set PS. Next, a third step could be either a refitting step or a back fitting step. Both consist of tuning certain parameters of the pruned tree model in order to improve its approximation capabilities further. These steps use the whole learning set: LS =GS $\cup$PS. At the end of every intermediate stage, the obtained trees (fully developed, pruned, refitted or backfitted) may be tested in order to quantify their generalization capability. A third sample, independent from the learning set, called test set TS, is used to evaluate the predictive accuracy of these trees. Thus, a given dataset is split initially into two disjoint parts, the learning set LS and the test set TS. The learning set is then used to create two other disjoint sets: the growing GS and the pruning PS sets. Growing, pruning and test sets are (normally) composed of mutually independent samples, as far as one can assume that this is the case for the original dataset.



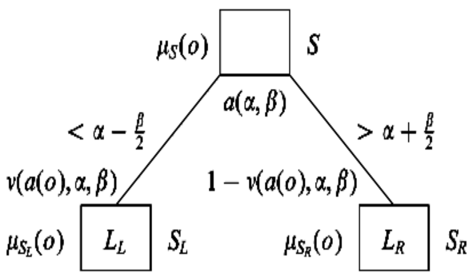


Fig.7 The procedure of building a SDT. Fig.8 Fuzzy partitioning of a node in a SDT.

Fault Classification

The Confusion Matrix, shown in Table 2 is a convenient way of examining the classification accuracy of the models and their distribution in various classes. It gives the count of the correctly classified instances.

Table2. The Confusion Matrix obtained from the decision tree model

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	F0	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
F0	89		6							6	
F1		187	2	7	2			2			
F2		2	134							4	
F3			2	33						2	
F4					14			2		3	
F5						9					
F6											
F7					2			8			
F8									1	4	
F9	5	2	4	2	4	4			3	121	
F10											

Correctly classified instances 588 92.52 %

Incorrectly classified instances 58 8.85 %

The diagonal elements are the correctly classified faults, and the off-diagonal elements are the incorrectly classified faults. One can preprocess a dataset, feed it into a learning scheme, and analyze the resulting classifier and its performance. The learning methods are called classifiers. A soft decision tree (SDT), cross fold validation or a multilayer perceptron can be used to classify instances.

IV. Steam turbine fault diagnostics

Steam turbine faults are generally classified into twenty types listed in Table 3 based on field experts' experience and theoretical analyses.

In any faults diagnosis, feature extraction is an important step for detecting steam turbine faults. Features can be extracted from the frequency domain of a typical steam turbine vibration analysis. However, analysis of the steam turbine data requires a detailed understanding of the steam turbine design, operation, and maintenance. Vibration spectrum analysis is a practical and powerful tool for steam turbine fault diagnosis because it is based on a great deal of engineering experience. Although there have recently been many new methods applied to fault diagnosis, most approaches are based on or related to the vibration spectrum data. However, the fault cannot be easily related to the spectrum data because the steam turbine system is very complex and influenced by numerous process parameters. The best method is to use the feature-fault relationship matrices in well-established machining reference databases, expert intelligence for the reasoning and decision-making and experimental results of signal characteristics for various working conditions. Table 5 show a fuzzy feature-faults relationship matrix for a steam turbine developed using fuzzy mathematics. The table relates the typical twenty steam turbine faults with ten vibration spectrum features. The alphabetic symbols used to describe the spectrum and process features are listed in Table 4. The notation n・X in the second column of table 4 denotes a frequency component (or range) in the spectrum at n times the turbine's rotational speed.

Table 3 Steam turbine fault classification.

Fault No.	Description	Fault No.	Description
F0	Normal	F10	Pedestal looseness
F1	Imbalance	F11	Foundation looseness
F2	Components missing	F12	Worn coupling
F3	Bent shaft	F13	Electricity magnet excited
F4	Shaft-seal rubbing	F14	Sub-harmonic vibration
F5	Axial rubbing	F15	Oil whirl
F6	Axial misalignment	F16	Oil-whip
F7	Eccentricity faults	F17	Steam excited vibration
F8	Rotor crack	F18	Valve vibration
F9	Shrunk-on-disc failure	F19	Power disturbance

The relationships listed in Table 5 show that some faults such as an imbalance, F1 and a bent shaft, F3 cannot be distinguished since they have similar spectrum features. Therefore, a second relationship matrix given in Table 6 is used to relate the process features to the steam turbine faults. Table 5 was derived directly from the author and other field expert experience, so it can be used to efficiently diagnose faults. The two relationship charts in Tables 5 and 6 provide the basis for steam turbine fault diagnosis.

Table 4 Symbols for vibration frequency and process feature description.

Frequency feature	Description	Process feature	Description
F1	0.015~0.41X	P1	Amplitude jump during operation
F2	0.42~0.52X	P2	Vibration at various power load
F3	0.56X	P3	Axial vibration
F4	0.57~1.01X	P4	Shaft average centerline
F5	1.5X	P5	Critical speed spectrum
F6	2.5X	P6	Stable at various running speed
F7	3.5~5.7X	P7	Vibration level increase during running up
F8	Odd of X	P8	Level jump during run up
F9	High X	P9	3x at 1/3 critical speed
F10	Power line	P10	Half-speed whirl

Table 5 Spectrum feature-fault relationship chart.

Fault	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
F0	0	0	0	0	0.51	0	0	0	0	0
F1	0	0	0	0	0.97	0.058	0.059	0	0	0
F2	0	0	0	0	0.96	0.054	0.055	0	0	0
F3	0	0	0	0	0.94	0.052	0.056	0	0	0
F4	0.14	0.13	0	0.11	0.23	0.11	0.25	0.15	0.19	0
F5	0.13	0.15	0	0.18	0.28	0.16	0.26	0.15	0.14	0
F6	0	0	0	0	0.46	0.52	0.12	0	0	0
F7	0	0	0	0	0.84	0.24	0	0	0	0
F8	0	0	0	0	0.43	0.23	0.24	0	0.26	0
F9	0.46	0.43	0	0.13	0	0	0	0.15	0	0
F10	0.52	0.44	0	0	0	0	0.15	0	0	0
F11	0.33	0.25	0	0	0	0	0	0.56	0	0
F12	0.15	0.23	0	0.14	0.22	0.34	0.16	0	0	0
F13	0	0	0	0	0.46	0.22	0.25	0.24	0	0
F14	0	0	1.3	0	0	0	0	0	0	0
F15	0	1.4	0	0	0	0	0	0	0	0
F16	0	1.7	0	0	0	0	0	0	0	0
F17	0	0.37	0.16	0.65	0	0	0	0	0	0
F18	0	0	0	0	0	0	0	0	1.4	0
F19	0	0	0	0	0	0	0	0	0	1.7

Table 6 Process feature- fault relation chart.

Fault	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
F0	N	N	L	L	N	N	Y	N	N	N
F1	N	N	L	L	N	N	Y	N	N	N
F2	Y	N	L	L	N	N	N	N	N	N
F3	N	Y	L	L	N	N	N	N	N	N
F4	N	N	L	L	N	N	N	N	N	N
F5	N	N	H	L	N	N	N	N	N	N
F6	N	N	H	L	N	N	N	N	N	N
F7	N	N	L	H	N	N	N	N	N	N
F8	N	N	L	L	N	N	N	N	Y	N
F9	N	N	L	L	N	N	N	Y	N	N
F10	N	N	M	L	N	N	N	P	N	N
F11	N	N	L	L	N	N	N	Y	N	N
F12	N	N	L	L	N	N	N	N	N	N
F13	N	N	L	L	N	N	N	Y	N	N
F14	N	N	L	L	N	N	N	N	N	N
F15	N	N	L	L	N	N	N	N	N	Y
F16	N	N	L	L	Y	N	N	N	N	N
F17	N	P	L	L	P	N	N	N	N	N
F18	N	N	L	L	N	Y	N	N	N	N
F19	N	N	L	L	N	N	N	N	N	N

V. Problem Simulation

Interval Type-2 Fuzzy Inference System (IT2FIS)

An Interval Type-2 Fuzzy Inference System (IT2FIS) are used for automatically generate the necessary rules. The phase of data mining using Interval Type-2 Fuzzy Inference Systems (IT2FIS) becomes complicated, as there are enough rules to determine which variables one should take into account. The search method of back-propagation and hybrid learning (BP+RLS) is more efficient in other methods. Since the IT2FIS method seems to produce more accurate models with fewer rules is widely used as a numerical method to minimize an objective function in a multidimensional space, find the approximate global optimal solution to a problem with N variables, which minimize n the function, varies smoothly.

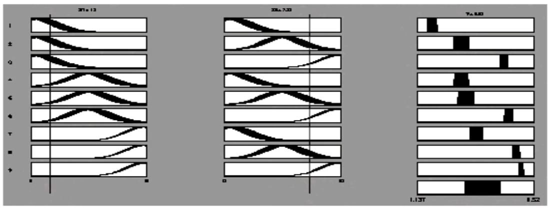

Fig.9 Rules on a Type-2 Fuzzy Inference System.

With the application of this grouping algorithm we obtain the rules, the agent receives input data from its environment and chooses an action in an autonomous and flexible way to fulfill its function. We create an Interval Type-2 Fuzzy Inference System as how we could represent different agencies as a decision-making system into agents.

The Fig.10 shows a type-2 fuzzy inference system for steam turbine fault diagnosis. It depicts a set of input-output variables and a rule set. Output variables are healthy and unhealthy as a response of the system. We could use the difference between both values to make decisions into an agent as a preference decision-making system. The Fig.11 depicts the resolution example of the rules by the fuzzy inference system. Different quantitative input values could be introduced and the system resolve creating different responses. Depending of the combination of inputs, we can expect different responses of the system. An agent will use this inference system as a decision-making system to show different behaviors depending of the situation.

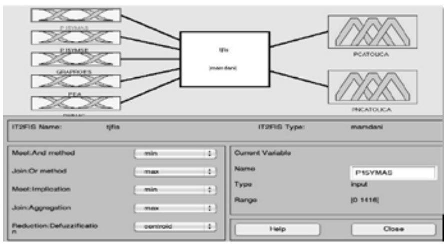

Fig.10 Fuzzy Inference System for steam turbine fault diagnosis.

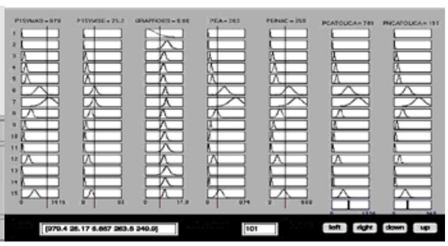

Fig.11 Fuzzy Inference System Rule Set Evaluation for Steam Turbine Fault Diagnosis.

Table.7 Classification results for various purities.

Maximum purity	Training set misclassification rate	Test set misclassification rate
98%	0.01%	1.79%
94%	0.01%	1.81%
92%	0.01%	1.68%
87%	0.03%	1.43%
74%	0.02%	0.57%
71%	0.04%	1.21%
69%	0.01%	1.89%

VI. Application of data mining to steam turbine fault diagnosis

A numerical simulation was developed based on the two relationship matrices in Tables 3 and 4 to test the soft decision tree classifier. The simulation firstly generated one hundred data points including spectrum features and process features for each type of steam turbine fault for a total of 2000 data points. Then, the data set was randomly divided into training and test sets. Next, the Ctree software was used to analyze the data set and to grow the soft decision tree. The pruning technique was used to generate a stable tree. The maximum purity of the tree was adjusted to get better results.

For example, for a maximum purity rate of 100%, the misclassification rate for the training set was 0% and for the test set was 1.8%. However, when maximum purity was reduced to 75%, the misclassification rate for test set was reduced to 0.50%. Table 9 lists the results for various purities.

Table 8 Classification Tree Information for a purity of 75%.

Tree information item	Value	Tree information item	Value
Number of training observations	987	Total number of nodes	45
Number of test observations	1021	Number of leaf nodes	27
Number of predictors	24	Number of levels	17
Class variable	Faults	Training data misclassification rate	0.01%
Number of classes	26	Test data Misclassification rate	0.49%

Table 9 Test set results.

Rule ID	Fault class	Length	Support	Confidence	Capture
1	F14	1	5.5%	100.0%	100.0%
2	F8	2	5.3%	100.0%	100.0%
3	F6	3	5.7%	100.0%	100.0%
4	F1	5	5.4%	100.0%	100.0%
5	F10	6	4.8%	100.0%	100.0%
6	F18	6	5.5%	100.0%	100.0%
7	F0	6	4.5%	100.0%	100.0%
8	F3	6	4.9%	100.0%	100.0%
9	F2	6	5.6%	100.0%	100.0%
10	F19	8	5.3%	100.0%	100.0%
11	F12	8	4.9%	100.0%	100.0%
12	F17	3	4.7%	96.8%	100.0%
13	F11	10	4.7%	100.0%	100.0%
14	F9	3	5.2%	97.2%	100.0%
15	F13	10	5.6%	100.0%	100.0%
16	F7	2	7.1%	95.30%	100.0%
17	F5	10	5.6%	100.0%	100.0%
18	F4	10	4.8%	100.0%	100.0%
19	F15	11	4.5%	100.0%	100.0%
20	F16	11	4.2%	100.0%	100.0%

VII. Simulation Results

Tables 6, 7, and 8 list the classification results for the simulated steam turbine faults data. Table 6 describes the resulting soft decision tree for a maximum purity of 75%. The misclassification rate is sufficiently low for common engineering applications. The soft decision tree was then used to develop the IF-THEN rules used by engineers to analyze and interpret the fault diagnosis results. The method can automatically extract the knowledge from the data as part of a fault diagnosis expert system. Table 7 summarizes the rule results for the test set, including the support, confidence and capture rates. The support rate measures how widely applicable the rule is in the training set. The confidence rate measures the accuracy of the rule. The capture indicates how many records of a fault were correctly captured by the rule. The twenty rules after pruning correspond to the twenty types of faults. Most of the confidence rates were 100%, with only 3 confidence rates less than 100% due to misclassification of the test data. Table 8 lists the specific rules for each fault type. The rules agree well with spectrum analysis theory. In addition, many process features from the field experts' experience are integrated into the rules to improve the classification process.

VIII. Conclusions

Soft Decision Tree Classifier using Interval Type-2 Fuzzy Logic Rule based Data mining was used to classify simulated data and real data into known classes for Steam Turbine Fault Analysis of a Power System Rotatory Machine Component. The use of the simulated data enabled the system to directly capture the field experts' knowledge into the resulting classification rules. The classification rules were automatically extracted from the data sets for use by engineers to diagnose and interpret steam turbine faults. The simulation results and the results using actual data from operating power plants shows that the soft decision tree classifier using interval type-2 fuzzy logic rule based data mining methods can be effectively applied to steam turbine fault diagnostics. The automatic extraction of the classification rules shows that these machine learning methods can be applied to large turbo-machinery databases and can include engineering knowledge and field experience. The results can then be used for fault diagnosis of large rotating machines, such as steam turbines.

Table 10 Rules derived from the classification tree.

Rule	IF	Then
1	F3 ≥ .1031	F14
2	F3 < .1031,P9=Y	F8
3	F3 < .1031, F6 ≥ .46009, P9=N	F6
4	F1 ≥ .84567,F3 < .1031, F6<.46009, P7=Y, P9=N	F1
5	F1<.84567, F3<.1031, F5≥.46031, F6<.46009, P6=N,P9=N	F10
6	F1<.0094769, F3<.1031, F6<.46009, P6=Y P9=N	F18
7	F1< .84567, F1≥ .0094769, F3< .1031,F6<.46009, P6=Y,P9=N	F0
8	F1≥.84567, F3<.1031, F6<.46009, P1=N,P7=N, P9=N	F3
9	F1≥.84567, F3<.1031, F6<.46009, P1=Y, P7=N, P9=N	F2
10	F1<.17895,F2<.0094769, F3<.1031,F5<.46031, F6<.46009,P6=N,P9=N	F19
11	F1<.84374, F1≥.198,F2≥.178, F3<.107,F5<.46031,F6<.46009, P6=N,P9=N	F12
12	F2<.36761, F2≥.00944567,F5<.095618	F17
13	F1<.187,.008≤F2<.23,F3<.107,.095118≤F5<.477,F6<.476, P6=N,P9=N	F11
14	F2≥.20876,F5<.46031,F5≥.095518	F9
15	.187≤F1<.415,F2<.0953,F3<.107,F5<.46031,F6<.46009 , P6=N,P9=N	F13
16	F1< .85169, F1≥ .3881,	F7
17	.17≤F1<.85,F2<.18,F2≥.096,F3<.11,F5<.480,F6<.44 P3=H,P6=N,P9=N	F5
18	.18≤F1<.87,F2<.183,F2≥.098,F3<.17,F5<.49,F6<.48 P3=L,P6=N,P9=N	F4
19	F1<.18865, F2≥.37651,F3<.1031,F5<.094678,F6<.476,P5=N,P6=N,P9=N	F15
20	F1<.18565, F2≥.3686,F3<.107,F5<.09512,F6<.478,P5=N,P6=N,P9=N	F16

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