International Journal of Industrial Engineering & Production Research

International Journal of Industrial Engineering & Production Research

June 2011, Volume 22 Number 2
pp. 91-98

http://IJIEPR.iust.ac.ir/

ISSN: 2008-4889

A Fuzzy Rule Based System for Fault Diagnosis, Using Oil Analysis Results

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KEYWORDS

Condition Monitoring,
Oil Analysis, Wear Behavior,
Fuzzy Rule Based System

ABSTRACT

Maintenance, as a support function, plays an important role in manufacturing companies and operational organizations. In this paper, fuzzy rules used to interpret linguistic variables for determination of priorities. Using this approach, such verbal expressions, which cannot be explicitly analyzed or statistically expressed, are herein quantified and used in decision making.

In this research, it is intended to justify the importance of historic data in oil analysis for fault detection. Initial rules derived by decision trees and visualization then these fault diagnosis rules corrected by experts. With the access to decent information sources, the wear behaviors of diesel engines are studied. Also, the relation between the final status of engine and selected features in oil analysis is analyzed. The dissertation and analysis of determining effective features in condition monitoring of equipments and their contribution, is the issue that has been studied through a Data Mining model.

1. Introduction

Although nowadays machinery oil analysis Condition Monitoring (CM) techniques are known as an effective method in abnormal wear in equipments and mechanical systems fault diagnosis; issues like wear behavior, technical features, and previous records of oil analysis results are essential and determinant in the process of interpreting the results of oil analysis in implementing CM programs.

Proper maintenance of equipment to prevent failures has become increasingly important. For manufacturing companies, it enables uninterrupted production to support lean manufacturing. For commercial carriers, it ensures the safety of passengers and crew members. Maintenance technology has progressed from time-based to condition-based. The idea of condition-based maintenance (CBM) is to monitor equipment to enable diagnosis of impending failures and prognosis of equipment health. The success of CBM hinges on the ability to develop accurate diagnosis/prognosis models. These models must be cognitive friendly for them to gain user acceptance, especially in safety critical applications [1].

Condition-based maintenance (CBM) refers to the practice of triggering maintenance activities as necessitated by the condition of the target system. CBM thus entails the process of diagnosis of the target system and timely identification of incipient or existing failures, popularly known as failure detection and identification (FDI). FDI has been given due research focus; however, there is a dearth of autonomous yet interactive decision making tools that would perform diagnosis and prognosis under the precepts of CBM.

Once a system or a piece of equipment has been purchased, it must be maintained [2]. Experience, judgment and vendor recommendations are the common bases for determining the content and frequency of a maintenance task. Maintenance can be defined like the activities intended to preserve or

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Paper first received Dec. 10, 2010, and in revised form May. 12, 201 .

promptly restore the safety, performance, reliability, and availability of plant structures, systems, and components to ensure superior performance of their intended function when required[3,4].

Production and service systems are heavily affected by their respective maintenance systems. Maintenance systems operate in parallel to the production systems to keep them serviceable and safe to operate at minimum cost [5]. The effectiveness of maintenance management depends significantly on proper deployment of resources in the form of spare parts and other maintenance materials, manpower, necessary tools and instruments, and ultimately life cycle profit for an organization [6].

Fuzzy and neuro-fuzzy systems have been used for various CBM applications. Amin et al used Fuzzy inference and fusion for health state diagnosis of hydraulic pumps and motors [7]. Bocaniala et all developed A novel fuzzy classification solution for fault diagnosis [8]. Soft computing methods widely used in fault diagnosis [9, 10, 11, 12]. Some of fuzzy diagnosis systems used in robots [13] and power transformers [14].

In this paper, we introduced a 4 step model for extracting and using rules for a fuzzy rule based system. This approach has some other important problems which are the identification of aware experts, difficulties in verbalizing knowledge and providing irrelevant, incomplete, inconsistent and incorrect knowledge. Furthermore, the number of selected equipments in given factory was limited, fuzzy operators were also simplified; intersection, aggregation and defuzzification methods were the simplest methods which can compare with other methods.

2. Fault Diagnosis Using Oil Analysis

To appraise whether the obtained measures in oil analysis show a proper conditions or are showing unusual conditions in machinery, it's essential to exist some criteria to classify these measures into usual or suspicious measures.

Recognition of these criteria and appraisal methods of test results has been always one of the major challenges in oil analysis programs. For this purpose equipment manufacturers, oil producer companies and oil analysis laboratories represent criteria and methods for oil condition appraisal. Each of these criteria is based on viewpoints which awareness of them is essential in use time. Various methods of results analysis and appraisal have been used in this article and also it's been tried to access to oil analysis baseline through different methods combination and adaptation.

One of these methods is establishing limitations in which parameters measurements have to be [15]. It is essential to note that oil conditions is influenced by several factors such function conditions, machinery loading and utilizing, machinery general specifications and machinery special specifications such lifetime, looseness and etc and as a result using these methods as a general solution and without considering other conditions can not involve desirable results [16]. Importance of noting these cases is so that some authorized engines manufacturers believe it's not possible to appraise correctly and reliably only by using wear metal measurement and complementary analysis has to be used in order to correct diagnosis [17].

Different criteria for result analysis are used in this article to obtain the best and the most correct results.

2-1. Fixed LimitsD etermination

In this approach fixed bounds are defined for quantities which usually include three normal, abnormal and critical bounds. This quantity usually can be wear or contamination absolute measure or wear or contamination rate in running hours. To determine machinery status measures from the test are compared with determined limits and machinery conditions are appraised. In this method measures less than mean plus standard deviation, are normal and measures greater than mean plus double the standard deviation are counted as critical and measures between these two limits are abnormal [18].

2-2. Family Analysis

In this method results from tests of a set of similar machineries (a model) working in the same conditions are compared. Then obtained results are statistically analyzed and the bounds are determined like the defined bounds in fixed limits determination [19].

2-3. Trending Analysis

In this method quantity changes are appraised for specific machinery and machinery's present and future status are determined by assessing these changes. If sampling conditions and distances are fixed desirable results can be obtained by awareness of machinery performing conditions and following the parameters changes. Rate and measure of changes have to be considered simultaneously in result appraisal. Any abnormal changes in rate or measure of changes must be counted as a warning. This method's most important preference is independence to machinery's general and special conditions so that it just depends on machinery's running and loading conditions and is performable easily for any kind of machineries [20].

2-4. Criteria Defined by Manufacturer

Most of manufacturers provide criteria and guides for oil status appraisal. These criteria are mainly contaminants authorized limit to avoid damaging the machinery [18].

Oil producers also determine authorized limits for measures of contaminants existing in oil. It is clear that regarding these limits is essential for machinery performance.

2-5. Methods Combination

Inspections and performed activities has shown that for implementation of an efficient condition monitoring system it's better to apply all three above methods simultaneously thus more reliable results will be obtained from appraisal [23].

Furthermore you are advised to appraise below dimensionless parameter instead of wear absolute measure in wear metals appraisal [15]:

$$\frac{\text{Mean normal wear} - \text{Wear measure}}{\text{Mean model or type wear}}$$

2-6. Design and Development of the Fuzzy Rule Based System

Fuzzy set theory was first introduced in 1965 by Lotfi A. Zadeh [24]. A classical set can be regarded as a grouping together of elements, all of which have at least one common characteristic. If an element possesses this characteristic, it belongs to the set. If an element does not possess this characteristic, it does not belong to the set. In fuzzy set theory, the set is no longer restricted to this binary (yes/no) definition of set membership, but rather allows a graduated definition of membership. This means that a degree of membership to a set can be specified for each element. This set is then referred to as a fuzzy set. In the fuzzy set theory, uncertainty is viewed as a degree of set membership (e.g., the degree of presence of a symptom). Degrees of membership are numerical values in the interval [0,1], where 1 means that an object is a member, 0 means that an object is not a member, and an intermediate value means that an object is a partial member.

Maintenance is rarely mentioned in such papers, mostly when discussing simple examples of fuzzy logic application in modeling rules of the so-called ‘‘approximate reasoning’’ (for example If the quality of maintenance is good, then equipment reliability is high ; and If the quality of maintenance is bad, then equipment reliability is low). However, the approach based on fuzzy logic and decision making under uncertainty is very logical and fully convenient. When we refer to operations and maintenance, special difficulties arise from the fact that some data are insuficiently precise or uncertain.

In this paper, uncertainty is treated under the fuzzy set theory. In other words, along with the well-known application of fuzzy logic in expert system bases of rules for accessing knowledge from knowledge bases, this paper points to the possibility of feeding verbal expressions and observations about the state of the equipments.

These observations are noted in operation and maintenance documents by drivers, controllers, maintenance workers and other persons. Such verbal expressions, which cannot be explicitly analyzed or statistically expressed, are herein quantified and used in decision making [3].

2-7. Fuzzy Rule Based System

The method of devising a rule based system is divided into 4 steps:

1. Specify the important factors and establish from the data the ranges of these factors.
2. Defining the linguistic variables and the linguistic symbols for each factor.
3. Construction of the rules.
4. Test and verify the system by test data.

The problem of extracting expert knowledge is by no means trivial; knowledge acquisition being quite justifiably described in the literature of artificial intelligence as the "bottleneck" in the generation of knowledge-based systems. Against this however, the application of fuzzy technologies offers the advantage of being able to approximate the notions of these human experts.

We shall assume that our expert knows which variables are relevant to diagnosing a fault and which relationships exist between these variables. Experts generally know which variables are of relevance in the decision making process.

Valuations are transformed into Integer numbers that defined below for easier calculations. Table 1 contains elements and effective factors, which are measured in oil analysis.

Tab. 1.The features which are measured in oil analysis

Abr.	Feature
Fe	Iron
Pb	Lead
Cu	Copper
Al	Aluminum
Si	Silicon
PQ	Particle Quantity
Vis	Viscosity
F.T	Fault Type

Table 2 contains possible values of features, which is suggested from extracted baselines for oil analysis boundaries based on oil analysis data base with 1584 records.

Tab. 2.The values which may allocate for each feature

Feature	Valuations
Fe … Vis	(Normal, Boundary, Boundary Unacceptable, Critical)

The terms relating to 'Fe' for example are: Normal, Boundary, Boundary Unacceptable, and Critical. Ultimately, it is his empirical knowledge which the expert uses in order to specify value ranges for these terms. Fuzzy logic accommodates the experts here especially. In contrast to conventional expert systems, these value ranges do not have to be disjunctive

(either-or ranges), but can rather and indeed should overlap. There are however circumstances which linguistic variables cannot represent so well. In the current example the fault diagnosis is made using measured parameters.
The output of the system being a variable 'fault' which should specify in which category the fault falls. In addition a measure of the certainty of the diagnosis is given.

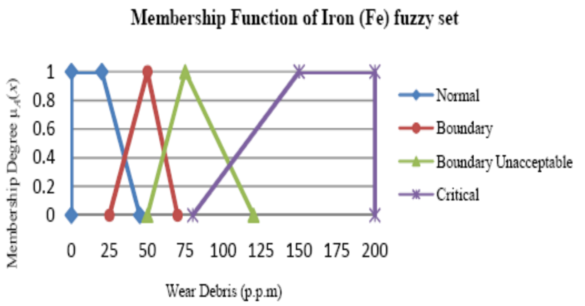

Fig. 1. Fuzzy Baseline of Iron (Fe)

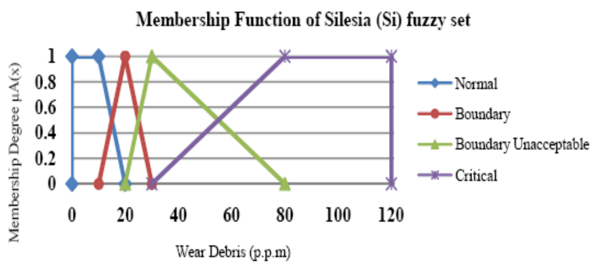

Fig. 2. Fuzzy Baseline of Silesia (Si)

Fuzzy inference systems (FIS), specially the Mamdani type, can be capably used as a bridge between the area expert and a CBM system. FIS works on knowledge bases that are in easily comprehensible “IF…THEN’’ format.
However, this particular class of algorithms does not possess any form of automatic learning, hence require considerable amount of manual tuning in the generation of the solution. Since the knowledge is both in a functional form (network) and generalized form (rule base), it is possible to integrate with the other business functions previously mentioned.

3. Case Study: Results & Analyzes

In oil analysis used in various equipments a unique strategy is applied but we have to note that result measurement and analysis criteria are depend on numerous parameters such oil type, machinery type, parts kind and etc. Therefore following a unique strategy and also continuity in this manner can be both effective in oil analysis extension and enforceable easily to new equipments [25].
Designed approach has 4 steps that are:

1. Preprocessing of data:
Row data of oil analysis results are in an information bank in access database. First Determine oil analysis affecting factors. Then the data preprocessed by Implementing descriptive statistics on data Omitting or correcting outlier data in analyzers viewpoint about wear elements and oil features.

2. Generate Rules from data:
Initial rules derived by Implementation of techniques: statistical analysis, decision tree, visualization, rules extraction. Generate rules by assistant of experts

3. Result appraisal:
Correct rules by expert's opinions. Generate rules by assistant of experts and Result analysis and appraisal by experts and analyzers.

4. Knowledge representation:
Generate a decision support system using fuzzy rule based system.

3-1. Oil Analysis Foundations in Diesel Engines

In case of running engines, oil has to be sampled and in addition to viscosity ocular inspection the water pollution and its alkalis number have to be measured. If there is unsolvable material or water in ocular inspection or any of below states we have to send oil to laboratory for more accurate tests [18]:

- More than 10 percent viscosity changes from new oil
- TBN less than 8
- Water pollution greater than 0.2 percent

If test results were undesirable on the engine below complementary tests have to be done in laboratory:

- Viscosity in 40 and 100 centigrade degree
- TBN
- Water pollution
- Unsolvable material
- Fuel pollution

3-2. Results of Visualization

A figure can give us much information in a few seconds and one can extract rapidly important information from it. An example of visualization shows in chart1 , 2.
According to this chart we will understand lower limit of wear measure is 0 ppm and also it is clear for upper limit since measures between 7.5 and 8 ppm include 40 samples, these measures are placed in upper limit of the situation and measures greater than 8 ppm include border situation lower limit. Thus upper, median and lower limit indices for aluminum wear element in normal situation are orderly (0, 4.6, 8 ppm).

Tab. 3. Frequency and descriptive statistics for different situations of Aluminum

Descriptive Statistics	N	Min	Max	Mean	Std. Deviation
Al normal situations	1288	.7	12.5	4.58	1.79
Al boundary situations	207	3.3	18.9	11.23	2.38
Al boundary unacceptable situations	70	10.3	40.3	20.95	5.56
Al critical situations	19	28.4	183	49.80	34.56

Some of used data showed in table 4.

Tab. 4. Some of oil analysis data

N	Diesel Engines N.	Fe	Pb	Cu	Al	Si	PQ	VIS40	N	Diesel Engines N.	Fe	Pb	Cu	Al	Si	PQ	VIS40
1	DE1-1	42.3	8.2	1	11.3	25	20	132	**42**	DE8-4	21.1	0	1.1	3	4.1	23	22
2	DE1-2	17.9	1.2	0.8	2.3	4.9	20	98	**43**	DE9-3	48	4.7	1.4	9.9	32.4	23	159
3	DE2-1	56	1.2	1.8	3.9	6.7	20	100	**44**	DE9-4	25.8	2.6	0.4	3.8	5.9	42	64
4	DE2-2	10.2	2.2	0.2	1.6	7	31	94	**45**	DE10-3	15.9	2.5	0.4	2.8	5.6	97	119
5	DE3-1	44.2	3.5	5.9	4.7	4.5	37	80	**46**	DE10-4	48.9	4.6	1.3	6.5	7.5	45	142
6	DE3-2	30	1.2	0.7	2.8	5.6	21	125	**47**	DE11-3	75	7.1	1.3	8.5	14.8	75	74
7	DE4-1	33.9	1.3	1.5	2.7	7.3	16	129	**48**	DE11-4	5.9	2.6	0.2	1.7	4	230	150
8	DE4-2	92	2.4	1.6	9.2	17.8	38	52	**49**	DE12-3	79	18.7	4.8	10.3	19.8	39	120
9	DE5-1	64	4.4	1.5	7.2	8.7	72	123	**50**	DE12-4	27.8	4.8	1.2	4.8	5.8	49	121
10	DE5-2	10.6	3.2	1	3.2	5.4	24	145	**51**	DE13-3	38.4	3.4	0.5	3.7	10.1	49	137
11	DE6-1	58	4.3	1.4	12.1	22.5	55	138	**52**	DE13-4	26.5	6.4	3.2	3.5	8.1	34	131

This method provides the possibility of utilizing statistical and visualization techniques specially frequencies normal distribution chart as well in addition to determine wear measure control level spans in three level of upper, mean and lower limit and determine wear behavior baseline indices in a high confidence. Baseline indices for aluminum wear element are determined in different situations according to total frequency table and frequency charts of each situation and is shown as below table.

Tab. 5. Baseline indices measures in different situation of Aluminum wear in crisp format

Control level	Number of samples-1584	**Table5. Baseline indices measures in different situation of Aluminum wear element**			
		Aluminum- Al			
		Normal (0)	**Boundary (1)**	**Boundary (Unacceptable) (2)**	**Critical (3)**
Upper limit	**P.P.M**	**10**	**20**	**45**	**70**
Mean limit		**4.6**	**11**	**21**	**50**
Lower limit		**0**	**8.5**	**10**	**20**

According to table 5 (Crisp baseline index), fuzzy baseline chart can be drawn for various situations of aluminum measures as below:

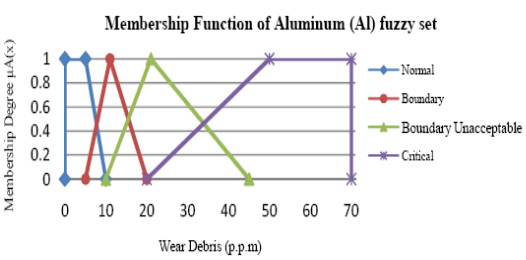

Fig. 3. Fuzzy definition of Aluminum (Al)

3-3. Results of Decision tree for Engine Situation Determination

As illustrated in above example, the baselines can be calculated accurately using effective statistical tools such as descriptive statistical tables and normal distribution curves. The correctness of extracted baselines is confirmed by CART as it is illustrated below. Here, as an example, Figure 4 depicts the iron decision tree (CART). Three numbers are recognized as base indices in this tree which divides the records in four groups. These three indices are: (35.95 ppm, 57.5 ppm, 99.5 ppm) While the four spans are shown in figure 5.

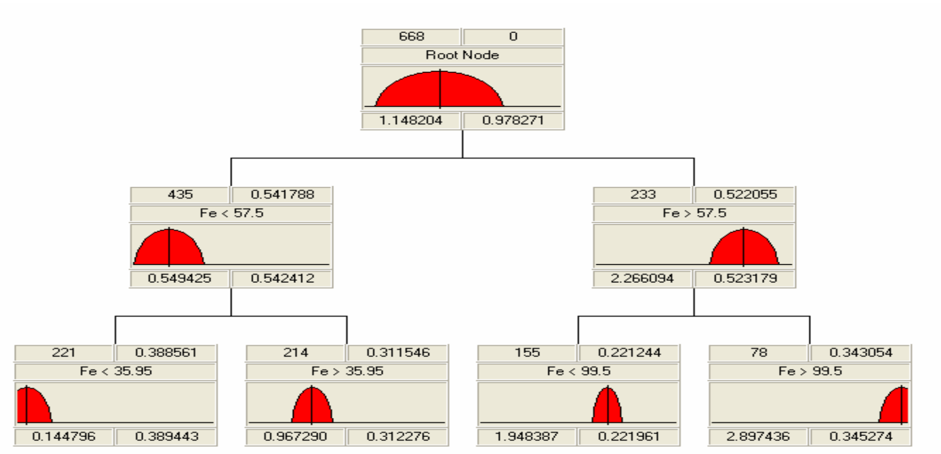

Fig. 4. Fe situation decision tree according to Fe measures

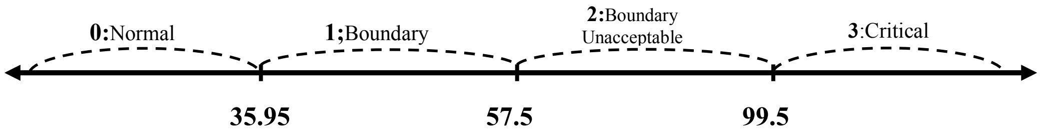

Fig. 5. Iron situation three indices

These four spans are named according to the standard coding of this research (normal, boundary, boundary unacceptable, critical). On the other hand, baseline indices for iron which were introduced as outgoing measure are exactly (0.144, 0.967, 1.948, 2.897). Their approximation to the closest integers of (0, 1, 2, and 3) is, in fact, the same coding used for the four situations (normal, boundary, boundary unacceptable, critical).
The first branch was introduced with (Fe <35.95 P.P.M) condition and has 221 oil samples of existing 668 records in this bank. The outgoing index (situation) mean is 0.144. This means that the iron situation is normal in this branch and is shown by 0 codes. This description can be explained as below If → Then rule:

1- IF Fe < 57.5 AND Fe < 35.95
THEN stFe; Support = 221.0; Evidence = 0.38; Number of errors = 0.389;
Mean value = 0.144~0: (Normal); Std. deviation = 0.38

Also third branch can be explained as below If → Then rule:

3- IF Fe > 57.5 AND Fe < 99.5 THEN
stFe; Support = 155; Evidence = 0.221; Number of errors = 0.2;
Mean value = 1.94~2: (Boundary Unacceptable); Std. deviation = 0.22

3-4. Fuzzy Rule Based System

The core of expert knowledge lies in the relationships between the variables that are the knowledge relating to the possible consequences of different individual pieces of information. The rules can be represented in the form of trees. Some rules was formulated in the following manner:

IF Pb is Critical AND Cu is Boundary Unacceptable AND Al is Critical AND Fe is Boundary,
THEN Fault is "Bearing Failure".

IF Vis is Critical AND Fe is Boundary Unacceptable AND TBN is Critical AND Al is Boundary,
THEN Fault is "Needle Injector Failure".

IF Si is Critical AND PQ is Boundary Unacceptable AND Fe is Critical AND Al is Boundary,
THEN Fault is "Air Filter Failure".

After defining the rules, data are used to diagnosis faults of engines. Figure 6 shows an example of fault diagnosis by this model. From the data for the first diesel engine it can be seen to be in very good condition, all of its variables having values somewhere in the region of what they should be. The rest of the data records have variables with measurements deviating, to differing degrees, away from these required values. As would be expected, no fault was diagnosed for this diesel engine were diagnosed either for diesel engines 1, 6 or 10.

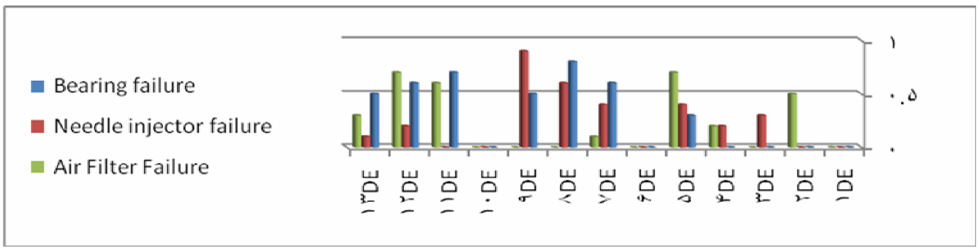

Fig. 6. Fault Classification in Diesel Engines

The effects of variations in the input variables can be easily investigated by changing the values in the fuzzy rule base editor of the input file and running the inference process again.

There are two prevalent types of fuzzy systems, the Sugeno type and the Mamdani type. They differ in the format of rule consequents. The rule consequent of a Sugeno fuzzy system is in from of a function; whereas that in a Mamdani fuzzy system is in the form of a linguistic term. Mamdani fuzzy systems are more compatible with the reasoning process of human operators. Therefore, we advocate the use of such systems for CBM applications. There are two common approaches to make Mamdani fuzzy systems adaptive (i.e., ability to adjust its membership functions based on available data).

4. Conclusions

This paper presents a fuzzy modeling approach utilizing IF-THEN rules and demonstrated its usefulness in CBM applications. The benefits that can be realized using this non-traditional modeling approach are as follows:

- Rule-based knowledge representation, coupled with rule extraction, provides a means to integrate data-driven modeling with physics-based modeling.
- Rule-based model is compatible with human heuristic reasoning, thus allowing domain experts to directly contribute to model building.
- Rule-based model is transparent to the user. How a decision is made can be clearly explained so the system can quickly gain user trust. This is especially important in safety-critical applications where human lives are at stake.

This paper has presented a discussion of the intelligent fault-diagnosis model with oil analusis data. Seven elements and features of iron, cooper, aluminum, silicon, PQ and viscosity were introduced as incoming indices, and the final engine situation as the outgoing index.

Decision support systems (DSS) established for decision-makers using the fuzzy expert system. The user can detect and predict the final engine situation by measuring the changes in the amount of elements in oil. By using the established DSS model, some nonlinear rules in data were extracted. Developed model for some years past and current cases was executed and in previous cases with condition of equipment and in the current cases was compared with expert opinions. The result of this research can also be a valuable basis and criteria for future researches. Some general gains and results of this research are summarized below:

1. Using calculated baselines in this research is useful for determining of each oil element for all types of truck engines.
2. It is possible to diagnose and predict the final engine situation for any related database.
3. The decision-making procedure will be faster and more accurate, which helps experts to find a suitable solution.
4. It will be practical to create a database for fault situations and wear behaviors.

For continue this research we suggest using other techniques such as verity kind of neural networks. And if there is an adequate amount of data we suggest using neuro fuzzy systems. Developing software based on this model could have very advantages. Authors also suggest using other sensors data for example vibration data, heat data and so on.

5. Acknowledgments

We thank Professor A.Memariani for supporting this work. We also thank Dr.A.Masoudi, Manager of Alborz.T. Research Co. for providing us Mercedes-Benz truck engine oil analysis data. This research was supported by Study & Research Center of Logistics.

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