A New Feature Reduction Method and Its Application in the Reciprocating Engine Fault Diagnosis

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Abstract: On the basis of complicated fault feature of the reciprocating engine, a new feature reduction method based on the principle of the knowledge granularity to estimate the significance of symptomatic parameters is presented in this paper. The current problem that in the process of reducing and compressing the symptomatic parameters of fault diagnosis, the smallest symptom sets obtained is not always the smallest and optimal one, has been solved by the new method. By calculating on two instance of reciprocating engine knowledge set, the feature reduction method is effective.

Key-Words: symptomatic parameter, reciprocating engine, granularity entropy, fault diagnosis, fault feature, knowledge granularity

1 Introduction

According to the complicated structure and movement type (e.g. rotating movement and reciprocating movement) of reciprocating engine, the fault diagnosis is a sort of typical information fusion process [1,2]. Most of the engine signal (e.g. the vibration, the temperature, the pressure, the orbit, etc.) can reflect the engine's running state [2,3]. Thus, the feature information should be extracted from the engine signals, and then be reduced to optimal fault diagnosis process. The paper presents a new method to simplify feature set.

At present, the reduction or compression of the symptomatic parameter set in fault diagnosis is basically calculated by rough sets [4,5]. The smallest symptom sets can be obtained by rough sets theory, but the sets are always more than one. Thus a new subject has been put forward on how to get the smallest and optimal symptom set. The granularity concept is therefore introduced as a theoretical foundation for the problem. Through the research on the principle of knowledge granularity, we can use the concept of granularity entropy to estimate the significance of symptomatic parameters. Then the optimal and smallest symptom set can be taken by the granularity theory method. The method is useful for reducing mechanical fault feature sets. And both the efficiency and the reliability of the fault diagnosis will be improved.

2 The granularity theory

The concept of granular computing was initially called information granularity or information granulation related to the research of fuzzy sets in Zadeh's early papers [6]. As a physical concept, granularity itself is defined as "the average measurement of the particle size". The knowledge granularity is referred to as the measurement of the knowledge refined in different levels, which is used as "the average measurement of the knowledge magnitude" in the artificial intelligence and cognition. In the process of cognizing and dealing with problems in reality, for the same problem, we always observe it from different levels, and analyze it with extremely different granularities. The concept of knowledge granularity can help to improve the capability of humankind [6,7,8,9,10,11].

2.1 The description of the knowledge granularity

The formalized definition of the knowledge granularity is described as below:

A question can be described as a triad（X， F ， Γ）, the components of which are:

X: referred to as the universe of discourse of the question, i.e. the set of the basic elements involved.

F: referred to as the attribute function, defined as $F: X \rightarrow Y$, and Y referred to as the property set of the elements.

Γ: referred to as the structure of the universe of discourse, defined as the relations among the basic elements in the universe of discourse.

From a relatively "rougher" point of view, actually we are simplifying X, by considering those elements with resemble properties as equivalent, putting them into one category, and regarding the whole category as a new element. Thus a bigger universe of discourse [X] is formed, and the initial problem (X, F, Γ) is transformed into a new one $([X],[F],[\Gamma])$ in a new level.

There is a close relation between the knowledge granularity and the equivalence of the rough concentration. In fact, the concept of simplification mentioned above is equivalent with that of the reduction of the rough concentration.

2.2 The calculation of the knowledge granularity

Definition 1 [10] (Fundamental Granularity):

Assume that U is a universe of discourse, R is an equivalence relation on U, and the set X is a partition on U with regard to the knowledge R. Then, based on the description of the fundamental sets of R, we can partition X into U/R (fundamental knowledge). The equivalence class (the fundamental knowledge granule) $X_i \in U/R$. In another word, if the partition on U educed by R is U/R: $U/R = \{X_1, X_2, X_3, \cdots, X_n\}$, then the granularity of the fundamental knowledge X is:

$$G(X_i) = |X_i| / |U| \quad (1)$$

Where $|\bullet|$ denotes the radix number of a set.

Proposition 1 [10]:

Assume that R is the knowledge in the repository $K = (U, R)$, $U/R = \{X_1, X_2, X_3, \cdots, X_n\}$. Then

$$G(U/R) = \sum_{i=1}^{n} G(X_i) / |U| = \sum_{i=1}^{n} |X_i| / |U|^2 \quad (2)$$

If there is an equal relation in U/R, i.e. $R = \omega$, then $G(U/R) = 1/|U|$, and the granularity reaches the minimum; if there is a universe of discourse relation in U/R, i.e. $R = \delta$, then $G(U/R) = 1$, and granularity reaches the maximum. Generally, $1/|U| \le G(U/R) \le 1$, and the knowledge granularity can denote the discriminability of the knowledge. If $(u,v) \in X_i$, the objects are undiscriminable and belong to one equivalence class (the knowledge granularity), otherwise, they are discriminable, and belong to different equivalence classes X_i. Thus $G(U/R)$ can also denote the likelihood that two objects in U are undiscriminable, and the bigger the $G(U/R)$ is, the higher the likelihood is.

2.3 The knowledge granularity entropy

It is known to all that the entropy is a measurement of the knowledge granulation. The larger the granularity is and the more roughly the objects are partitioned, the smaller the entropy is; on the contrary, the smaller the granularity is and the more precisely the partition is, the larger the entropy is. Thus the knowledge granularity entropy can be defined according to the definition of the information entropy.

Definition 2 [10]**:**

Assume that $U/R=\{X_1,X_2,X_3,\cdots,X_n\}$ is the knowledge defined in the universe of discourse U. Then the knowledge granularity entropy is:

$$I(U/R)=-\sum_{i=1}^{n}G(X_i)\log G(X_i) \quad (3)$$

Definition 3 [10]**:**

The relative granularity entropy for the knowledge $Q(U/IND(Q)=|Y_1,Y_2,\cdots,Y_m|)$ relative to $P(U/IND(P)=|X_1,X_2,\cdots,X_n|)$ is:

$$I(Q/P)=-\sum_{i=1}^{n}G(X_i)\sum_{j}^{m}(G(Y_j/X_i)\log(G(Y_j/X_i))) \quad (4)$$

Where

$$G(Y_j/X_i)=|Y_j\cap X_i|/X_i, i=1,2,\cdots,n; j=1,2,\cdots,m \quad .$$

Though the classic theory of the rough set discriminates classification precisions of different knowledge, not all of condition can be discriminated at times.

For example, a rough set X={A , B , C , D , E , F}, $R_-(X)$ = {A , B , C , D}, $R^-(X)$ = {A , B , C , D , E , F , G , H , I}. The approximation regions can be obtained by the equivalence class as follow:

A_1 = {[A , B , C , D] , [E , G , H] , [F , I]}

A_2 = {[A , B] , [C , D] , [E , G , H] , [F , I]}

A_3 = {[A] , [B] , [C] , [D] , [E , G, H] , [F , I]}

The classes have the same upper and lower approximation. According to the calculating formula of rough set, their rough concentration is the same. However, it obviously shows that the knowledge rough concentration of A1, A2, A3 are different. Thus, rough set has limitation for the definition of knowledge granularity.

The knowledge granularity entropy can solve the limitation of rough set. The results calculated by granularity entropy are as follow:

I (A 1) =-[(4/9) log (4/9) + (3/9) log (3/9) + (2/9) log (2/9)] =0.4607

I (A 2) =-[(2/9) log (2/9) + (2/9) log (2/9) + (3/9) log (3/9) + (2/9) log (2/9)] =0.594

I (A 3) =-[4 (1/9) log (1/9) + (3/9) log (3/9) + (2/9) log (2/9)] =0.728

The results above show that compared with the traditional rough set, the granularity entropy, as the evaluation information criteria, is superior. The granularity entropy lets the "particle" to have level conception and to obtain quantitative analysis information so that the reduction of the information domain is the minimum and the best. They also show that the larger entropy is, the more precise classification has.

3 The calculation of the significance of symptomatic parameters

In the repository of the mechanical fault diagnosis, the attribute set is composed of the symptomatic parameter set and the fault set. As far as the decision table is concerned, the symptomatic parameter set is exactly the conditional attribute set, and the mechanical fault set the decision attribute set. In the symptomatic parameter set of the decision table for the mechanical failure diagnosis, the capturing difficulty and reliability of every single symptomatic parameter is different from one another in its reliability and capturing difficulty. Looking at these two aspects, now reorder the symptomatic parameter set following the rule that parameters with lower catching difficulty and higher reliability are moved forward. The significance of symptomatic parameters is obtained according to the estimation of its granularity entropy.

Definition 4 [10]**:**

Given a knowledge system $S=(U,A,V,f)$, the significance of the attribute $a\in A$ in A is:

$$Sig_A(a)=I(U/(A-\{a\}))-I(U/A) \tag{5}$$

Equation (5) denotes that the significance of the attribute $a\in A$ is measured by the information change on the granularity entropy after $\{a\}$ is removed from A.

Theorem 1 [10]**:**

The necessary and sufficient condition of the conclusion that the attribute $a\in A$ is necessary in A is $Sig_A(a)>0$.

Theorem 2[10]**:**

Specify a knowledge system $S=(U,A,V,f)$, $P\subset A$. The necessary and sufficient condition of $U/IND(P)=U/IND(A)$ is $I(P)=I(A)$.

Theorem 3[10]**:**

Specify a knowledge system $S=(U,A,V,f)$. If $A=C\cup D$, where C is a finite set of conditional attributes, D a finite set of decision attributes, and the universe of discourse U in A is relatively consistent with D, then the necessary and sufficient condition of that the attribute P in A is unnecessary for C relative to D is $I(D/C)=I(D/\{C-P\})$.

Definition 5[10]**:**

Specify a knowledge system $S=(U,A,V,f)$. If $A=C\cup D$, where C is a finite set of conditional attributes, D a finite set of decision attributes, and $P\subset C$, then the significance of any attribute $a\in C-P$ relative to the attribute set P is:

$$Sig_P(a)=I(U/(P\cup\{a\}))-I(U/P) \tag{6}$$

Definition 6 [10]**:**

Specify a knowledge system $S=(U,A,V,f)$. If $A=C\cup D$, where C a finite set of conditional is attributes, D a finite set of decision attributes, and $P\subset C$, then the significance of any attribute $a\in C-P$ relative to the decision attribute D is:

$$Sig\ (a,P,D)=I(D/P)-I(D/(P\cup\{a\})) \tag{7}$$

If $P=\Phi$, then $Sig\ (a,D)=I(U/D)-I(D/(P\cup\{a\}))$ is named the mutual information between the attribute a and decision attribute D.

The significance of the symptomatic parameters calculated based on the granularity entropy can be used as the criterion during the selection of the symptomatic parameters, and the process of the optimal symptomatic parameter set is as follows:

Step 1:

Calculate $I(D/C)$, and get the granularity entropy of the symptomatic parameter set relative to the fault set in the decision table. D is the fault set, and C the symptomatic parameter set.

Step 2:

Calculate the granularity entropy $I(U/\{c\})$ of each symptomatic parameter in the set C where $c\in C$, and set P as the symptomatic parameter corresponding to $\max\{I(U/\{c\})\}$.

Step 3:

Judge if $I(D/P)=I(D/C)$: If the equation is established, jump to Step 6; else to Step 4.

Step 4:

Calculate each $Sig_P(c)$ value of $c\in C-P$, and take every ci that meets the equation $Sig_P(ci) = \{\max(Sig_P(c)) | c \in C - P\}$.

Step 5:

Set $P \leftarrow P \cup \{ci\}$, and then jump to Step 3.

Step 6:

Set $RED(C) = P$, and output the optimal reduction $RED(C)$.

The flow graph of the optimal symptomatic parameter set is as follows:

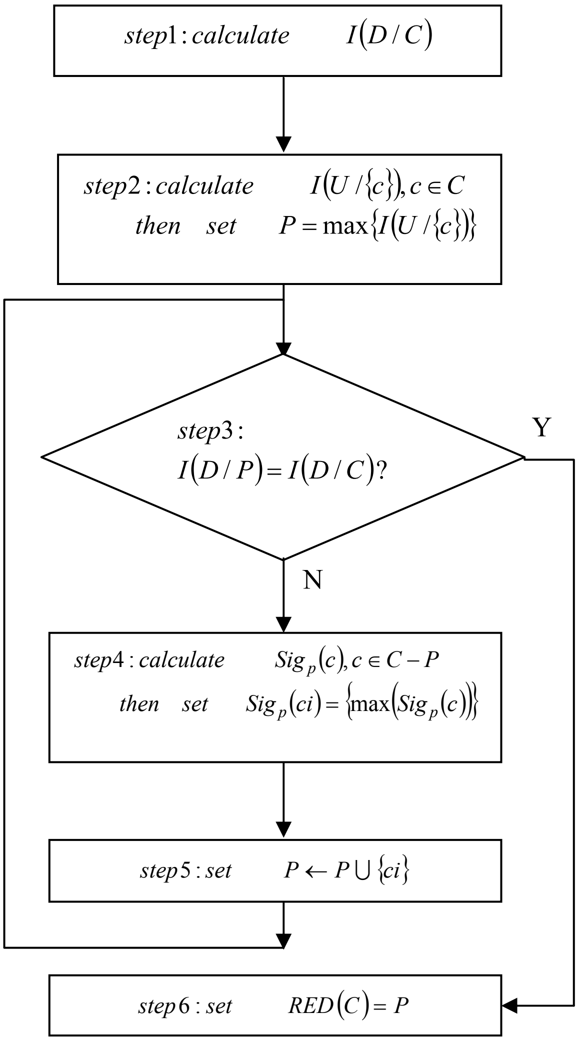

Figure 1 the flow graph of the optimal symptomatic parameter set

Note: In the process of feature reduction, if more than one maximum value is obtained, the former comer in the symptomatic parameter set is prior to the latter one.

The core of attributes is not taken into account in this algorithm of reduction. After reducing the decision set following this algorithm, the symptomatic parameter set obtained is not only optimal but the smallest. Also, because the traditional rough set reduction method, such as Pawlak [4,5], MIBARK [11], etc., is based on core calculation, its reduction becomes more complex and takes more time.

4 Two Instances Analysis

In order to clarify how to get the optimal decision system and verify the effectiveness of the method above, we take the diagnosis data of the reciprocating engine and diesel engine for example.

4.1 The reciprocating compressor fault set

The data of Table 1 is tested on the L model reciprocating compressor, is shown as figure 2-5. The high frequency accelerometers (PCB 608A11 Model) are installed on the each cylinder. The dynamic pressure sensors (Bently 166815 Model) are installed on the top dead center and the bottom dead center of each cylinder. The X and Y direction eddy sensors (Bently 11mm Model) are installed on the stuffing box. The RTD temperature sensors are installed on the gas valves cover. The keyway is corresponding with the top dead center of the low pressure cylinder, and the eddy sensor (Bently 11mm Model) faces to keyway of the flywheel. The sampling frequency of all data is 10240. The sampling points are 6144. The fault data of the Table 1 are from artificial damage to the machine parts, such as the gas valve, cylinder bush, guide ring and so on.

The vibration data, pressure data, piston rod position data, and valve temperature data, are obtained and processed by the signal acquisition processor system, which is shown as figure 6.

The noise is canceled by hardware low-pass and software mean value band-pass filter method. The symptomatic parameters, such as shock number, peak value, piston rod run-out value, etc. are calculated by the signal time-domain and spectrum-domain analysis method [12-14].

Figure 2 the L model reciprocating compressor and the sensors

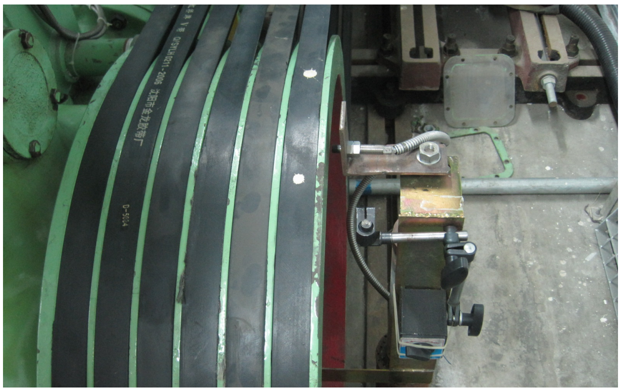

Figure 3 the L model reciprocating compressor and the key phase sensors

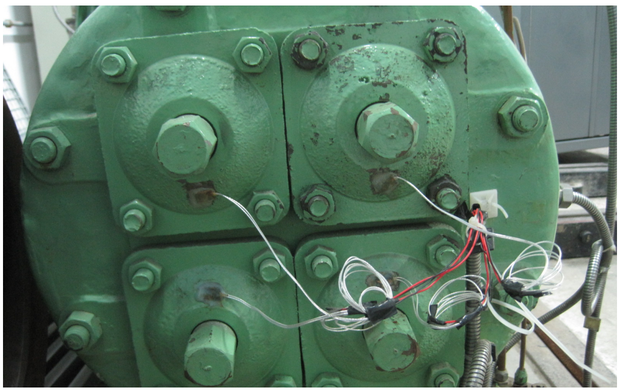

Figure 4 the L model reciprocating compressor and the gas valve temperature sensors

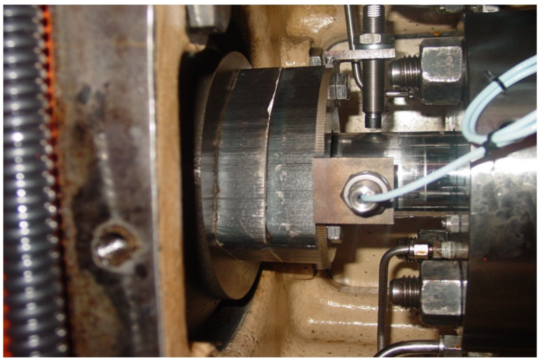

Figure 5 the L model reciprocating compressor and the piston rod position sensors

Figure 6 the signal acquisition processor system

All the symptomatic parameters are shown in Table 1:

c1: the shock number of the vibration (1:2-4; 2:6-8; 3:9-16);

c2: the amplitude of vibration waveform (1: increase; 2: stable);

c3: the amplitude of vibration spectrum (1: high frequency increase; 2: low frequency increase; 3: unstable; 4: over-all increase; 5: excitation frequency increase);

Table 1 the decision table for reciprocating engine fault diagnosis

U	c1	c2	c3	c4	c5	c6	c7	d
1	1	1	1	2	2	2	3	d1
2	1	1	1	2	2	2	3	d2
3	1	2	3	1	2	2	3	d3

4	1	2	3	1	2	2	3	d4
5	3	1	5	3	1	1	3	d5
6	2	1	1	1	1	1	3	d6
7	2	1	5	1	1	1	3	d7
8	2	1	2	3	2	2	4	d8
9	2	1	2	1	2	2	4	d9
10	2	1	6	3	2	2	4	d10

U	c8	c9	c10	c11	c12	c13	d
1	2	3	3	2	1	1	d1
2	2	3	3	1	2	1	d2
3	1	2	1	1	1	1	d3
4	1	1	2	1	1	1	d4
5	1	2	1	2	2	1	d5
6	2	3	3	1	1	2	d6
7	2	3	3	1	1	2	d7
8	2	3	3	1	1	2	d8
9	2	3	3	1	1	2	d9
10	2	3	3	1	1	2	d10

c4: the angle of vibration peak (1: stable; 2: delay; 3: over-all);

c5: the horizontal direction run-out of piston rod (1: unstable; 2: stable);

c6: the vertical direction run-out of piston rod (1: unstable; 2: stable);

c7: the orbit of piston rod (1: long axis changed; 2: short axis changed; 3: two axis changed; 4: constant);

c8: the temperature of valve (1: increase; 2: constant);

c9: the expansion speed of dynamic pressure (1: slow; 2: fast; 3: constant);

c10: the compress speed of dynamic pressure (1: slow; 2: fast; 3: constant);

c11: the intake time of dynamic pressure (1: stable; 2: unstable);

c12: the discharge time of dynamic pressure (1: stable; 2: unstable);

c13: the indicated power graph (1: changed; 2: constant);

d denotes the reciprocating engine faults, with d1…d10 respectively: plate block of inlet valve, plate block of outlet valve, leak of inlet valve, leak of outlet valve, scuffing of cylinder bore, striking of cylinder, crack of guide ring, loose of crosshead pin, wear of crosshead pin block, mechanical resonance.

C={c1,c2,c3,c4,c5,c6,c7,c8,c9,c10,c11,c12,c13} is the symptomatic parameter set of diagnostic decisions, and D={d1,d2,d3,d4,d5,d6,d7,d8,d9,d10} the fault set.

The reducing process mentioned in the third part is adopted to calculate by MATLAB R2010a software:

$U/IND(C)=\{\{1\},\{2\},\{3\},\{4\},\{5\},\{6\},\{7\},\{8\},\{9\},\{10\},\{11\},\{12\},\{13\}\}$

$U/IND(D)=\{\{1\},\{2\},\{3\},\{4\},\{5\},\{6\},\{7\},\{8\},\{9\},\{10\}\}$

1） Calculate $I(D/C)=0$

2） Calculate $I(U/\{c\})$ respectively. The value of

$\max\{I(U/\{ci\})\}$ is $I(U/\{c3\})=0.6461$,

so $P=\{c3\}$.

3） $I(D/\{c3\})=0.3238$, not equal to $I(D/C)$

4） Calculate $Sig_P(c)$ respectively,

where

$c\in\{c1,c2,c4,c5,c6,c7,c8,c9,c10,c11,c12,c13\}$, and

the result is $Sig_P(c4)=\max\{Sig_P(c)\}$, i.e.

$P\leftarrow P\cup\{c4\}$

5） $I(D/\{c3,c4\})=0.1204$, not equal to $I(D/C)$.

6） Calculate $Sig_P(c)$ respectively,

where

$c \in \{c1, c2, c5, c6, c7, c8, c9, c10, c11, c12, c13\}$,

and the result is $Sig_P(c9) = \max\{Sig_P(c)\}$,i.e.

$P \leftarrow P \cup \{c9\}$

7） $I(D/\{c3, c4, c9\}) = 0.0602$, not equal to $I(D/C)$.

8） Calculate $Sig_P(c)$ respectively,

where $c \in \{c1, c2, c5, c6, c7, c8, c10, c11, c12, c13\}$, and

the result is $Sig_P(c11) = \max\{Sig_P(c)\}$,which

is $P \leftarrow P \cup \{c11\}$

9） $I(D/\{c3, c4, c9, c11\}) = 0$,equal to $I(D/C)$

10) The final optimal reduction of the decision table is $RED(C) = \{\mathrm{c3, c4, c9, c11}\}$.

According to the software Rosetta developed by the Warsaw University and the Norway University of Science and Technology [15], the decision table for the fault diagnosis is reduced to {c3,c4,c9,c11}, {c3, c4, c9, c12}, {c3, c4, c10, c11}, {c3, c4, c10, c12}, a total of four relatively minimum reductions.

Thus it is difficult to select one from them. However, if we adopt the algorithm above instead, we will obtain the smallest and optimal reduction {c3, c4, c9, c11}. Table 2 below shows the optimal decision for the reciprocating engine fault diagnosis. The new method can be used to plant condition monitoring and fault diagnosis system for further proof its effectiveness.

Table 2 the optimal decision table for reciprocating engine fault diagnosis

U	c3	c4	c9	c11	d
1	1	2	3	3	d1
2	1	2	2	1	d2
3	3	1	2	3	d3
4	3	1	3	3	d4
5	5	3	3	3	d5
6	1	1	2	1	d6
7	5	1	1	1	d7
8	2	3	2	1	d8
9	2	1	1	1	d9
10	6	3	1	1	d10

4.2 The diesel engine fault set

Table 3 shows how the fault of the oil circuit system in a diesel engie is related to the waveform features of the pressure in the oil pipe, the instance data is tested on a 4315 model diesel engine. The data of the table 3 is derived from the reference [16]. The changes in the pressure waveform can reflect all kinds of faults of the oil circuit system.

Table 3 the relationship between the fault of the oil circuit system in a diesel and the waveform features of the pressure in the oil pipe

e	s1	s2	s3	s4	s5	s6
e1	1	1	2	2	1	1
e2	2	2	2	2	3	1
e3	2	3	1	1	2	1
e4	2	3	2	1	1	1
e5	3	2	1	1	2	1
e6	1	1	2	2	1	1
e7	1	2	2	1	2	2
e8	3	1	2	2	1	2
e9	1	1	2	2	3	3
e10	3	1	2	2	1	3

P_r (s1): the residual pressure of oil pipe at the start point of ejection (1: down; 2: up; 3: remain);

P_{max} (s2): the maximum ejection pressure (1: down; 2: up; 3: remain);

P_2 (s3): the secondary ejection pressure (1: yes; 2: no);

P_3 (s4): the third peak amplitude of ejection pressure (1: yes; 2: no);

$\Delta P \bullet \Delta\theta^{-1}$ (s5): the pressure rise rate (1: down; 2: up; 3: remain);

θ_s (s6): the pre-ejection angle (1: down; 2: up; 3: remain).

e={e1,e2,e3,e4,e5,e6,e7,e8,e9,e10}: fault of the oil circuit system.

e1: oil-fuel injector needle-valve abrasion.

e2: oil-fuel injector needle-valve lock.

e3: early in oil supply.

e4: delay in oil supply.

e5: excessively high oil injection pressure.

e6: excessively low oil injection pressure.

e7: excess oil supply.

e8: lack oil supply.

e9: abrasion on the dial of the ejection valve.

e10: leak in oil connection.

Reference [10] has adopted the method of the attribute reduction based on the rough set theory to simplify Table 3, and obtained four smallest attribute sets:{s1,s2,s6}, {s1,s4,s6}, {s1,s5,s6} and {s2,s5,s6}, with a uniform categorical measure of 0.8. Thus it is impossible to determine which one is the optimal. Instead, following the granularity algorithm presented in this paper, we can obtain the smallest and optimal attribute set: {s1, s2, s6}.

Two instances above show that the granularity reduction method lets the "particle" to have level conception and to obtain quantitative analysis information so that the reduction of the information domain is the minimum and the best.

5 Conclusion

The further study and extended application of the symptomatic parameter granularity in the mechanical fault diagnosis have given the optimal feature reduction. The conclusions are as follows:

1) The principle of granularity is a new feature reduction method, and is effective for fault diagnosis.
2) The new feature reduction method based on granularity principle is superior to rough set.
3) The new feature reduction method is helpful for fault diagnosis expert system.
4) The deduction process can be simplified, and the efficiency of diagnosis will be improved as well as the cost cut down.

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