APPLICATION OF ROUGH SET THEORY TO MAINTENANCE LEVEL DECISION-MAKING FOR AERO-ENGINE MODULES BASED ON INCREMENTAL KNOWLEDGE LEARNING

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Abstract: The maintenance of an aero-engine usually includes three levels, and the maintenance cost and period greatly differ depending on the different maintenance levels. To plan a reasonable maintenance budget program, airlines would like to predict the maintenance level of aero-engine before repairing in terms of performance parameters, which can provide more economic benefits. The maintenance level decision rules are mined using the historical maintenance data of a civil aero-engine based on the rough set theory, and a variety of possible models of updating rules produced by newly increased maintenance cases added to the historical maintenance case database are investigated by the means of incremental machine learning. The continuously updated rules can provide reasonable guidance suggestions for engineers and decision support for planning a maintenance budget program before repairing. The results of an example show that the decision rules become more typical and robust, and they are more accurate to predict the maintenance level of an aero-engine module as the maintenance data increase, which illustrates the feasibility of the represented method.

Key words: civil aero-engine; maintenance level decision-making; rough set; incremental learning

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INTRODUCTION

As the service cycles and the operating time of aero-engines increase, their performance will slowly deteriorate. When the aero-engine's performance decreases below a certain level, it is not suitable for subsequent service and must be removed for maintenance[1-2]. The maintenance of an aero-engine usually includes visual check, performance overhaul and full overhaul, and the maintenance cost is a big part of the airline's expenses and greatly differs depending on the dirfferent maintenance levels. If the maintenance level is set to a high level before repairing, it involves a long maintenance period schedules, high costs budget, excessive remainder life loss of components, and the need for more back-up aero-engines, which will critically reduce the economic benefits of airlines. If the maintenance level is set to a low level before repairing, the time between maintenance and operations is shortened, which leads to high maintenance costs per flight hour and reduces the safety level of the aero-engine operation[3-5]. Therefore, to ensure the safe operation of aero-engines while keeping low maintenance costs, it is very important for airlines to decide the appropriate maintenance level of their aero-engine modules.

At present, engineers determine the technology status of an aero-engine by routinely monitoring the performance parameters, and decide on the appropriate moment for the removal and maintenance of the engine according to the aero-engine's manual and the practical engineering experience[6]. In fact, the aero-engine is a complicated system, and the parameters used in monitoring are appropriate for the entirety of aero-engine, while the maintenance level is associated with the

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modules of the aero-engine. The historical data of aero-engine maintenance levels are huge but decentralized, so it is difficult for engineers to decide on the maintenance level from historical maintenance data based on their engineering experience. Therefore, it is necessary to build an intelligent decision supporting system to provide reasonable guidance suggestions for engineers using the continuously growing historical maintenance data[3-4]. In this paper, the relationship of the performance parameters and maintenance level of the aero-engine modules in historical maintenance data is studied using the rough set theory, and the decision rules for maintenance level are mined by means of incremental knowledge learning.

1 BRIEF INTRODUCTION OF ROUGH SET THEORY

1.1 Basic definitions of rough sets

Definition 1: The relationship equation $K=(U,C,D,V,f)$ is defined as a knowledge representation system, where U is a universe, C a set consisting of condition attributes, D a set consisting of decision-making attributes, and $C\cap D=R$, V a set of values of all the attributes, and f a function $f: a(x)\rightarrow V_a$, here x is an object in $U(x\in U)$, a an attribute in $C\cap D$, $a(x)$ an attribute value of object x relative to attribute a, and V_a a set of values of the attribute a.

Definition 2: Assuming B is a subset of attributes R, the formula

$$\mathrm{IND}(B)=\{(x,y)\in U\times U,\forall b\in B,b(x)=b(y)\}$$

is defined as an indiscernibility relation of B[7]. The universe U is divided into $U/\mathrm{IND}(C)=\{X_1,X_2,\cdots,X_n\}$ by the indiscernibility relationship of C, where X_i is the ith condition equivalence class of knowledge representation system. The indiscernibility relation of D is similar to that of C, and $U/\mathrm{IND}(D)=\{Y_1,Y_2,\cdots,Y_m\}$, where $Y_l=\{x\in U \mid D(x)=l\}(l=1,2,\cdots,m)$[7-8].

Definition 3: Assuming B is an arbitrary subset of attributes C, the formula

$$\mathrm{IND}(\theta_B(X))=\{(X_\alpha,X_\beta)\in U/\mathrm{IND}(B),\&\ \theta_B(X_\alpha)=\theta_B(X_\beta)\}$$

is defined as the indiscernibility relationship of the θ-decision value of K, where $\theta_B(x)=\{l \mid \exists x'\in U, x'\mathrm{IND}(B)x, \&\ D(x')=l\}$ is a B-classified function of the decision value of K, which means if two objects x and x' belong to the equivalence class $X_i(x,x'\in X_i)$, X_i meets with $\vee Y_l(X_i\rightarrow\vee Y_l)$. The universe U is divided into $\{Q_1,Q_2,\cdots,Q_r\}$ again by the indiscernibility relationship of the θ-decision value of K, and any incompatible system is transformed into a compatible system by this relationship.

Definition 4: Assuming the indiscernibility relation of C is expressed as $U/\mathrm{IND}(C)=\{X_1,X_2,\cdots,X_n\}$ in K, the θ-decision matrix of K is defined as

$$\boldsymbol{M}(K)=(m_{ij})_{n\times n} \tag{1}$$

where $m_{ij}=\{a\in C, a(X_i)\neq a(X_j)\ \&\ D(X_i)\neq D(X_j)\}$, i, $j=1,2,\cdots,n$.

Definition 5: Assuming $(m_{ij})_{n\times n}$ is the element of the θ-decision matrix of K, and A_i is defined as a decision function of condition equivalence class X_i

$$A_i=\bigwedge_j \bigvee_{a\in m_{ij}} a \tag{2}$$

where $\wedge$ and $\vee$ denote the conjunction and disjunction of the Boolean operation, respectively.

1.2 Evaluation of rules

Generally, two intension indexes are used to evaluate rules being strong or weak: One is the confidence of rules and the other is the coverage of rules[9]. The confidence expression indicates the reliability of the specific rule for the decision-making, shown as

$$CF(X\rightarrow Y)=|X\cap Y|/|X| \tag{3}$$

where $X\rightarrow Y$ represents a rule, and X and Y are the left-hand side (LHS) and right-hand side (RHS) of the rule, respectively [10]. The coverage expression is

$$CV(X\rightarrow Y)=|X\cap Y|/|Y| \tag{4}$$

Eq. (4) refers to the supporting proportion of the specific rule accounting for the relevant decision class.

In Eqs. (3,4), X and Y stand for a certain condition equivalence class and decision equivalence class, respectively, and $|\cdot|$ indicates the radix of "•". These two indexes have a range of [0, 1] and we select the effective rules with first higher confidence value and then greater coverage value[9].

2 INCREMENTAL LEARNING MODELS

When a newly increased maintenance decision case, which is hereinafter referred to as a newly increases object x, is added to the historical maintenance case database (namely, the knowledge representation system mentioned above), it may produce compatible or incompatible, and certain or uncertain decision rules[11-14]. Regardless of any situation ahead, the new object will update the existing rules. This paper discusses following four events that arise when a new object x is added ($x: x_\alpha \rightarrow x_\beta$, where x_α and x_β are LHS and RHS of the maintenance decision case, respectively).

2.1 Event 1

In the event of $x_\alpha \in X_i (i=1,2,\cdots,n)$ and $x_\beta \in Y_l (l=1, 2,\cdots,m)$, which means that the condition equivalence class X_i and the decision equivalence class Y_l of the existing rules set are not changed by the newly increased object, the rules will not be updated, but the intension of some existing rules will change. Four possible cases are listed below.

(1) If $X_i \cap Y_l = X_i$, the updated intension is following.

For$(X_i \rightarrow Y_l)$, the updated confidence $CF' = 1$(same as the current), and the updated coverage $CV' = (|X_i \cap Y_l|+1)/(|Y_l|+1)$. For $(X_t \rightarrow Y_l)$ $(t \neq i)$, $CF' = (|X_t \cap Y_l|)/(|X_t|)$ (same as the current), and $CV' = (|X_t \cap Y_l|)/(|Y_l|+1)$.

(2) If $X_i \cap Y_l \neq \Phi$ & $X_i \cap Y_l \neq X_i$, the updated intension is following.

For $(X_i \rightarrow Y_l)$, $CF' = (|X_i \cap Y_l|+1)/(|X_i|+1)$ and $CV' = (|X_i \cap Y_l|+1)/(|Y_l|+1)$. For $(X_t \rightarrow Y_l)$ $(t \neq i)$, $CF' = (|X_t \cap Y_l|)/(|X_t|)$ (same as the current) and $CV' = (|X_t \cap Y_l|)/(|Y_l|+1)$. For $(X_i \rightarrow Y_s)$ $(s \neq l)$, $CF' = (|X_i \cap Y_s|)/(|X_i|+1)$ and $CV' = (|X_i \cap Y_s|)/(|Y_s|)$ (same as the current).

(3) If $x_\alpha \in X_i (i=1,2,\cdots,n), x_\beta \in Y_{l'} \subset \mathrm{IND}/(D) (l' \in l, l=1,2,\cdots,m)$, and $X_i \cap Y_{l'} = \Phi$, supposing $X_i \subseteq Q_p = \bigcup_{ip} X_{ip}$, X_i meets $X_i \subseteq Q_q = \bigcup_{iq} X_{iq} (q \neq p)$ & $Q_q \subset \mathrm{IND}(\theta(X))$. Now, the existing elements $m_{iq,i} (iq<i)$ and $m_{i,iq} (i<iq)$ are deleted, and new elements $m_{ip,i}$ and $m_{i,ip}$ are added into the θ-decision matrix. The decision functions of X_i, X_{ip} and X_{iq} are updated and the others are same as the current. Meanwhile, X_i, Q_p, and Q_q are expressed as

$$X_i = X_i \cup \{x\},\ Q_p = \bigcup_{ip \neq i} X_{ip},\ Q_q = \bigcup_{iq} X_{iq} \cup X_i$$

For $(X_i \rightarrow Y_{l'})$, $CF' = 1/(|X_i|+1)$ and $CV' = 1/(|Y_{l'}|+1)$. For $(X_i \rightarrow Y_l)$ $(l \neq l')$, $CF' = (|X_i \cap Y_l|)/(|X_i|+1)$ and $CV' = (|X_t \cap Y_l|)/|Y_l|$ (same as the current). For $(X_k \rightarrow Y_{l'})$ $(k \neq i)$, $CF' = (|X_k \cap Y_{l'}|)/|X_k|$ (same as the current) and $CV' = (|X_k \cap Y_{l'}|)/(|Y_{l'}|+1)$.

(4) If $x_\alpha \in X_i (i=1,2,\cdots,n)$, $x_\beta \in Y_{l'} \subset \mathrm{IND}/(D) (l' \in l, l=1,2,\cdots,m)$, and $X_i \cap Y_{l'} = \Phi$, supposing $X_i \subseteq Q_p = \bigcup_{ip} X_{ip}$, X_i meets $X_i \subseteq Q_q \not\subset \mathrm{IND}(\theta(X))$. Now, the new elements $m_{ip,i}$ and $m_{i,ip}$ are added into the θ-decision matrix. The decision function of X_{ip} is updated and the others are the same as the current. Meanwhile, X_i, Q_p, and Q_q are expressed as $X_i = X_i \cup \{x\}$, the new θ-decision equivalence class $Q_q = Q_{r+1}$, and the existing θ-decision equivalence class $Q_p = (\bigcup_{ip \neq i} X_{ip})$, respectively.

For $(X_i \rightarrow Y_{l'})$, $CF' = 1/(|X_i|+1)$ and $CV' = 1/(|Y_{l'}|+1)$. For $(X_i \rightarrow Y_l)(l \neq l')$, $CF' = (|X_i \cap Y_l|)/(|X_i|+1)$ and $CV' = (|X_t \cap Y_l|)/|Y_l|$ (same as the current). For $(X_k \rightarrow Y_{l'})$ $(k \neq i)$, $CF' = (|X_k \cap Y_{l'}|)/|X_k|$ (same as the current) and $CV' = (|X_k \cap Y_{l'}|)/(|Y_{l'}|+1)$.

2.2 Event 2

In the event of $x_\alpha \notin X_i (i=1,2,\cdots,n)$ and $x_\beta \in Y_l (l=1, 2,\cdots,m)$, the new condition equivalence class is formed by the newly increased object x.

Supposing the new condition equivalence class defined as

$$X_{n+1} \in Q_p \ \&\ Q_p = (\bigcup_{ip} X_{ip}) \in U/\mathrm{IND}(\theta_C(X))$$

$$p=1,2,\cdots,r$$

a new increased column X_{n+1} is added to the decision class Q_p of the θ-decision matrix, and the element $m_{i,n+1}(i=1,2,\cdots,n \,\&\, i\neq ip)$ of the decision function of X_{n+1} is produced. Then, the decision function is updated and $Q_p=(\bigcup_{ip} X_{ip} \cup X_{n+1}) \in (U \cup \{X_{n+1}\})/\mathrm{IND}(\theta_C(X))$.

For $(X_{n+1}\rightarrow Y_l)$, $CF'=1$ (same as the current) and $CV'=1/(|Y_l|+1)$. For $(X_i\rightarrow Y_l)$ $(i=1,2,\cdots,n)$, $CF'=|X_i\cap Y_l|/|X_i|$ (same as the current) and $CV'=|X_i\cap Y_l|/(|Y_l|+1)$.

2.3 Event 3

In the event of $x_\alpha\in X_i\,(i=1,2,\cdots,n)$ and $x_\beta\notin Y_l(l=1,2,\cdots,m)$, the new decision equivalence class is formed by the newly increased object x.

Supposing X_i and Q_p are obtained by

$$X_i\in Q_p \,\&\, Q_p=(\bigcup_{ip} X_{ip})\in U/\mathrm{IND}(\theta_C(X))$$

$$ip_{\min}<i<ip_{\max}$$

the newly increased elememts $m_{ip,i}$ and $m_{i,ip}$ are added to the θ-decision matrix, shown as

$$m_{ip,i}=\{a\in C, a(X_i)\neq a(X_{ip})\} \quad ip<i$$

$$m_{i,ip}=\{a\in C, a(X_i)\neq a(X_{ip})\} \quad i<ip$$

The decision functions of X_i and X_{ip} are updated and the others are the same as the current. Meanwhile, X_i, Q_p, and Q_q are expressed as $X_i=X_i\cup\{x\}$, the new θ-decision equivalence class $Q_q=Q_{r+1}$, and the existing θ-decision equivalence class $Q_p=(\bigcup_{ip\neq i} X_{ip})$, respectively.

2.4 Event 4

In the event of $x_\alpha\notin X_i\,(i=1,2,\cdots,n)$ and $x_\beta\notin Y_l(l=1,2,\cdots,m)$, the new condition equivalence class X_{n+1} and decision equivalence class Y_{m+1} are formed because of the newly increased object x.

The decision matrix element $m_{i,n+1}(i=1,2,\cdots,n)$ of the equivalence class X_{n+1}, which is added into the θ-decision matrix as $(n+1)$th column, is produced and then the θ-decision matrix after being updated is converted into a $(n+1)\times(n+1)$-order matrix.

For $(X_{n+1}\rightarrow Y_{m+1})$, $CF'=CV'=1$. For $(X_i\rightarrow Y_l)$ $(i=1,2,\cdots,n,\ l=1,2,\cdots,m)$, $CF'=|X_i\cap Y_l|/(|X_i|)$ (same as the current) and $CV'=|X_i\cap Y_l|/|Y_l|$ (same as the current).

3 REDUCTION AND COMBINATION OF RULES

For the updated decision rules: $(X_i\rightarrow Y_l)(i=1,2,\cdots,n,j=1,2,\cdots,m)$, if their intensions CF' and CV' are indicated by

$$CF'(X_i\rightarrow Y_l)=|X_i\cap Y_l|/|X_i|$$

$$CV'(X_i\rightarrow Y_l)=|X_i\cap Y_l|/|Y_l|$$

the new rule intensions after combination of the same decision functions are shown as follows[9,15]

$$CF'(\overline{X}\rightarrow Y_{l'})=\sum_{i=1}^{w}|X_{i'}\cap Y_{l'}|/\sum_{i=1}^{w}|X_{i'}|$$

$$CV'(\overline{X}\rightarrow Y_{l'})=\sum_{i=1}^{w}|X_{i'}\cap Y_{l'}|/|Y_{l'}|$$

where the same decision functions $X_{i'}(i=1,2,\cdots,w)$ are described as $\overline{X}$ and w is the number of the same decision functions, $Y_{l'}$ a certain decision equivalence class and $Y_{l'}\in U/\mathrm{IND}(D)$.

After combination of rules and the intension update of the same rule in different condition equivalence classes corresponding to a certain decision class, the generalized rules are selected, and the set of typical rules is created.

4 EXAMPLES AND RESULTS

Based on previous studies[1,3], this paper chooses the aero-engine CF6-80C2A5 that is widely used in airlines, and selects the maintenance data of China Eastern Airline in a set period of time. The civil aviation aero-engine is composed of five modules: Low-pressure compressor, low-pressure turbine, high-pressure compressor, high-pressure turbine, and combustor. And the maintenance levels include visual check, performance overhaul, and full overhaul. The performance parameters are described by DEGT, DN2, DWF, ZVB1F, ZVB2R, GEGTMC, and GN2MC, in which DEGT, DN2, and DWF are the most important parameters[2]. Consequently, DEGT, DN2 and DWF are regarded as condition attributes and correspond to a, b and c of the condition attribute set C in the numerical example, respectively. The high-pressure turbine (HPT) is regarded as a decision attribute, and corresponds to Y of the decision attribute set D in the following case. The discretization of attribute values is taken from Ref. [3], and the attribute value set V is $V=\{a_1, a_2, a_3, b_1, b_2, b_3, c_1, c_2, c_3, Y_1, Y_2, Y_3\}$, where a_i, b_i and c_i are condition attribute values and Y_i the decision attribute values ($i=1,2,3$). Table 1 is the knowledge system formed by first 20 objects from Ref. [3].

Table 1 Historical HPT data of civil aero-engine CF6-80C2A5

No.	Condition attribute (value)			Decision attribute (value)	No.	Condition attribute (value)			Decision attribute (value)
	a	b	c	Y		a	b	c	Y
1	a_2	b_1	c_2	Y_3	11	a_2	b_3	c_2	Y_3
2	a_2	b_2	c_2	Y_3	12	a_3	b_1	c_3	Y_3
3	a_3	b_2	c_3	Y_3	13	a_3	b_1	c_3	Y_3
4	a_2	b_3	c_2	Y_2	14	a_1	b_1	c_2	Y_2
5	a_2	b_2	c_2	Y_2	15	a_3	b_1	c_3	Y_3
6	a_2	b_1	c_3	Y_3	16	a_2	b_3	c_1	Y_1
7	a_1	b_2	c_1	Y_2	17	a_3	b_1	c_2	Y_3
8	a_2	b_2	c_2	Y_2	18	a_1	b_3	c_2	Y_2
9	a_3	b_3	c_2	Y_3	19	a_3	b_1	c_3	Y_3
10	a_1	b_3	c_1	Y_2	20	a_2	b_3	c_1	Y_2

Obviously, Table 1 is an incompatible decision system. The objects of the same attribute values including the condition attributes and decision attributes together are combined, and the θ-decision matrix is formed as Table 2 in terms of the front description.

If a newly increased object $x^{(1)}$ is presented as ($a_2 \wedge b_2 \wedge c_1 \rightarrow Y_1$), the condition attribute value $a_2 \wedge b_2 \wedge c_1$ displays that the levels of DEGT, DN2 and DWF are 2, 3 and 1, respectively. The maintenance level of HTP will be decided according to the condition attribute value. A few rules with their intension related to the condition attribute value of $x^{(1)}$ selected from the decision matrix of Table 2 are listed in Table 3. If the specified intension thresholds of maintenance decision rules of the aero-engine module are 0.6 (CF_0) and 0.2(CV_0), the rule obtained from Table 3 is $a_2 \wedge b_2 \rightarrow Y_2$, which means the maintenance decision level of HTP judged by the existing rules and condition parameters of the aero-engine module is a performance overhaul (POH). Actually, the maintenance level of HTP in a factory is Y_1 (it means that visual check is carried out), which indicates the decision attribute value predicated in terms of the existing rules produced by the historical maintenance data is not true. Once $x^{(1)}$ is added to the historical maintenance database, it accords with the model of Event 4, and a new condition equivalence class and decision class are formed. The newly increased decision matrix of X_{14} is $\boldsymbol{M}(X_{14})=[a \vee b \vee c, a, a \vee b, a \vee b \vee c, c, b \vee c, b, b \vee c, b \vee c, a \vee b \vee c, a \vee b \vee c, a \vee c, a \vee b \vee c]^{\mathrm{T}}$ and the updated rules with their intensions are shown in Table 4.

If the next newly increased object $x^{(2)}$ is presented as ($a_3 \wedge b_2 \wedge c_2 \rightarrow Y_3$), we can receive the rule $a_3 \rightarrow Y_3$ with the specified intension thresholds 0.6(CF_0) and 0.2(CV_0) in terms of Table 4, which shows that the predicted maintenance level of the aero-engine module is in line with that in practice based on the last updated rules and the condition parameters of the aero-engine module. When $x^{(2)}$ is added sequentially, it accords with the model of Event 2, and the rules with their intensions will be further updated. Any newly increased object can produce corresponding updated decision rules and their intensions on the basis of the models described above, and it is unnecessary to illustrate one by one.

Table 2 θ-decision matrix and rules with their intensions

θ-decision class	Condition equivalence class	a	b	c	Y	Same object number	Q_1				Q_2		Q_3	Q_4						Rule	CF	CV
							X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}		$(X_i \to Y_l)$	
Q_1	X_1	a_1	b_1	c_2	Y_2	1					$a \vee b$	$a \vee b$	$a \vee b \vee c$	a	$a \vee c$	a	$a \vee c$	$a \vee b \vee c$	$a \vee b$	$a_1 \to Y_2$	1/1	1/8
	X_2	a_1	b_2	c_1	Y_2	1					$a \vee c$	$a \vee b \vee c$	$a \vee b$	$a \vee b \vee c$	$a \vee b \vee c$	$a \vee b \vee c$	$a \vee b \vee c$	$a \vee b \vee c$	$a \vee b \vee c$	$a_1 \to Y_2$ $b_2 \wedge c_1 \to Y_2$	1/1 1/1	1/8 1/8
	X_3	a_1	b_3	c_1	Y_2	1					$a \vee b \vee c$	$a \vee c$	a	$a \vee b \vee c$	$a \vee b \vee c$	$a \vee b \vee c$	$a \vee b \vee c$	$a \vee b \vee c$	$a \vee c$	$a_1 \to Y_2$	1/1	1/8
	X_4	a_1	b_3	c_2	Y_2	1					$a \vee b$	a	$a \vee c$	$a \vee b$	$a \vee b \vee c$	$a \vee b$	$a \vee b \vee c$	$a \vee b \vee c$	a	$a_1 \to Y_2$	1/1	1/8
Q_2	X_5	a_2	b_2	c_2	Y_2	2							$b \vee c$	b	$b \vee c$	$a \vee b$	$a \vee b \vee c$	$a \vee c$	$a \vee b$	$a_2 \wedge b_2 \to Y_2$ $b_2 \wedge c_2 \to Y_2$	2/3 2/3	2/8 2/8
		a_2	b_2	c_2	Y_3	1														$a_2 \wedge b_2 \to Y_3$ $b_2 \wedge c_2 \to Y_3$	1/3 1/3	1/11 1/11
	X_6	a_2	b_3	c_2	Y_2	2							c	b	$b \vee c$	$a \vee b$	$a \vee b \vee c$	$a \vee b \vee c$	a	$a_2 \wedge b_3 \wedge c_2 \to Y_2$	1/2	1/8
		a_2	b_3	c_2	Y_3	1														$a_2 \wedge b_3 \wedge c_2 \to Y_3$	1/2	1/11
Q_3	X_7	a_2	b_3	c_1	Y_1	1								$b \vee c$	$b \vee c$	$a \vee b \vee c$	$a \vee b \vee c$	$a \vee b \vee c$	$a \vee c$	$a_2 \wedge c_1 \to Y_1$	1/2	1/1
		a_2	b_3	c_1	Y_2	1														$a_2 \wedge c_1 \to Y_2$	1/2	1/8
Q_4	X_8	a_2	b_1	c_2	Y_3	1														$a_2 \wedge b_1 \to Y_3$	1/1	1/11
	X_9	a_2	b_1	c_3	Y_3	1														$a_2 \wedge b_1 \to Y_3$ $c_3 \to Y_3$	1/1 1/1	1/11 1/11
	X_{10}	a_3	b_1	c_2	Y_3	1														$a_3 \to Y_3$	1/1	1/11
	X_{11}	a_3	b_1	c_3	Y_3	4														$a_3 \wedge c_3 \to Y_3$	4/4	4/11
	X_{12}	a_3	b_2	c_3	Y_3	1														$a_3 \wedge c_3 \to Y_3$	1/1	1/11
	X_{13}	a_3	b_3	c_2	Y_3	1														$a_3 \to Y_3$	1/1	1/11

Table 3 Rules with their intension related to condition attribute value of *x*

Rule	Confidence	Coverage
$2 \wedge b_2 \to Y_2$	2/3	2/8
$a_2 \wedge b_2 \to Y_3$	1/3	1/11
$a_2 \wedge c_1 \to Y_1$	1/2	1/1
$a_2 \wedge c_1 \to Y_2$	1/2	1/8
$b_2 \wedge c_1 \to Y_2$	1/1	1/8

Table 4 Updated rules and their intension

Rule	Confidence	Coverage
$a_2 \wedge b_3 \wedge c_1 \to Y_1$	1/2	1/2
$a_1 \to Y_2$	4/4	4/8
$a_2 \wedge b_3 \wedge c_1 \to Y_2$	1/2	1/8
$a_2 \wedge b_3 \wedge c_2 \to Y_2$	1/2	1/8
$b_2 \wedge c_2 \to Y_2$	2/3	2/8
$b_2 \wedge c_2 \to Y_3$	1/3	1/11
$a_2 \wedge b_1 \to Y_3$	2/2	2/11
$a_2 \wedge b_3 \wedge c_2 \to Y_3$	1/2	1/11
$a_3 \to Y_3$	7/7	7/11
$c_3 \to Y_3$	6/6	6/11

5 CONCLUSION

From the example and the results, we can see that it is feasible to reasonably determine the maintenance level of aero-engine modules if rough set theory is applied to extract rules from the historical maintenance data. When the historical maintenance data are little, the intensions are scattered and unstable, with which the rules can not adequately reflect the generalized laws and the error decision-making may be produced sometimes. The distribution of the intension values of the constantly updated decision-making rules shows a tendency to be robust with the newly and continuously added objects. In this way, the generalized and typical rules are obtained, with which the engineers can predict the maintenance level of the aero-engine modules reasonably and accurately while airlines can plan the maintenance budget on good grounds.

The rough set theory has been widely and successfully applied in engineering fields, but it is only suitable for discrete data. In engineering, many data sets are continuous values and the discretization of the continuous values has a great affect on decision result. Any newly increased object with continuous values may change the discretization and clustering of the whole system[16-17]. In particular, in the case of the aero-engine with high level of complexity, there exist consanguineously physical relationships between the measured values of different indexes. Hence, data discretization and cluster decision-making can not completely depend on machine learning, sometimes the experience and knowledge of the professionals in their fields are necessary. In summary, it is worth further studying to build the decision supporting system of maintenance levels of aero-engine modules based on more methods mixed together.

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