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An Inference Method for Personalized Automotive Service Based on Rough Set and Evidential Reasoning

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Abstract

With the increasing development of China's automobile market, the automotive service profits have become a major part of the industry's profits. However, the after-sale service is still on passive service mode. This mode has some limitations, such as the low service quality of the recommended service items and the lack of personalized service, which seriously affect the quality of the automotive service. In order to solve problems, such as lack of personalized service in the current automotive service mode, an inference method for personalized automotive service based on rough set and evidential reasoning was proposed. First, the information entropy reduction algorithm was used to reduce the customer's driving behavior attributes, and then, the attributes that affected the status of the major components of the automobile significantly were used as evidence. Second, the weight of evidence was measured by the calculation algorithm of attributes importance. Third, the customer's personalized service requirements were inferred by the evidence synthesis algorithm. Finally, the method's effectiveness was verified by the service data of automotive brake system of an automotive service provider from FAW-Volkswagen. Results demonstrate that the rough set method can effectively extract the attributes that have important influence on customer's personalized service requirements from many customer driving behavior attributes as reasoning evidence, the belief degree of the personalized service requirements of all samples can be calculated by using the evidential reasoning method, and the minimum and the average difference between the maximum and the second largest belief degrees are larger than 0.2. These findings indicate that customer's personalized service requirements can be inferred by the method effectively. The proposed method provides a new way for personalized service requirements inference in the filed of automotive service.

Keywords: Automotive service, Personalized service requirements, Rough set, Evidential reasoning

1. Introduction

The service profit has become a major part of the overall profit of the automotive industry. According to Juehling, in a mature auto market, the car sales profit accounted for about 20% of the profits of the entire industry; the main spare parts supply profits accounted for 20%; the maintenance, decoration and related services profits accounted for about 50%-60%; the proportion of service profit was still rising [1]. However, the after-sales service in China still rested on passive service mode such as "fault occurs-diagnosis-solution" [2]. The passive service mode had some disadvantages. First, in this service mode, most customers repaired their cars when damaged, and then, the cars had missed the best maintenance time. Second, the service items recommended by service providers often did not meet the customers' need, thereby reducing customer satisfaction. Finally, the service provider provided a standardized maintenance service for the customer every 6 months or when the customer's car reached a certain mileage. This mode did not consider that the driving preference of different customer had a different impact on the customer service requirements. In theoretical dimension, Kesslerv, Liang, Wang and other scholars also showed that the passive service model had some shortcomings, such as "service lag", "the agreement degree between service and customer's requirements was lower" and "lack of personalized service" [3-5].

In fact, customer's driving preference has a great influence on the wear and tear of the automotive parts. Such preference leads to the difference in the service requirements among different customers. The brake system can be used as an example. Some customers' brake block needs to be replaced when the mileage reaches 20,000 km, but some customers need to replace the brake block at 40,000 km. Therefore, providing the personalized service for customer based on the customer's driving behavior data is of great significance to eliminate the dilemma of the passive service model and effectively improve the service quality.

2. State of the art

The current research on the automotive after-sales service mainly focuses on the service quality management, automotive parts management, and other fields. Yu et al. used F-AHP method to evaluate the quality of the automotive service [6]. Jeddi et al. used WINTESS software to simulate the situation of automotive service process. A

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kind of after-sales service strategy was presented to shorten waiting time and improve customer satisfaction [7]. Velimirović et al. analyzed the factors that influenced the quality of automotive service and presented nine critical factors [8]. Gaiardelli et al. constructed the index system to evaluate the performance of the automotive service network, and this index system was verified by the data of automotive service provider [9]. Qian et al. designed a customer service system based on customer history maintenance data to improve customer satisfaction [10].

For the field of parts management in automotive service, Hsieh et al. constructed an inventory management system to reduce the uncertainty in automotive after-sales service [11]. Liao et al. analyzed the relationship between the part failure rule and the replacement of spare parts in the automotive after-service process and presented a personalized requirements forecasting model for automotive parts based on dynamic failure rule of automotive parts [12]. Weng et al. believed that customer's driving preference had an important impact on service requirements. They also believed that customer service requirements can be inferred from the customer's historical maintenance records [13].

For the field of personalized service inference, Liao et al. used the association rule extraction method to analyze online customer behavior data for inferring the customer's personalized service requirements [14]. Soroush et al. used the multiple logistic regression method to analyze the customer's historical purchase behavior data for predicting the customer's personalized service requirements [15]. Ishigaki, et al. proposed an extended PLSI model and used the model to analyze online customers' behavior to predict customer's personalized service requirements [16]. Cheung et al. used the hidden Markov chain method to forecast customer's personalized service requirements based on the customer's historical purchase records [17].

According to abovementioned literature, the current research on automotive service mainly focuses on the service quality evaluation, parts management and other fields. However, the research on personalized service inference in automotive after-sales service is relatively lacking, and research on personalized service inference mainly focuses on the field of e-commerce. In the field, regression analysis, hidden Markov chain, and other statistical methods have been used to infer the customer's personalized service requirements. These methods have the advantage of high accuracy, but they have shortcomings. For example, these methods require a high data quality and are unable to deal with descriptive or uncertain data. In fact, descriptive and uncertainty data often emerge in the process of automotive service inference, such as road conditions and customer's driving skill. Therefore, the inference methods for personalized service in e-commerce are difficult to use for inferring customer's personalized service requirements in automotive service. To consider of the characteristics of automotive customers' driving behavior data, the discrete method is used to process the descriptive data in customers' driving behavior. Then, the information entropy reduction algorithm is used to extract the attributes that significantly impacted the status of the critical components of the car from the customer's driving behavior data as evidence. Afterward, the weight of every attribute is calculated by using the attribute importance method. Finally, the evidential reasoning algorithm is used to synthesize the evidence, and then, the customer's personalized service requirements are inferred.

The remainder of this paper is organized as follows. The evidence determination method based on information entropy reduction algorithm, the calculation method for evidence weight based on attributes importance, and evidence synthesis algorithm based on evidential reasoning are established in Section 3. In Section 4, by using the service data of the brake system of an automotive service provider of FAW-Volkswagen as example, the inference process for customer's personalized service requirements is illustrated. The validity of the method is also analyzed in this section. The conclusions are summarized in Section 5.

3. Methodology

3.1 Determination method for evidence

As there are many attributes in customer's driving behavior, and some attributes can not affect the status of the critical components of the car. The attributes can not affect the customer's personalized service requirements. Moreover, there may be some interactions among these attributes. These can lead to uncertainty in the customer behavior data. The rough set can deal with the uncertainty data. Thus, it can be used to determine the critical attributes that have important influence on the state of the car from customer's driving behavior attributes as reasoning evidence. The essence of determining the evidence is the reduction of the customer's driving behavior attributes. Many incompatible data are present in customer's driving behavior, thus the reduction algorithm based on rough entropy is used to determine the evidence.

Definition 1: The entropy of knowledge P is expressed by the following formula:

$$H(P) = -\sum_{i=1}^{n} P(x_i) log_2 P(x_i) \tag{1}$$

$P(x_i)$ represents the probability of x_i in U/P, where $U/P = \{x_1, x_2, ..., x_n\}$. $P(x_i)$ can be calculated by the following formula:

$$P(x_i) = \frac{|x_i|}{|U|}, i = 1,2,...,n \tag{2}$$

Definition 2: The conditional entropy of knowledge P corresponding to knowledge Q can be defined as follows:

$$H(Q|P) = -\sum_{i=1}^{n} P(x_i) \sum_{j=1}^{m} P(y_j | x_i) log_2 P(y_j | x_i) \tag{3}$$

$P(y_j | x_i)$ can be calculated by the following formula.

$$P(y_j | x_i) = \frac{|y_j \cap x_i|}{|x_i|}, i = 1,2,...n; j = 1,2,...m \tag{4}$$

Definition 3: $I(P,Q)$ is the mutual information between P and Q. It can be calculated by the following formula.

$$I(P,Q) = H(Q) - H(Q|P) \tag{5}$$

Definition 4: A customer's driving behavior decision table T exists. $T = < U, C \cup D, V, f >$, where U is the objects set. $C(C_1, C_2, ..., C_n)$ is the condition attribute set, which comprises the customer's driving behavior attributes. D represents the decision attributes set. V represents value range of condition attributes set C and decision attributes set D. f represents the relational mapping in decision table, $f : U \times (C \cup D) \rightarrow V$. Let $a \in C$; if the inequality of $I(C,D) > I(C - \{a\}, D)$ is established, then a is called the core attribute. The set consisting of all the core attributes is called core attributes set, which is expressed by C_0 .

The evidence for automotive service inference can be determined by the following process.

Step 1: According to formulas (1) to (5), the mutual information $I(C,D)$ between the conditional attributes set C and the decision attributes set D in compatible decision table T can be calculated.

Step 2: According to the definition 4 in Section 3.2, all the core attributes of the decision table T can be calculated. The core attributes set C_0 can be obtained. Then, let $B = C_0$.

Step 3: According to the formula (5), $I(B,D)$ can be calculated. If the equation of $I(B,D=I(C,D)$ is established, the algorithm is end, and B is the set of the telecom critical behavior attributes. If the equation is not established, step 4 is performed.

Step 4: Let $C'=C-B$. Each attribute i (i□C') is selected. All the value of $I(B \cup \{i\}, D)$ are calculated. Attribute i_{max} is selected, in which the value of $I(B \cup \{i_{max}\}, D)$ is the maximum value of all the values of $I(B \cup \{i\}, D)$. Then, let $B = B \cup \{i_{max}\}$, and go to step3.

3.2 Calculating the weight of the evidence

In abovementioned section, the evidence for personalized service inference has been determined. Different driving behavior attributes have different impacts on the status of the main components of automobile. Thus, the weight of the evidence is important for personalized automotive service inference. The influence of the attributes on the status of the main components is complicated and the weights given by the experts have the disadvantages of subjectivity. Therefore, weight corresponding to each evidence is calculated by the attribute importance of the rough set. The process of calculating weight is as follows:

Definition 5: In knowledge system K, $K=(U,R)$. For each subset $X(X \subseteq U)$, and any one of the equivalence relationship R, $R \in ind(K)$. The subsets $\overline{R}(X)$ and $\underline{R}(X)$ can be defined as follows:

$$\begin{aligned} \underline{R}(X) &= \cup\{Y \in U / R \mid Y \subseteq X\} \\ \overline{R}(X) &= \cup\{Y \in U / R \mid Y \cap X \neq \phi\} \end{aligned} \tag{6}$$

$\overline{R}(X)$ is the R-upper approximation of X . $\underline{R}(X)$ is the R-lower approximation of X .

Definition 6: In knowledge system K, $\forall P,Q \in IND(K)$. The expression $Pos_P(Q)$ is called positive region of Q with respect to P .It can be expressed by the following formula:

$$Pos_P(Q) = \bigcup_{X \in U/Q} \underline{P}(X) \tag{7}$$

Definition 7: When the knowledge system is a decision table T. Where U is the objects set, $C(C_1, C_2, ..., C_n)$ is the condition attributes set, which comprises reasoning evidences, and D is decision attributes set, which reflects customer's service requirements. According to the definition 2, the dependency degree by which depends on can be expressed by the following formula:

$$\gamma_C(D) = k = \frac{|Pos_C(D)|}{|U|} = \frac{|\bigcup_{X \in U/D} \underline{P}(X)|}{|U|} \tag{8}$$

Definition 8: For the decision table T. $sig(C_i)$ represents the significance of condition attribute C_i with respect to decision attributes D. $sig(C_i)$ can be expressed by the following formula:

$$sig(C_i) = \gamma_C(D) - \gamma_{\{C - C_i\}}(D) \tag{9}$$

All $sig(C_i)(C_i \in C)$ can be calculated by using the previously presented formulas. Then, $sig(C_i)$ can reflect influence degree of the effect of evidence C_i on service requirements. After normalization, the weight of evidence C_i , represented by W_i , can be determined by the following formula:

$$W_i = \frac{\gamma_C(D) - \gamma_{C-C_i}(D)}{\sum_{i=1}^{n} (\gamma_C(D) - \gamma_{C-C_i}(D))} \tag{10}$$

3.3 Calculating the BPA (Basic Probability Assignment) of the evidence

The evidence for personalized service inference and the weight of evidence can be determined by the method in Section 3.1 and 3.2. The driving behavior preferences of different types of customers are differ. Thus, different types of customers have different values on the evidence. Therefore, determination of the BPA of evidence based on the customer's value corresponding to the evidence is important for customer's personalized service requirements inference. The BPA corresponding to each evidence can be calculated by decision rule strength method.

Definition 9: In decision table T, $\forall x \in U$. $\overline{C}x$ is the upper approximation set of x corresponding to C . $\overline{D}x$ is the upper approximation set of x corresponding to D . The strength of the decision rule $f(x,C) \rightarrow f(x,D)$ can be defined as following formulas:

$$u = \frac{|\overline{C}x \cap \overline{D}x|}{|\overline{C}x|} \quad (11)$$

Definition 10: In decision table T , $\forall \alpha \in C$, there are $U/\alpha = \{X_1, X_2, ..., X_n\}$ and $U/D = \{Y_1, Y_2, ..., Y_n\}$ .Then, let $H = \{\alpha, D\}$, $U/H = \{H_1, H_2, ..., H_m\}$ and $B_j = \{H_i \mid \bigcup_{H_i \subset X_j} H_i = X_j, X_j \in U/a\}$. $|B_j| = k$. V_D represents the value range of the D . u_i represents the decision rules strength of any object in H_i . u_i can be calculated by the formula (11). Let P be the hypothesis of identification model $\Theta(P \in 2^{\Theta})$.The BPA of the hypothesis P can be calculated by the following formula.

$$m(P) = u_P / (1 + \prod_{i=1}^{n} u_i) \quad (12)$$

3.4 Personalized service inference based on evidence synthesis

The BPA corresponding to all the evidence can be calculated by the method in Section 3.3. The BPA of each evidence can be synthesized by the recursive algorithm of evidential reasoning. Then, the customer's personalized service requirements can be inferred. The process is as follows:

Step 1: Define $\beta_{j,i}$ as the BPA of evidence j supports hypothesis i. Define w_j as the weight of the evidence j. Then, $m_{j,i}$ represents the evidence reliability that the evidence j supports hypothesis i .Then, let $m_{j,\Theta} = \overline{m}_{j,\Theta} + \widetilde{m}_{j,\Theta}$ .Where $\overline{m}_{j,\Theta}$ represents the unallocated reliability caused by the weight of the evidence; $\widetilde{m}_{j,\Theta}$ represents the unallocated reliability caused by the uncertainty of the evidence. $\overline{m}_{j,\Theta}$ and $\widetilde{m}_{j,\Theta}$ can be calculated by the following formula:

$$m_{j,i} = w_j \beta_{j,i}, \overline{m}_{j,\Theta} = 1 - w_j, \widetilde{m}_{j,\Theta} = w_j [1 - \sum_{i=1}^{n} \beta_{j,i}] \quad (13)$$

Step 2: Define $E_{I(j)}$ as a subset that consist of first j evidenc . $E_{I(j)} = \{e_1, e_2, ..., e_j\}$. Then, let $m_{I(j),i}$ represents the reliability that the evidence set $E_{I(j)}$ support the hypothesis θ_j . $m_{I(j),\Theta}$ represents the unallocated reliability. $m_{I(j),i}$ and $m_{I(j),\Theta}$ can be calculated by the following formula:

$$m_{I(j+1),i} = K_{I(j+1)}(m_{I(j),i} m_{j+1,i} + m_{I(j),i} m_{j+1,\Theta} + m_{I(j),\Theta} m_{j+1,i}) \quad (14)$$

$$m_{I(j),\Theta} = \overline{m}_{I(j),\Theta} + \widetilde{m}_{I(j),\Theta} \quad (15)$$

$$\widetilde{m}_{I(j+1),\Theta} = K_{I(j+1)}(\widetilde{m}_{I(j),\Theta} \widetilde{m}_{j+1,\Theta} + \overline{m}_{I(j),\Theta} \widetilde{m}_{j+1,\Theta} + \widetilde{m}_{I(j),\Theta} \overline{m}_{j+1,\Theta}) \quad (16)$$

$$\overline{m}_{I(j+1),\Theta} = K_{I(j+1)} \overline{m}_{I(j),\Theta} \overline{m}_{j+1,\Theta} \quad (17)$$

In abovementioned formulas, $K_{I(j+1)}$ represents the coefficient of the reliability. It can be calculated by the following formula:

$$K_{I(j+1)} = [1 - \sum_{j=1}^{n} \sum_{i=1, i \neq j}^{n} m_{I(j)} m_{j+1,i}]^{-1} \quad (18)$$

Step 3: After all the evidence are combined by abovementioned formula, the credibility that the evidence set supports on the identification model Θ , which is expressed by function $S(E) = \{\theta_i(m_i), i = 1, ..., n\}$, can be calculated by the following formula. Finally, the customer's personalized service requirements can be inferred based on the credibility.

$$\{\theta_i\} : m_i = \frac{m_{I(L),i}}{1 - \overline{m}_{I(L),\Theta}}; \{\Theta\} : m_{\Theta} = \frac{\widetilde{m}_{I(L),\Theta}}{1 - \overline{m}_{I(L),\Theta}} \quad (19)$$

Step 4: Taking the max value in $\{\theta_i(m_i)\}$ as m_{max} , let i represent the type of the service required by the customer, corresponding to m_{max} . Take the second largest value in $\{\theta_i(m_i)\}$ as m_{sec} , and let j represent the type of the service required by the customer, corresponding to m_{sec} . A threshold represented by symbol ε is set with the establishments of $m_{max} - m_{sec} \geq \varepsilon$. Then, it can be inferred that the personalized service requirements of the customer is i.

4. Result analysis and discussion

4.1 Calculation process of the method

The brake system is a critical component in vehicular safety. There are three types of maintenance services for brake system. The first type of service is to clear the stain on the brake system, fasten the screw, and other simple maintenance procedures. The second type of service is to replace the brake oil and inspect the brake pads and other main components of the brake system. The third type of service is to disassemble the entire brake system for maintenance and replace the brake pads and other main components of the brake system. Service requirements for brake system are greatly affected by the customer's driving behavior. Meanwhile, customer's driving behavior has a personalized characteristic. Therefore, service requirements for brake system also have a personalized feature. According to the automotive service guide and the experiences of the service staff, the customer driving behavior attributes that may impact the brake system are listed. The attributes include "mileage interval", "time intervals", "average driving speed", "average fuel consumption", "road condition" and "customer's driving skill". They are represented by symbols C_1 , C_2 , C_3 , C_4 , C_5 and C_6 . About 60 customers' driving behavior and brake system maintenance data for SAGITAR model have been collected from an automotive service provider of FAW-Volkswagen. After discrete processing of these data according to the rules presented in Tab.1, Tab.2 can be obtained.

Table 1. Discrete rules

Attributes	1	2	3
C_1	≤15,000 (km)	>15,000 and ≤30,000 (km)	>30,000 (km)
C_2	≤1 (year)	>1 and ≤2 (years)	>2 (years)
C_3	≤30 (km/h)	>30 and ≤50 (km/h)	>50 (km/h)
C_4	≤8 (L/100km)	>8 and ≤12 (L/100km)	>12(L/100km)
C_5	Worse	General	Better
C_6	Poor	General	Better
D	Simple maintenance	Inspection and brake oil replacement	Main parts Replacement

Table 2. Personalized service decision table for brake system

U	C_1	C_2	C_3	C_4	C_5	C_6	D	**Samples**
U_1	1	1	3	3	2	3	1	11
U_2	1	2	3	2	3	2	1	2
U_3	3	1	3	3	2	3	2	7
U_4	2	1	1	3	2	2	2	5
U_5	2	2	2	2	2	2	2	10
U_6	3	2	2	2	2	2	2	6
U_7	3	2	1	2	2	2	3	5
U_8	2	2	2	2	1	2	3	6
U_9	3	2	1	2	1	2	3	5
U_{10}	1	3	1	2	1	2	2	3

(1) Determination of the evidence

According to the method in Section 3.1, the reasoning evidence for brake system service can be determined. The steps are as follows:

$$U/C=\{U_1,U_2,U_3,U_4,U_5,U_6,U_7,U_8,U_9,U_{10}\}$$

$$U/D=\{(U_1,U_2),(U_3,U_4,U_5,U_6,U_{10}),(U_7,U_8,U_9)\}$$

Then, according to the formulas (1) and (2), the following equations can be obtained.

$$H(D=-(\frac{2}{10}log_2\frac{2}{10}+\frac{5}{10}log_2\frac{5}{10}+\frac{3}{10}log_2\frac{3}{10})=1.4854$$

According to the formulas (3) and (4), $H(D|C)$ can be calculated as follows:

$$H(D|C)=-(\frac{1}{10}(1log_2 1+0+0)+\frac{1}{10}(1log_2 1+0+0)+\frac{1}{10}(0+1log_2 1+0)+...+\frac{1}{10}(0+0+1log_2 1)+\frac{1}{10}(0+1log_2 1+0))=0$$

According to the formula (5), $I(C,D)$ can be calculated as follows:

$$I(C,D)=H(D)-H(D|C)=1.4854$$

Then, the same calculation process is then applied to derive the following expressions:

$$I(C-\{C_1\},D)=1.2854,\ I(C-\{C_2\},D)=1.4854$$

$$I(C-\{C_3\},D)=1.2854,\ I(C-\{C_4\},D)=1.4854$$

$$I(C-\{C_5\},D)=1.2854,\ I(C-\{C_6\},D)=1.4854$$

According the evidence determination method in Section 3.1, due to the establishment of $I(C,D)>I(C-\{C_1\},D)$, C_1 is a core attribute. Similar to the determination process of , C_3 and C_5 are also the core attributes. Then, the core attributes set C_0 consist of C_1 , C_3 and C_5 , as follows: $C_0=\{C_1,C_3,C_5\}$. Let $C'=C_0$; according to the formulas (1) to (5), $I(C',D)$ can be calculated. $I(C',D)=1.4854$ .With the establishment of $I(C,D)=I(C',D)$, C' is the evidence set for brake system service inference. Tab.2 can be reduced by the evidence set C' . Then, Tab.3 can be obtained.

Table 3. Personalized service inference table for brake system

U	C_1	C_3	C_5	D	***Samples***
U_1	1	3	2	1	11
U_2	1	3	3	1	2
U_3	3	3	2	2	7
U_4	2	1	2	2	5
U_5	2	2	2	2	10
U_6	3	2	2	2	6
U_7	3	1	2	3	5
U_8	2	2	1	3	6
U_9	3	1	1	3	2
U_{10}	1	1	1	2	6

(2) Calculation the weight of evidence

According to the formulas (6), (7), and (8), we can derive the following equations:

$$Pos_C(D)=U,Pos_{C-C_1}(D)=U-\{U_1,U_3\}$$

$$Pos_{C-C_3}(D)=U-\{U_3,U_6,U_7\},Pos_{C-C_5}(D)=U-\{U_5,U_8\}$$

According to formula (8), $\gamma_C(D)$, $\gamma_{C-C_1}(D)$,

$\gamma_{C-C_3}(D)$, and $\gamma_{C-C_5}(D)$ can be obtained.

$$\gamma_C(D) = \frac{|Pos_C(D)|}{|U|} = \frac{|U|}{|U|} = 1, \gamma_{C\text{-}C1}(D) = 0.7,$$

$$\gamma_{C\text{-}C3}(D) = 0.7, \gamma_{C\text{-}C5}(D) = 0.733$$

according to the formula (9), the following expressions can be obtained.

$$sig(C_1) = \gamma_C(D) - \gamma_{C-C_1}(D) = 1 - 0.7 = 0.3,$$
$$sig(C_3) = 0.3, sig(C_5) = 0.267$$

At last, according to the formula (10), the weight of evidence can be calculated.

$$W_{C_1} = 0.346, W_{C_3} = 0346, W_{C_5} = 0.308$$

(3) Personalized service inference for brake system

There is a customer A. The value corresponding to C_1 , C_3 and C_5 are as follows : $C_1 = 2$, $C_3 = 1$ and $C_5 = 1$. The same object as A can not be found in Table 3. Thus, this customer's personalized service requirements can not be inferred directly. However, the customer's personalized service requirements can be inferred by the method in Section 3.

First, according to the BPA calculation method in Section 3.3, the BPA corresponding to C_1 , C_3 and C_5 can be calculated. The calculation process is as follows.

According to definition 10 in Section 3.3, $U/\{C_1,D\}$ can be obtained, as follows.

$$U/\{C_1,D\} = \{(U_1,U_2),(U_3,U_6),(U_4,U_5),(U_7,U_9), U_8,U_{10}\}$$

$C_1 = 2$ can lead to B_1 being obtained. i.e., $B_1 = \{(U_4,U_5),U_8\} = \{D_2,D_3\}$. In set B_1, the value of all objects on evidence C_1 is equal to 2. However, the values of these objects on attribute D are different. For the objects in U_4 and U_5 ,the value on attribute D is equal to 2. For the objects in U_8, the value on attribute D is equal to 3. Then, according to the formula (11), the rule strength u_{D2} that corresponds to set $\{U_4,U_5\}$ can be calculated.

$$u_{D2} = \frac{|D_2 \cap B_1|}{|B_1|} = \frac{5+10}{5+10+6} = 0.714$$

The same calculation process is employed to calculate rule strength u_{D3} . $u_{D3} = 0.286$. No object satisfies $C_1 = 2$ and $D = 1$; thus, $u_{D1} = 0$ .Then, the BPA that the customer A needs the first kind of the service when $C_1 = 2$ is established can be calculated by formula (12), as follows.

$$\beta_{C1=2,1} = \frac{u_{D1}}{1 + u_{D1}u_{D2}u_{D3}} = \frac{0}{1 + 0 \times 0.714 \times 0.286} = 0$$

The same calculation process is employed to calculate $\beta_{C1=2,2}$ and $\beta_{C1=2,3}$. The results are as follows: $\beta_{C1=2,2} = 0.714$ and $\beta_{C1=2,3} = 0.286$.

The same as abovementioned calculation process, the BPA corresponding to $C_3 = 1$ and $C_5 = 1$ can be determined. The results are as follows.

$$\beta_{C3=1,1} = 0, \ \beta_{C3=1,2} = 0.61, \ \beta_{C3=1,3} = 0.39$$

$$\beta_{C5=1,1} = 0, \ \beta_{C5=1,2} = 0.43, \ \beta_{C5=1,3} = 0.57$$

Second, the BPA corresponding to C_1 , C_3 and C_5 can be combined based on the method in section 3.4. The process is as follows.

According to the formula (13), the evidence reliability corresponding to C_1 can be calculated. The results are as follows.

$$m_{C1,1} = \beta_{C1,1}W_{C1} = 0 \times 0.346 = 0,$$

$$m_{C1,2} = \beta_{C1,2}W_{C1} = 0.247, \ m_{C1,3} = 0.099$$

According o the formula (13), $\overline{m}_{C1,\Theta}$, $\widetilde{m}_{C1,\Theta}$, and $m_{C1,\Theta}$ can be calculated.

$$\overline{m}_{C1,\Theta} = 1 - W_{C1} = 0.654$$
$$\widetilde{m}_{C1,\Theta} = W_{C1}(1 - \sum_{i=1}^{3} \beta_{c1,i})$$
$$= 0.346 \times (1 - (0 + 0.714 + 0.286)) = 0$$
$$m_{C1,\Theta} = \overline{m}_{C1,\Theta} + \widetilde{m}_{C1,\Theta} = 0.654 + 0 = 0.654$$

The same calculation process is employed to calculate $m_{C3,1}$, $m_{C3,2}$, $m_{C3,3}$, $\overline{m}_{C3,\Theta}$, $\widetilde{m}_{C3,\Theta}$, and $m_{C3,\Theta}$. The results are as follows:

$$m_{C3=1,1} = 0, \ m_{C3=1,2} = 0.211, \ m_{C3=1,3} = 0.135$$

$$\overline{m}_{C3,\Theta} = 0.654, \ \widetilde{m}_{C3,\Theta} = 0, \ m_{C3,\Theta} = 0.654$$

Afterward, according to the method mentioned in Section 3.4, the reliabilities corresponding to C_1 and C_3 can be combined. The process is as follows.

Let $m_{(1),1} = m_{C1,1}$, $m_{(1),2} = m_{C1,2}$, $m_{(1),3} = m_{C1,3}$ and $m_{(1),\Theta} = m_{C1,\Theta}$. Then, according to the formula (18), the coefficient $K_{(2)}$ can be calculated.

$$K_{(2)} = [1 - \sum_{i=1}^{3} \sum_{j=1, j \neq i}^{3} m_{(1),i} m_{C3,j}]^{-1} = [1 - (m_{(1),1} m_{C3,2} +$$

$$m_{(1),1} m_{C3,3} + m_{(1),2} m_{C3,1} + \ldots + m_{(1),3} m_{C3,2}]^{-1} \approx 1.057$$

According to the formula (14), $m_{(2),1}$, $m_{(2),2}$ and $m_{(2),3}$ can be obtained.

$$m_{(2),1} = K_{(2)}(m_{(1),1}m_{C3,1} + m_{(1),1}m_{C3,\Theta} + m_{(1),\Theta}m_{C3,1})$$
$$= 1.057 \times (0 + 0 \times 0.654 + 0.654 \times 0) = 0$$

$$m_{(2),2} = 0.372, m_{(2),3} = 0.176$$

According to formulas (15) to (17), $\overline{m}_{(2),\Theta}$, $\tilde{m}_{(2),\Theta}$ and $m_{(2),\Theta}$ can be obtained.

$$\tilde{m}_{(2),\Theta} = K_{(2)}(\tilde{m}_{(1),\Theta}\tilde{m}_{C3,\Theta} + \overline{m}_{(1),\Theta}\tilde{m}_{C3,\Theta} + \tilde{m}_{(1),\Theta}\overline{m}_{C3,\Theta})$$
$$= 1.057 \times (0 + 0.654 \times 0 + 0 \times 0.654) = 0$$

$$\overline{m}_{(2),\Theta} = K_{(2)}\overline{m}_{(1),\Theta}\overline{m}_{C3,\Theta}$$
$$= 1.057 \times 0.654 \times 0.654 = 0.452$$

$$m_{(2),\Theta} = \overline{m}_{(2),\Theta} + \tilde{m}_{(2),\Theta} = 0.452 + 0 = 0.452$$

The same as abovementioned calculation process, $m_{(3),1}$, $m_{(3),2}$, $m_{(3),3}$, $\overline{m}_{(3),\Theta}$, $\tilde{m}_{(3),\Theta}$ and $m_{(3),\Theta}$ can be calculated. The reuslts are as follows.

$$m_{(3),1} = 0,\ m_{(3),2} = 0.402,\ m_{(3),3} = 0.255$$

$$\overline{m}_{(3),\Theta} = 0.343,\ \tilde{m}_{(3),\Theta} = 0,\ m_{(3),\Theta} = 0.343$$

On the basis of the abovementioned results, the probability for the customer A's personalized service requirement can be calculated by using formula (19). $m(1)$, $m(2)$, $m(3)$, and $m(\Theta)$ can be calculated. The results are obtained as follows and are shown in Fig.1.

$$m(1) = \frac{m_{(3),1}}{1 - \overline{m}_{(3),\Theta}} = 0,\ m(2) = \frac{m_{(3),2}}{1 - \overline{m}_{(3),\Theta}} = 0.612$$

$$m(3) = \frac{m_{(3),3}}{1 - \overline{m}_{(3),\Theta}} = 0.388,\ m(\Theta) = \frac{m_{(3),\Theta}}{1 - \overline{m}_{(3),\Theta}} = 0$$

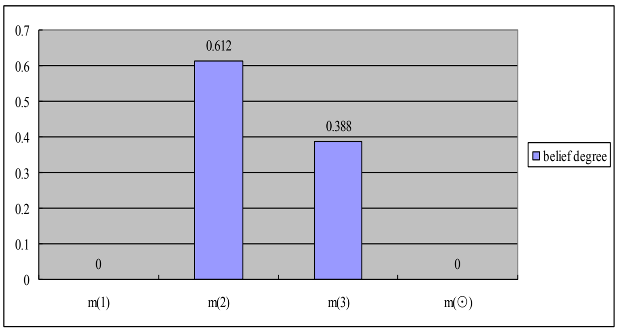

Fig. 1. The belief degree of personalized service requirements for brake system

According to Fig.1, the belief degree that A needs the second type of service is much greater than the belief degree that A needs the third type of service. Then, let $\varepsilon = 0.2$, and $m(2) - m(3) > \varepsilon$ is established. The brake system of the customer A's car needs to be inspected, and the brake oil needs to be replaced.

4.2 Method validity analysis

In order to verify the validity of the method, five sets of data that do not belong to the decision Table 3 are selected as samples. The data are represented as following. $T_1 = \{C_1 = 1, C_3 = 1, C_5 = 1\}$, $T_2 = \{C_1 = 2, C_3 = 1, C_5 = 3\}$, $T_3 = \{C_1 = 2, C_3 = 3, C_5 = 2\}$, $T_4 = \{C_1 = 3, C_3 = 1, C_5 = 3\}$, $T_5 = \{C_1 = 3, C_3 = 2, C_5 = 1\}$. The abovementioned samples can not be found in Table 3. Thus, the personalized service requirements corresponding to these samples can not be inferred directly. However, the personalized service requirements of these samples can be inferred by using the method based on the rough set and evidence reasoning. The results are shown in Table 4.

According to the results in Table 4, the difference between the maximum belief degree and the second largest belief degree of each sample are obtained and presented in Fig.2

Table 4. The inference results of the method based on rough set and evidence reasoning

Samples	$m(1)$	$m(2)$	$m(3)$	$m(\Theta)$
$T_1 = \{C_1 = 1, C_3 = 1, C_5 = 1\}$	0.292	0.556	0.152	0
$T_2 = \{C_1 = 2, C_3 = 1, C_5 = 3\}$	0.269	0.496	0.235	0
$T_3 = \{C_1 = 2, C_3 = 3, C_5 = 2\}$	0.058	0.716	0.226	0
$T_4 = \{C_1 = 3, C_3 = 1, C_5 = 3\}$	0.269	0.471	0.26	0
$T_5 = \{C_1 = 3, C_3 = 2, C_5 = 1\}$	0	0.635	0.365	0

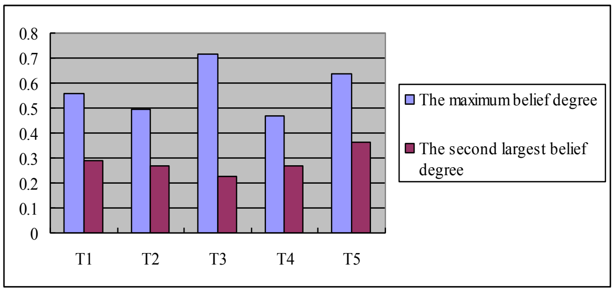

Fig. 2 The difference between the maximum belief degree and the second largest belief degree

Fig. 2 indicates that the maximum belief degree of all samples is significantly higher than the second largest belief degree. Moreover, the minimum and average values of the difference between the maximum belief degree and the second largest belief degree are more than 0.2. Therefore, the method can effectively infer the personalized service requirements for the customer's brake system.

5 Conclusions

To realize the personalized service in automotive after-sales service, an inference method based on rough set and evidence reasoning was proposed in this study to infer the customer's personalized service requirements. The validity of the method was verified by the service data of automotive brake system of an automotive service provider from FAW-Volkswagen. The following conclusions can be obtained:

(1) The rough set can be used to determine the critical attributes from the customer's driving behavior attributes as reasoning evidence. Moreover, the weight of each evidence also can be determined by attribute importance calculation method in the rough set theory. In the example of the

personalized service requirements inference for brake system, it can be found that “mileage interval”, “average driving speed” and “road condition” can be extracted from the customer’s driving behavior attributes as evidence.

(2) The evidence can be effectively synthesized by the evidential reasoning method, and the belief degree of the customer’s personalized service requirements can be obtained. Moreover, in the process of determining the personalized service requirement inference for the brake system, the maximum belief degree of all samples is significantly higher than the second largest belief degree, and the minimum and the average difference between the maximum belief degree and the second largest belief degree are more than 0.2. Therefore, the evidential reasoning method can effectively infer the customer’s personalized service requirements.

The proposed method can not only be used to infer the automotive customer’s personalized service requirements, but also can be used in other fields. For example, the method can be used to estimate the risk of the project. However, the method also has some limitations. For example, the method does not consider the conflict and logical association in the evidence data. The further study needs to infer the personalized service requirements in the case of the conflict and logical association in the evidence data.

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