Study of Mechanical Product Platform Module based on User Big Data

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Abstract: This paper studies how to extract the knowledge required of mechanical product platform module information from data redundancy and inconsistent data for the mechanical product platform. By analyzing the data obtained by users concerned about the attribute of mechanical product module, the fuzzy rough set is proposed. Knowledge discovery is performed to eliminate the redundancy of these attributes and turn them into consistency decision problems. To this end, the information system of the mechanical product platform module attributes based on user data is first extended, and then according to the characteristics of the user module attributes. It is determined that the distribution of decision table dt is used for reduction and decision table conversion, which realizes the reduction and inconsistency of module attribute data redundancy when the mechanical product platform is established, which provides help for the correct establishment of mechanical product modules. Finally, taking the film supply module of the packaging machine as an example, through the distribution reduction of the rough set decision table dt, the reduction and consistency conversion of the user demand attribute when the platform film supply module is established is realized, and the established module is more in line with the user group. The requirements indicate that the method is feasible.

1. Introduction

Future products are typical customized products. How to achieve low-carbon rapid customization is the key to occupying the market and enhance competitiveness. Product platform technology is an effective solution for fast and low-carbon customization [1]. For the establishment of mechanical products, regardless of Whether it is based on parameters or based on structure, it is initially based on various technical requirements and attributes obtained by user demand big data [2~3]. Mechanical product construction requirements and parameters are generally obtained by converting user group requirements through qfd. When the user group requirements are collected, the representation of the user group requirements is vague and repetitive, so that after converting them into the knowledge attributes and requirements of the product platform design, these attributes may have redundancy and inconsistency, and the products will be Platform creation and program decision-making have an impact, and even the established product platform deviates from the actual needs of the user group. Therefore, how to reduce the redundant attributes obtained by the user big data and transform it into consistency decision through knowledge discovery, in the mechanical product module Under the premise that the classification or decision-making ability of the information system remains unchanged, the deletion is not related to the user's demand or the establishment of production The unimportant knowledge attribute of the platform is of great significance to the rational construction of the product. The domestic and international response to the establishment of product module attributes is usually to first modularize the product, create knowledge on the product module, and respond to the actual needs of the product. Modules are combined to obtain accurate conclusions by establishing mathematical models and choosing the correct algorithm.

In obtaining the simplest attributes of building mechanical product modules, the process of knowledge discovery provides a lot of support for the contradictions and conflicts in solution design. Knowledge discovery is one of the core issues of Rough set theory[4,6].The earliest information system knowledge reductions were mostly carried out under the Pawlak rough set model[7].But Pawlak can only handle consistency decision tables and the objects it handles are known, so it has a lot of limitations. However, in practical applications, it needs to be improved and popularized. Many scholars have improved the Pawlak rough set model and proposed a new method [8~14]. For the module attribute problem of product platform construction, it is a complex inconsistent decision table, and the knowledge reduction problem of inconsistent decision table must be studied. For the literature [15], the reduction of the five forms of the inconsistent decision table is discussed, and it is pointed out that the distribution reduction (DR) and the distribution reduction (AR) are basic reduction forms. The literature [16,17] proposed another concept of knowledge reduction based on the literature [15], namely the maximum distribution reduction (MDR), and gave the identifiable attribute matrix of the reduction, thus obtaining the calculation of this approximation. Jane's method. By citing these research results to the construction of the product platform, it can solve the feature attribute redundancy and the attribute importance determination of big data in the product platform construction, and prevent the product platform from deviating due to the redundancy of the feature attributes when the product platform is built. Platform builds failed.

Before the establishment of the enterprise product platform, the research obtained a large number of users' attribute attributes that are of interest to the product family. Due to the redundancy and inconsistency of the data information, it is convenient to build a product platform through knowledge discovery.

2. User Big Data Acquisition

The establishment of a customized product platform is inseparable from the acquisition of big data. In today's Internet development, multiple choices of users constitute a large amount of data. These users' big data are gathered in a specific location, thus forming a sea of data. The establishment of a product platform has had a huge impact. The characteristics of big data are a lot of sex, diversity, speed and authenticity. Traditional data processing methods can no longer meet the needs of the current situation. We need to use a certain algorithm to simplify the classification of these knowledge data to obtain the most useful information, which provides a strong basis for enterprise production.

For the acquisition of user big data, building product platforms is more through the user purchase, sales and Internet business to collect user behavior data, such as: user access, click to browse, purchase, payment, comments and video audio UGC data, etc. In this way, the data information about the user's preference attributes can be fully obtained, and it is also beneficial to establish a more complete product platform.

3. Attribute Reduction Algorithm for Mechanical Product Platform

3.1 Rough Set Reduction Theory

By data mining the attributes of the product platform module system and knowledge discovery using fuzzy rough set theory, in order to simplify the process of knowledge discovery, the product platform module attributes need to be informationized, and the product platform module The information system can be represented as a triple: T = (U, A, f).Where U, A is a non-empty finite set, U is all individuals in the planned product platform module, and A is a feature attribute obtained by the user platform module. If the feature attribute set A can be divided into a condition attribute set C and a decision attribute set D, $C \cup D = A, C \cap B = \Phi$ Then, the information system forms a decision table about D, which can be expressed as DT=(U, $C \cup D$, f).

In the product platform module information system T=(U, A, f), for the individual subset of the planned product platform module $x \subseteq U$ And a subset of feature attributes obtained by the user platform and the product platform module $R \subseteq A$ The approximate set of r under the literature [18]x and the approximate set on r are as shown in Equations 1 and 2:

$$\underline{R}X = \cup\{Y \in U/R \mid Y \subseteq X\} \tag{1}$$

$$\overline{R}X = \cup\{Y \in U/R \mid Y \cap X \neq \phi\} \tag{2}$$

At the same time, the product platform module information system T=(U, A, f) can be obtained. $P \subseteq A, Q \subseteq A$ The p positive region of q is as shown in Equation 3:

$$POS_P Q = \bigcup_{x \in U/\overline{Q}} PX \tag{3}$$

In the product platform module decision table DT= (U, C∪D, f), since the attributes of the product platform are mainly from a large number of user groups and there are inconsistencies, this paper uses the inconsistent decision table method.

3.2 Decision Table Dt Distribution Reduction

As can be seen from the literature [15~17], in the inconsistent decision table DT=(U, C∪D, f), $B \subseteq C$ Time, when1>2. The reduction has the Pawlak reduction (PR) of the decision table DT; the distribution reduction (DR) of the decision table DT; the maximum distribution reduction (MDR) of the decision table DT; the distribution reduction (AR) of the decision table DT.

According to the characteristics of these four reductions, the distribution reduction can keep the degree of membership of each decision-making class unchanged in the decision table before and after the reduction; therefore, according to the characteristics of the product platform, for the feature attributes of the platform module Reduction, the distribution reduction of the decision table dt can be ensured by ensuring the degree of membership of each individual in the decision-making class in the decision table before and after the reduction, so as to ensure that the reduction does not affect the actual needs of the user and the construction of the product platform. Rationality and effectiveness.

In this paper, we use the method in [17] to convert the inconsistent decision table into a consistent decision table to reduce the feature attributes of the product platform module obtained by qfd. To this end, the consistency decision table is derived from the inconsistent decision table:

$$DT_\mu = (U, C \cup \{\mu_C\}, f') \tag{4}$$

Where f' is not the same as f on the mapping of individual decision attributes to decision attribute values. It can be seen from the literature that the derived decision table is a consistent decision table. The inconsistent decision table is transformed into a consistent decision table.

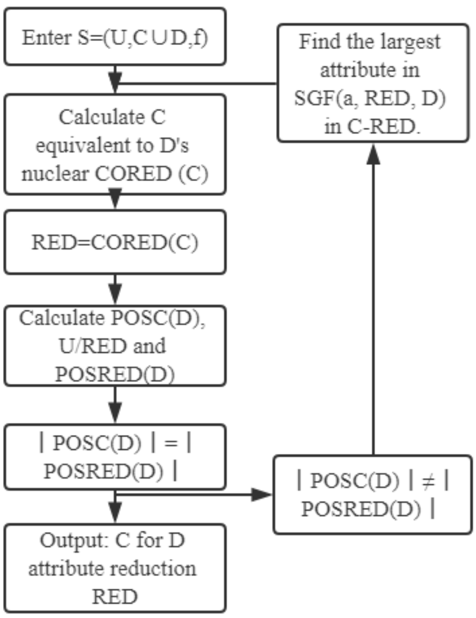

Figure 1. is based on a sequenced heuristic algorithm flow chart

When we reduce the inconsistent decision table, we usually use a sorting-based heuristic algorithm [11]. The algorithm content is shown in Figure 1:

In this way, the transformation to the consistency decision is realized while eliminating the attribute redundancy, which lays a foundation for the smooth establishment of the product platform.

4. Case Study

4.1 Modeling of the Film Supply Module of the Packaging Machine

Data collection for user groups in the market, using qfd to obtain a large number of user product attributes, these attributes still have redundancy and inconsistency, such as data collection and reduction of the characteristics of the film supply module of a packaging machine manufacturer: through online user survey After visiting the enterprise users, analysis and qfd conversion, the user obtained the technical characteristic attributes proposed by the packaging machine film module: film weight, maximum mold width; minimum film width; adjustment amount; fine adjustment amount, film roll diameter 6 characteristics Attribute. In order to verify the above conclusions, we randomly select 18 sets of user data, according to the 18 sets of user requirements, obtain the degree of interest in the above-mentioned feature attributes in the demand, and perform the reduction of the feature attributes according to the decision condition assignment. In decision table 1, 0 indicates that the user needs to have the least concern about the attribute description, 1 indicates that there is a certain concern, and 2 indicates that the concern is clearly expressed. The characteristic attribute decision table determined by the user demand of the packaging machine for the film supply module is shown in Table 1, by the literature [18] can be reduced.

4.2 Data Reduction

As can be seen from Table 1 of the user requirement table, the decision table DT= (U, $C \cup D$, f) of the module. The user demand set is U={ c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8, c_9, c_{10}, c_{11}, c_{12}, c_{13}, c_{14}, c_{15}, c_{16}, c_{17}, c_{18}}, the set of demand attributes is C={a, b, c, e, f, g}, the quick change decision set is D={d}; the classification of the decision table can be classified as U/C={{c_1 },{ c_2,c_3, c_{14}, c_{15}}, { c_4, c_5, c_6}, { c_7, c_8, c_9}, { c_{10}, c_{11}, c_{17}, c_{18}}, { c_{12}, c_{13}, c_{16}}}={C_1, C_2, C_3, C_4, C_5, C_6}; can be classified as a quick change decision U/D={{ c_1, c_2, c_{12}}, {c_3, c_4, c_6, c_9, c_{10}, c_{14}, c_{16}, c_{17},c_{18}}, { c_5, c_7, c_8, c_{11}, c_{13}, c_{15}}}={D_1, D_2, D_3 }.The decision table that can be derived from the literature [18] is shown in Table 2.Using the above algorithm to reduce, the distribution reduction of the feature attributes of the film supply module is {a, b, c, e, f}, that is, under the condition of quick change decision, the key feature attributes of the film supply module are: film weight The maximum film width, minimum film width, adjustment amount, and fine adjustment amount have obtained the attributes that the enterprise user group really cares about. Finally, by searching the example library and obtaining the user group of the packaging machine product platform, the characteristic attributes of the film supply module are shown in Table 3, which provides a basis for decision making, and the established platform module reflects the needs of the enterprise user group.

Table 1. Membrane module feature attribute decision table

	Membrane weight (a)	Maximum film width (b)	Minimum film width (c)	Adjustment amount (e)	Fine adjustment amount (f)	Film roll tube diameter (g)	Quick change (d)
User 1 (c_1)	0	0	0	0	0	0	0
User 2 (c_2)	1	0	0	0	0	0	0
User 3 (c_3)	1	0	0	0	0	0	1
User 4 (c_4)	0	1	1	1	1	1	1
User 5 (c_5)	0	1	1	1	1	1	2
User 6 (c_6)	0	1	1	1	1	1	1
User 7 (c_7)	0	0	0	1	0	0	2
User 8 (c_8)	0	0	0	1	0	0	2
User 9 (c_9)	0	0	0	1	0	0	1
User 10 (c_{10})	0	1	1	1	0	1	1
User 11 (c_{11})	0	1	1	1	0	1	2
User 12 (c_{12})	0	0	1	1	0	0	0
User 13 (c_{13})	0	0	1	1	0	0	2
User 14 (c_{14})	1	0	0	0	0	0	1
User 15 (c_{15})	1	0	0	0	0	0	2
User 16 (c_{16})	0	0	1	1	0	0	1
User 17 (c_{17})	0	1	1	1	0	1	1
User 18 (c_{18})	0	1	1	1	0	1	1

Table 2. Exported decision table

	a	b	c	e	f	g	μ_c
C_1	0	0	0	0	0	0	(1,0,0)
C_2	1	0	0	0	0	0	(0.25,0.5,0.25)
C_3	0	1	1	1	1	1	(0,0.667,0.333)
C_4	0	0	0	1	0	0	(0,0.333,0.667)
C_5	0	1	1	1	0	1	(0,0.75,0.25)
C_6	0	0	1	1	0	0	(0.333,0.333,0.333)

Table 3. packaging machine film supply module demand characteristic attribute value

	Membrane weight / (Kg)	Maximum film width / (m)	Minimum film width / (m)	Adjustment amount / (m)	Fine adjustment amount / (m)
User group 1	50	0.420	0.300	0.120	0.020
User group 2	50	0.500	0.160	0.340	0.030
User group 3	50	0.600	0.120	0.480	0.040
User group 4	50	0.320	0.180	0.140	0.025
User group 5	50	0.380	0.180	0.200	0.025

5. Conclusion

The acquisition and discovery of knowledge has a great impact on the establishment of the mechanical product platform. This paper uses the rough set to obtain the user's reduction of the different attributes of the product module, process the data and complete the acquisition of knowledge. The attribute of the mechanical product module concerned, through this example also verified the accuracy of the above conclusions, using this conclusion to make the products established through the module more in line with the actual needs of users.

By obtaining the attributes that the user really cares about, it is possible to reduce the workload and improve the customization of the mechanical product module system and enhance the market competitiveness of the mechanical products in the establishment of the mechanical products across the product family and the specific module design.

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