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INTELLIGENT DESIGN SYSTEM OF MECHANICAL PRODUCTS BASED ON DATA MINING AND KNOWLEDGE BASED ENGINEERING

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ABSTRACT

Although the intelligent design system is widely used in modern mechanical products design, the optimization of mechanical products design parameters and the method of knowledge acquisition etc. remain the key factors that restrict the development of intelligent design system. On the basis of analyzing data mining methods and knowledge based engineering (KBE) principles, an information model was built to find out the minimum attribute set of mechanical products design parameters with the improved ID_3 algorithm. Then a large numerous of finite element simulation results, combined with the rough set theory and data mining technology, was used to extract knowledge and rules and to fulfill the knowledge expression and reuse. Finally a gantry crane intelligent design system was established by adopting automation technology with the secondary development of CATIA and integrating the KBE extended module with CATIA. The example shows that the proposed gantry crane intelligent design system makes up for the deficiencies of the traditional intelligent design system and improves the design efficiency and the ability to respond to market.

Keywords: *Data Ming, Knowledge Based Engineering, Intelligent Design System, Rough Set*

1. INTRODUCTION

With the development of computer science and technology, the intelligent design system becomes the effective guarantee for optimizing design process, improving production efficiency and product quality [1, 2]. More and more enterprises have designed intelligent design systems according to the characteristics of their own products. Compared with the traditional experience design of engineers, intelligent design system has unparalleled advantages [3, 4, 5, 6]. But it still has a lot of problems, mainly in the following two aspects:

Design parameters issues. In order to achieve a combination of knowledge engineering and parametric modeling technology, intelligent design system commonly uses parametric techniques to express the design knowledge and knowledge model. In these systems, a three-dimensional model of the product is generated by intelligently solution and imposing constraints on the size variables in the case of using the size of drive parameters when the product structure and shape of the template have been determined [7, 8, 9]. But in the actual process of mechanical products design, there are many parameters. The coupling between parameters is either strong or weak, sometimes conflicting, which lead to the uncertainty of parameters' variation, trend and range, and thus resulting in the unsatisfactory design results during the course of products design.

Knowledge representation issues. Mechanical products design is a complex process which generally involves multi-conditions, multi-factors and multi-domains' iteration and collaborative design. More than one field of expertise and knowledge in the design process is needed, so the expression and acquisition of knowledge is particularly important [10, 11]. In the traditional intelligent design system, the intelligent design of mechanical products is carried out using object-oriented method with the aid of three driving method such as parameter-driven, table-driven and production rules, which realizes the expression and reuse of design knowledge [12, 13]. But these knowledge expressions have several disadvantages: (1) they are relatively simple; (2) they demand strict and accurate relationships between the size constraints; (3) at the same time it's easy to break the topology relationships of the model and (4) the model attributes are lack of class and inheritance

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relations. All of these are not conducive to the reuse of knowledge as well as the integrated design of mechanical products.

To address the above issues, we built a products design parameters information model by analyzing the internal relations of mechanical products design parameters in this paper. We used the improved ID_3 algorithm, combined with data mining technology, to find out the minimum attributes set which can represent the maximum amount of design parameters' information. We also extracted knowledge and rules hidden behind the large amounts of data using finite element simulation results and rough set method combining with data mining technology to achieve knowledge expression and further reuse. Finally the gantry crane intelligent design system is constructed by adopting the CATIA/Automation API module, making the reasoning mechanism of KBE and geometric data structure of CAD communicate directly and realizing seamless integration of KBE and CAD.

2. OPTIMIZATION OF DESIGN PARAMETERS

The mechanical products design is multi-target, multi-dimensional and multi-constraints, covering huge quantities of data and information, and the sub-target functions usually conflict with each other. Therefore, the core of intelligent design of mechanical products is to mine data in a sea of data and information, process various data units and find out useful design parameters. During the structural design process, the design variables of mechanical products amount to nearly a thousand and the functions (Including target functions and constraint parameters) to several hundreds. It's extremely difficult to design an optimal design program that embraces such huge quantities of variables and parameters. To solve the problem, this paper establishes the information model of the design parameters combined with data mining technology during the design process, as shown below.

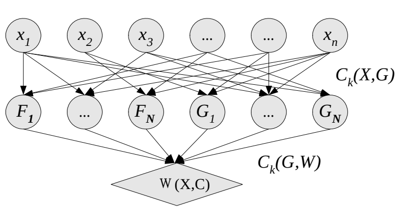

Figure 1: Design Parameters Information Model

In figure1, according to the requirements of user, x_1, x_2, x_3, • • •, x_n are basic design parameters included in the data entry process. F_1, F_2, F_3, • • •, F_N refer to target functions, G_1, G_2, G_3, • • •, G_N are constraint parameters; this is the stage of data analysis and processing. W(X, C) refers to rectification functions, which is the final output stage. During the stages of data entry, analysis and processing, the data transfer coefficients $C_k(X, G)$ (k=1, 2, 3, •••, n) are used to produce target functions and constraint functions with design variables. During the stages of data analysis and processing and final data output, data rectification factors C_k (G, W) (k=1, 2, 3, •••, N) are used to build the rectification function W(X, C) consists of target functions and constraint functions. This information model visualizes the deployment relations of the functions used during the whole calculation process and clarifies the relations between parameters. According to the characteristics of the information model, the ID_3 algorithm [14, 15] is improved combined with QFD (Quality Function Deployment) theory and McLaughlin formula to find a minimum attributes set that describe the mechanical product design parameters. The improved algorithm is as follows:

Supposed $E=F_1*F_2*\cdots*F_n$ is a n-dimensional finite vector space, P_E and N_E are respectively called positive example set and negative example set, which are two sub-sets belonging to E. p and n is the vector space size of P_E and N_E. So the information volume needed for a decision tree to accurately categorize an example is decided as below.

$$I(p,n) = -\frac{p}{p+n}\log_2\frac{p}{p+n} - \frac{n}{p+n}\log_2\frac{n}{p+n} \quad (1)$$

If take the attribute A as the root of decision tree, and A has values $\{V_1, V_2, \cdots, V_v\}$, then it divides E into subsets$\{E_1, E_2, \cdots, E_v\}$. Supposed there are P_i pro-example sets and N_i anti-example sets contained in E_i, and a_i is the weight factor, so the expectation information of E_i is $I(P_i, N_i)$.

$$I(P_i, N_i) = -\frac{p_i}{p_i+n_i}\log_2\frac{p_i}{p_i+n_i} - \frac{n_i}{p_i+n_i}\log_2\frac{n_i}{p_i+n_i} \quad (2)$$

Then the required expectation entropy as rooted by attribute A is:

$$E(A) = \sum_{i=1}^{v} a_i \frac{P_i + N_i}{p+n} I(P_i, N_i) \quad (3)$$

The information gain rooted by attribute A is:

$$Gain(A) = I(p,n) - E(A) \quad (4)$$

The Eq. (2) is substituted into the Eq. (3). Then we can get Eq. (5).

$$E(A) = \frac{a_i}{(p+n)\ln 2}\sum_{i=1}^{n}\left(-n_i \ln\frac{n_i}{p_i+n_i} - p_i \ln\frac{p_i}{p_i+n_i}\right) \quad (5)$$

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According to the McLaughlin formula:

$$\ln(1+x) = x-(1/2)x^2+(1/3)x^3-(1/4)x^4+\cdots \quad (6)$$

When x is of an extremely small value:

$$\ln(1+x) = x \quad (7)$$

In Eq. (2), $p_i/(p_i+n_i) \ll 1$ and $n_i/(p_i+n_i) \ll 1$, so we have:

$$\ln\frac{p_i}{p_i+n_i} = \ln(1-\frac{n_i}{p_i+n_i}) \approx -\frac{n_i}{p_i+n_i} \quad (8)$$

$$\ln\frac{n_i}{p_i+n_i} = \ln(1-\frac{p_i}{p_i+n_i}) \approx -\frac{p_i}{p_i+n_i} \quad (9)$$

The Eqs. (8) and (9) are substituted into the Eq. (5). Then we can get Eq. (10).

$$E(A) = \frac{2a_i}{(p+n)\ln 2}\sum_{i=1}^{n}\frac{n_i p_i}{p_i+n_i} \quad (10)$$

In Eq. (10), the value of $2/(p+n)*\ln 2$ is quantitative. So the minimum value of $\varepsilon(A)$ is chosen as the index of node attributes:

$$\varepsilon(A) = a_i\sum_{n=1}^{n}\frac{n_i}{p_i} \quad (11)$$

We can see that this attribute choice of minimum "entropy" is the same as that of ID_3 algorithm. Therefore, we can use Eq. (11) to calculate the "average entropy" of each attribute, and select the smallest "entropy" as the node attribute. So the minimum attributes set of the mechanical product design parameters can be found.

3. EXTRACTION OF MECHANICAL PRODUCTS DESIGN KNOWLEDGE

The knowledge acquisition process in the traditional mechanical products intelligent design system is actually a 3D parametric instance created process of mechanical products. Major steps include: establishing the assembly template, defining assembly constraints; dividing structure modules, clearing parts relationships; carrying out parametric design with the point, line, surface as a reference, driving 3D part models; completing module parameterized expression, generating parameterized instances. The design knowledge of Mechanical product obtained in this way is based on simply parameter configuration, constraint relations as well as a large number of design data. Therefore, it’s especially important to know how to extract deeper level of mechanical product design knowledge from the simply parameter configuration, constraint relations and a large number of design data.

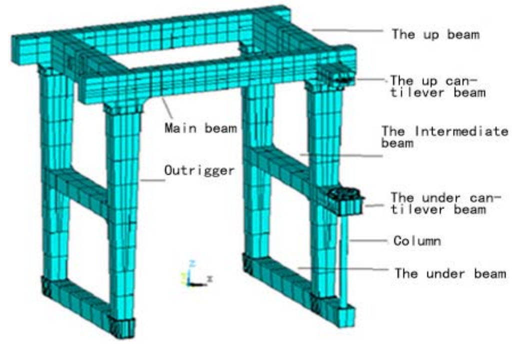

Figure 2: The FEM Model Of Gantry Mounting

In this paper, based on the actual engineering different design instances were obtained by changing the main design parameters (The main design parameters were determined by the parameters' minimum attribute set obtained from the second part of this paper) of parametric model, whose calculation results were from the finite element simulation calculation. After saving these results into database, data discretization method was used to store the configuration data and the results of finite element method. Then we used the rough set, a machine learning methods, to analyze finite element results and extract knowledge which is hidden behind a large amount of data combined with the data mining technology [16, 17]. Finally, the knowledge was summarized and saved into the knowledge base of intelligent design system.

We take gantry mounting, the important bearing member of gantry crane, as an example to explain the knowledge extraction method. According to practical experience and a large number of finite element simulation analysis results, the follow seven boundary condition parameters and geometric parameters are confirmed related with the force characteristics of the gantry mounting: (1) the thickness of the main beam (shortened as ZYT); (2) the thickness of the under cantilever beam (shortened as ZFT); (3) torque gantry suffered (shortened as RT1); (4) vertical load gantry Suffered (shortened as RT2); (5) the angle between the vertical direction and Outrigger at the initial conditions (AL); (6) the diameter of column rod (shortened as PPR); (7) the diameter of rotary table (shortened as TPR).

So the seven data is chosen as the condition attributes to analyze the impact relations of the gantry mounting structure. The stress situations of the key components decide the reasonableness of the decision-making attributes that is the relationship between the configuration parameters. The key components and whether its stress can satisfy the request of engineering are decided by the

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expert and the actual forces. Table 1 shows the results of the finite element simulation under different parameters conditions.

Table 1: Finite Element Simulation Results Under Different Parameters Conditions

No	ZYT (mm)	ZFT (mm)	RT1 (kn*m)	RT2 (kn)	AL (rad)	PPR (mm)	TPR (mm)	Max stress (Mpa)	The location of max stress
1	45	30	4340	13020	17.189	230	155	300	rotary table
2	55	25	5000	13020	17.189	230	155	320	rotary table
3	45	35	8000	9860	16.87	200	155	261	connection plate
4	25	40	6000	14430	16.87	200	200	295	rotary table
5	20	40	5000	13550	16.565	150	180	314	main beam
6	30	35	4000	22547	16.87	250	150	499	rotary table
7	35	20	3000	17515	16.27	220	160	408	rotary table
8	40	30	7000	12763	16.27	230	170	360	connection plate
9	55	45	5000	18876	15.985	250	190	383	rotary table
10	60	40	8000	18876	15.985	250	150	383	rotary table
11	45	40	8000	585	15.985	220	130	202	connection plate
12	25	20	1000	22651	15.985	250	130	564	main beam
13	45	20	4340	19052	17.189	230	155	441	rotary table
14	35	20	5000	13235	17.189	210	140	311	rotary table
15	40	30	5000	5294	17.189	210	170	257	connection plate
16	45	25	4000	10588	17.189	210	150	241	rotary table
17	50	30	6000	12701	17.189	230	155	259	rotary table
18	50	25	6000	12790	15.709	230	155	262	rotary table
19	20	45	8000	12790	15.709	230	155	342	main beam
20	30	45	7000	12970	15.709	200	140	297	main beam
21	40	25	6000	13337	15.709	210	130	304	main beam
22	25	30	5000	14637	15.709	220	150	321	main beam
23	40	20	4000	15998	15.709	230	120	406	main beam
24	25	40	4000	18926	15.442	250	155	491	main beam
25	30	55	6000	4845	15.442	200	130	168	connection plate
26	40	50	7000	4845	15.442	200	130	195	connection plate
27	25	45	5000	12815	15.442	230	140	275	main beam
28	40	30	4000	16019	15.442	230	130	360	main beam

As shown in table 1, the maximum stress focuses in three places: rotary table, connection plate between column and under beam, main beam. Before extracting the knowledge and rules, preprocessing data must be done first. That means a number of sets of data must be deleted with unobvious characteristics. And continuous data and real data must be discretized. Based on domain knowledge, Eq. (12) can be used to judge whether the characteristic of a set of data is unobvious.

$$a = |S_1 - S_2| / \max(S_1 - S_2) \times 100\% \qquad (12)$$

S1 and S2 are the maxim stress of the area mentioned before. The characteristics of the data is unobvious if $a \leqslant 10\%$.

According to the comparison, the stress of rotary table of No4, No6, No7, and No18 is maximum, but its stress on main beam also arrives at 261 MPa, 462 MPa, 360 MPa, 255MPa, so their data have unobvious characteristics. They must be deleted. The data of No5, No27, and No28 also must be deleted because their stress on main beam is large

and the stress of rotary table arrives at 287 MPa, 262 MPa, 327 MPa. The data of No 8 is deleted because its stress on main beam also arrives at 353 MPa while its stress on link board is maxim. Combine division standard of add class-reduce class and determinant calculation, data in table 1 is discretized in this paper by data clustering and

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knowledge kingdom. The finite element data can be divided into two levels, value 1 and 2, which respectively means structure is reasonable and structure is a failure. The location of maximum stress can be denoted L1, L2, and L3 as rotary table, main beam and connection plate as shown in table 2.

The parameters of table1 were discrete by the discrimination method of table2 provided. The final decision-making table of data mining was shown in table3.The various boundary conditions parameters and geometric parameters of the table are the conditions properties. Both Finite element data, the effectiveness of the structure, and the location of maximum stress are decision-making attributes.

Table 2 : Methods Of Discretizing Parameters

Parameters	L1	L2	L3
ZYT(mm)	ZYT<60	60<ZYT<75	ZYT>75
ZFT(mm)	ZFT<43	43<ZFT<67	ZFT>67
*RT1(kn*m)*	RT1<3333	3333<RT1<5667	RT1>5667
RT2(kn)	RT2<11000	11000<RT2<15000	RT2>15000
AL(radian)	AL<16.024	16.024<AL<16.606	AL >16.606
PPR(mm)	PPR<217	217<PPR<233	PPR>233
TPR(mm)	TPR<145	145<TPR<170	TPR>170
max stress (Mpa)	<350	>350	
the location of max stress	rotary table	main beam	connection plate

Table 3 : Decision-Making Table

No	ZYT	ZFT	RT1	RT2	AL	PPR	TPR	Max Stress	The location of max stress
1	2	1	2	2	3	2	2	1	1
2	3	1	2	2	3	2	2	1	1
3	2	2	3	1	3	1	2	1	3
4	3	2	2	3	1	3	3	2	1
5	3	2	3	3	1	3	2	2	1
6	3	2	3	1	1	2	1	1	3
7	1	1	1	3	1	3	1	2	2
8	2	1	2	3	3	2	2	2	1
9	1	1	2	2	3	1	1	1	1
10	1	1	3	1	3	1	2	1	3
11	2	1	2	2	3	1	2	1	1
12	3	2	3	2	3	2	2	1	1
13	1	3	3	2	1	2	2	1	2
14	1	3	3	2	1	1	1	1	2
15	1	2	3	2	1	1	1	1	2
16	1	2	2	2	1	2	2	1	2
17	1	1	2	3	1	2	1	2	2
18	1	1	2	3	1	3	2	2	2
19	1	3	3	1	1	1	1	1	3
20	1	3	3	1	1	1	1	1	3

After the generation of decision-making table, knowledge extracting can be done by using rough set theory. Attributes reduction will be done first to find the smallest attributes set. Then the reduction decision-making table set will be form. Sometimes the table will be imperfect or without measure because of the incomplete of analysis data and subjective factors in discrimination. Decision-making table must be corrected by experience. Finally, the design knowledge can be obtained as follows:

(1) RT1=3, ZFT=1.The maxim stress location is on L1. That means the torque of gantry mounting is larger. And as deformation of under cantilever's frontispiece and back are non-conforming, the rotary table's stress is maximum when under cantilever is filmier.

(2) ZYT=1, RT2=2or3, AL=2. The maxim stress location is on L2. That means the stress on part of main beam is larger when it is filmier and bear lager pressure and initial AL is smaller. Failure of

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local materials will appear when RT2=3 maxim stress will exceed its allowable stress. That shall be avoided in actual case.

(3) ZYT=3, RT2=2or3, AL=3. The maxim stress location is on L1. That means the stress on the regional board is largest which locates at the junction of the lower beam and column when it is thicker and bear lager pressure and initial alpha is larger. Failure of local materials will appear when RT2=3 maxim stress will exceed its allowable stress. That shall be avoided in actual case.

(4) RT2=2or3, AL=3. The maximum stress location is on L1. That means the stress on the regional board is largest which locates at the junction of the lower beam and column when it bear lager pressure and initial alpha is larger.

(5) PPR and TPR. The diameters of rotary table and column are not directly related to the total force characteristics of the gantry mounting. They are only related to bear pressure of themselves. So they can be removed from decision-making tables.

These rules can be proved by modifying some key data and maintain some other parameters. For example, in order to prove rule (1), by modifying torque and maintaining pressure and other parameters, we can get the relationship between torque and every key component of the door frame. As shown in figure 3, all relationships can be approximated to a straight line. And the slope of the regional board's is maxim, which means its stress is more sensitive to the torque. This indirectly proves the correctness of the knowledge. After analyzing and calculating repeatedly, a lot of design knowledge can be obtained by using the above method. This stored knowledge in the intelligent design system can achieve the knowledge expression and be reused in the product design process.

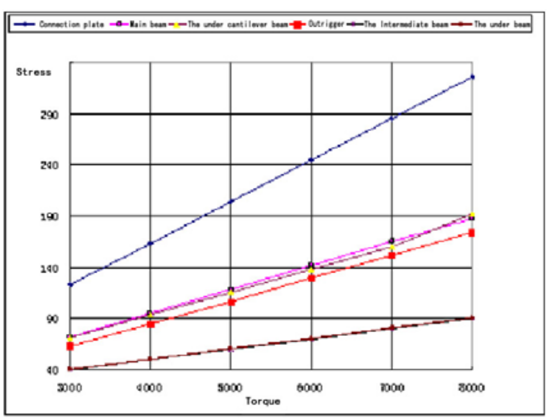

Figure 3: Curve Between Torque And Maximum Stress Of Key Components Of Gantry Mounting

4. THE REALIZATION OF INTELLIGENT DESIGN SYSTEM

The intelligent design is carried out with the knowledge extraction method described in the third part of this paper combined with two driving methods, parameterized drive and table-driven, based on CATIA / Automation API module. And the intelligent design system of gantry crane is constructed, which has the following modules:

(1) Human-Computer Interaction module. The module mainly includes the product type selection, products design parameters input, interactive modification of the entity assembly model, product structural finite element analysis and calculation, output of engineering drawings and other product design process.

(2) Background analysis module. The module consists of two parts: firstly, optimization of the basic design parameters of products and determination of the minimum attributes parameter set which can describe the design parameters of mechanical products; secondly, extraction of the design knowledge.

(3) Management and maintenance modules of knowledge base and rule base. This module is responsible for the definition, load, operation, and maintenance as well as consistency and integrity checking of the knowledge base and rule base. It consists of the large number of specific product data, instance of mature products, engineering data handbook, experience of experts in the field and rules, and is also responsible for the entry and update of extracted knowledge and rules.

Gantry crane is usually composed of gantry mounting, trolley frame, rotary crane, crane traveling mechanism and auxiliary devices. The gantry mounting and trolley frame are the key load-bearing components. Figure 4 shows the trolley frame design interface of Gantry crane in this system.

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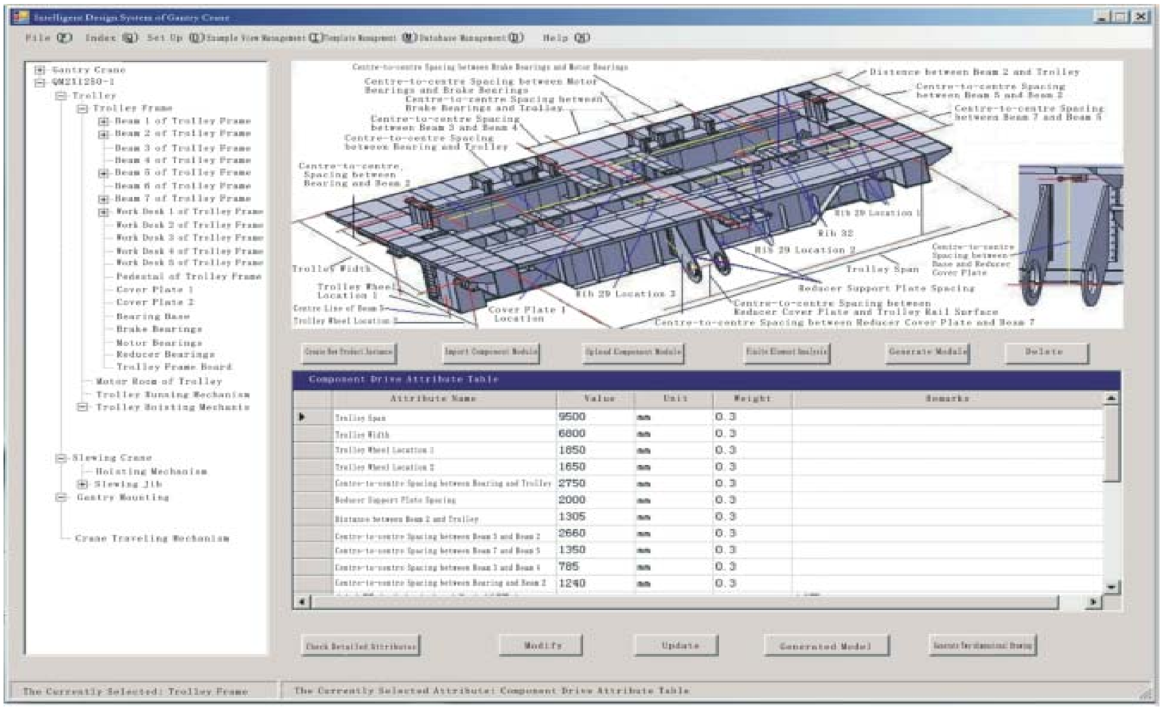

Figure 4: The Gantry Mounting Design Interface Of Gantry Crane

Under the guidance of user interface, the design steps are as follows: (1) Select new instance or existing instance; (2) Select design model, input parameters, retrieve existing instances; (3) Choose instance meeting the requirements, carry out detailed design; (4) Design components of the instance.

5. CONCLUSION

A gantry crane intelligent design system is developed in this paper, which has the following characteristics: (1) Optimizing the design parameters and determining the minimum parameters' attributes set of mechanical products. (2) Extracting knowledge and rules used to guide product design combined with data mining techniques and rough set theory and realizing the knowledge expression and reuse in the intelligent design system. Finally, taking the gantry crane intelligent design system as an example, we proves that the system provides good technical support system and intelligent integrated design platform and it greatly shortens the development cycle for the mechanical products design.

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