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RESEARCH ON DESIGN AND QUALITY TRACEABILITY OF AERO-ENGINE PRODUCTION BASED ON CBR

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Abstract: Productivity and traceability play an important role in aero-engine production. Aero-engine production is complex and there are many factors affecting its quality. CBR plays a significant role in this field. CBR model construction includes key technologies such as case entry, retrieval, revision and update. In terms of productive application, CBR can provide historical data reference, comprehensively evaluate performance indicators, consider cost factors, assist in evaluating manufacturability and reduce design risks. In the application of traceability, CBR is helpful to trace the source and use of parts, the history of production technology, the historical data of quality inspection, the history of failure and maintenance, and the performance and changes of raw materials. Through CBR technology, the productive design can be carried out in the product development stage, and the whole process of engine production can be effectively monitored and traced.
Keywords: CBR case-based reasoning; Aero-engine manufacturing; Productivity; Traceability

1 INTRODUCTION

In the global competitive environment, quality has become one of the key factors of national competitiveness, and building a quality power is an important strategic measure to promote the high-quality development of China's economy and enhance the comprehensive strength of the country. As a representative of high-end manufacturing industry, the quality level of aero-engine directly affects the competitiveness of China's aviation industry in the international market. The production of aero-engine involves a variety of parts and components, the production process is quite complicated, and there are many interference factors in the production process. At the same time, the operation process covers different links. The environment of the production workshop, the implementation of the production plan and the working environment of personnel will have an impact on the overall efficiency of the enterprise, which requires the design of product productivity in the product development stage[1]. Productive design originated from the technical document "Productive system guidelines-the five steps to success" published by the US Navy in 1999, in which the definition of productiveness is: measuring the relative ease of manufacturing products through indicators such as quality, time and cost is an ability to face the whole production process and consider whether the manufacturing process, materials, labor and cost meet the production standard products under certain circumstances. In addition, there are many factors that affect the quality of products, and every link from product design to delivery to customers will affect the final quality. In the past, it was difficult to effectively monitor the whole process of product manufacturing by simply relying on manual quality information collection and transmission. At the same time, with the increasing requirements of ISO9000 quality system and product quality supervision departments in China, it is of great significance to explore how to realize the traceability of engine production[2].

2 CBR APPLICATION STATUS

Case-based reasoning (CBR) is a kind of reasoning method based on empirical knowledge, which is suitable for fields where it is difficult to establish accurate mathematical models but there are a large number of case records. In 1982, the theory of dynamic memory structure put forward by Schank scholar was regarded as the embryonic form of this theory. After more than 30 years of development, it has been successfully used in many engineering fields[3]. The basic idea of CBR is to integrate historical successful cases into a case base and use information technology to retrieve similar cases to solve current problems[4]. It simulates human thinking, facilitates knowledge acquisition, and greatly improves the speed and quality of reasoning[5]. The reasoning of CBR usually includes four processes: case retrieval, matching/reuse, modification and storage. With the help of CBR technology and its theory, it is helpful to realize the manufacturability and traceability of aero-engines. Therefore, this paper explores the application of CBR in the two characteristics from this theory.

The initial target areas of CBR are problem diagnosis, decision order and strategic planning. However, with the continuous expansion of the understanding of CBR, CBR now has a very wide range of applications, which mainly cover: emergency decision-making, environmental monitoring, risk identification, fault diagnosis, product design, medical diagnosis, mapping and many other research directions.. Relying on a large number of cases to establish a case database, whether in the product design stage or in the production process traceability, can be traced. At the same time, with the continuous discovery of new problems in the production process, the database can be continuously expanded.

The work steps of CBR are mainly divided into four steps. First, the past cases are classified and integrated, and the database is established by relying on the past cases. Then, in the process of production or design, the relevant past cases are queried through data matching, and then the current plan is modified by combining the past cases. Finally, the modified scheme and modification process are stored in the database to further improve the database. The process is shown in the following figure1:

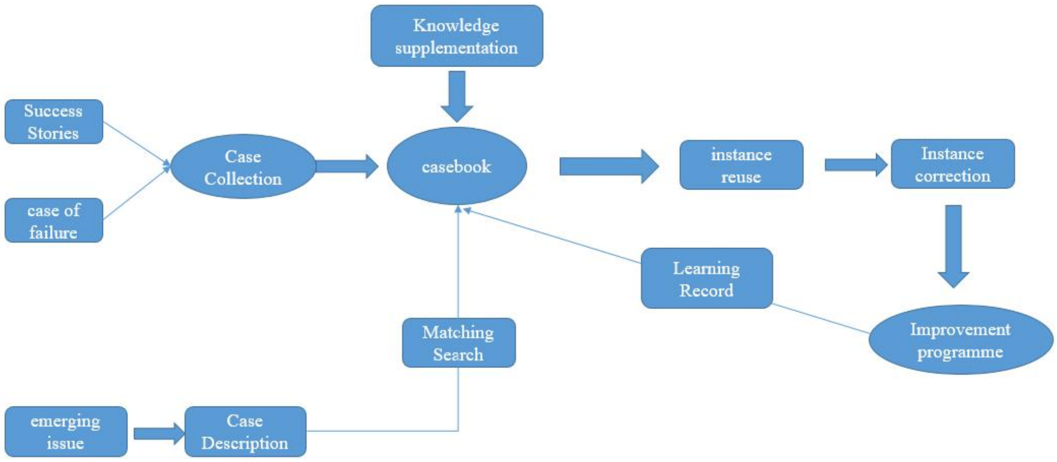

Figure 1 CBR Model

Enter the past success and failure cases into the case base, and then combine with expert opinions and national standards to improve. When new problems appear in the process of production and design, first describe the problems, then match them with the cases in the case base, then reuse the past solutions on the existing problems, and then modify and improve the problems to get the final solution, and finally enter the improved case plan into the case base again.

Key steps:

(A) case entry

The historical fault case data in the aero-engine production process are obtained, and they are preprocessed, classified and feature extracted in turn, so that the corresponding feature attributes of each category are obtained, and the fault case database is established accordingly.

Fault data collection: the collection of fault cases mainly comes from the collection and arrangement of troubleshooting and maintenance records in the engine production process, including fault maintenance manuals and maintenance service field work minutes. The fault maintenance manual covers descriptions and solutions of common engine faults by equipment parts manufacturers and users, including fault phenomena, fault equipment, fault causes and fault location. On-site work summary of maintenance service is the fault description and solution issued by equipment parts manufacturers and users when they carry out on-site maintenance for engines that have not occurred. In order to improve the quality and integrity of case data, the collected fault data are unified and eliminated. Then classify the fault data: divide the fault case data into mechanical system, electronic system and hydraulic system according to the production design system. Secondly, fault case feature extraction: define the feature attributes of each fault case according to the standard, and the feature attributes of each fault case can be expressed as pi = (pi1, Pi2, Pi3, Pi4), (I = 1, 2, ..., n), where n is the number of fault cases. Specifically, Pi1 represents the operating environment, with multi-category definitions, including temperature, humidity, salinity, altitude, etc. Recording this information can provide a basis for quickly matching similar faults triggered in the same operating environment. Pi2: indicates the fault, which is represented by three levels, and can be represented as component level, part level and component level. Each fault needs to record its component, part and component, and if it is a part or component level fault, the low level need not be recorded. For example, the hydraulic leg fails, and its components are hydraulic cylinder seals, parts are hydraulic cylinders, and parts are hydraulic legs. This representation method can quickly establish the correlation relationship for the subsequent failures of the same level and the same category. Pi3: indicates the fault phenomenon. By extracting the characteristic words of continuous information data, the keyword of the fault phenomenon can be obtained, and the number of this attribute is not limited. This attribute is the core attribute of this system and the basis of analysis and reasoning. Pi4: indicates the troubleshooting method, and this attribute corresponds to the Pi3 attribute. Finally, the fault classification is entered into the case base: after the fault case features are extracted, the fault features are saved into the case base according to the production system type.

(B) Case retrieval

After the case collection is completed, the RBF neural network is trained by using the case data in the fault case base to obtain the trained RBF neural network. RBF neural network calculates the similarity between the vector of target case feature elements and the vector of known case feature elements through the excitation function of hidden layer, and RBF neural network is equivalent to a similarity calculation network[6]. In this system, the fault cases are segmented by Chinese word segmentation algorithm (jieba word segmentation method), and then the features of the cases are extracted by TF-IDF keyword extraction algorithm, and converted into vectors according to the word frequency weights.

In this embodiment, the BoW(Bag of Words) word bag model is adopted for the digitization of feature words. The vectorized feature words are used as the input of RBF neural network. In RBF network, the input vector is x = [x1, x2, …xn]T, which is generated by the fault phenomenon in the fault case. The output vector is y = [y1, y2, ... ym] t, which is the cause of the fault.
In this study, radial basis function is used, and its weighted network output is:

$$y_j(x)=\sum_{i=1}^{h}\varpi_{ij}g_i(x)=\sum_{i=1}^{h}\varpi_{ij}\cdot\exp(\frac{-\|x-c_i\|}{\sigma_i^2}),(i=1,2,...h;j=1.2....m) \tag{1}$$

Where, it is the output of the j-th node of the output layer, the output of the i-th node of the hidden layer, the weighting coefficient from the hidden layer to the output layer, the center and variance of the Gaussian function of the i-th node, |||||| is the distance between the input x and, and n, h and m are the number of nodes in each layer. In RBF network, the center, variance and weighting coefficient of the hidden layer function are obtained through the learning and training process of the network to the actual case base. In the process of unsupervised learning, the center and variance of hidden layer basis function are solved; In the process of supervised learning, the weights between hidden layer and output layer are solved. The specific calculation process is as follows: $y_j(x)$ is the output of the jth node of the output layer, $g_i(x)$ is the output of the ith node of the implicit layer, c_i 、 σ_i is the center and variance of the Gaussian function of the ith node for ϖ_{ij} , ||·|| is the distance between the input x and c_i , n、 h、 mis the number of nodes in each layer. H centers are selected for clustering. For the radial basis of Gaussian kernel function, the variance is solved by the formula:

$$\sigma_i=\frac{c_{\max}}{\sqrt{2h}},(i=1,2,...h) \tag{2}$$

Where is the maximum distance between the selected center points. The weighting coefficient is directly calculated by the least square method, that is, the partial derivative of the loss function is solved to make it equal to 0, and the calculation formula is: $c_{\max}$ is the maximum distance between the selected center points. ϖ_{ij} is directly calculated by the least squares method to obtain, that is, the partial derivative about is solved for the loss function so that it is equal to 0. The formula is:

$$\varpi=\exp\left(\frac{h}{c_{\max}^2}\|x-c_i\|^2\right),(i=1.2,...h) \tag{3}$$

Step 3, feature extraction is carried out on the fault to be diagnosed, and corresponding key feature attributes and corresponding word vectors are obtained; According to this, the number of clustering center points is selected, and all relevant cases in the case base are clustered by K-means according to the word vector, so as to find cases with the same category as the target cases, that is, similar cases; The fault features of each similar case are transformed into word vectors and then input into the trained RBF neural network for retrieval and reasoning, and the similarity with each similar case is output.
After extracting the feature attributes of the fault to be diagnosed (that is, the target case), TF-IDF keyword extraction algorithm is used to extract the features of the case, mainly to extract the keywords from the case, to obtain the keywords with high word frequency in the case and low word frequency in other cases in the case base, and to vectorize them at the same time.
The TF-IDF value of keyword mountain in the case is:

$$TF-IDF_{\varpi}=TF_{\varpi}*IDF_{\varpi}=\frac{n_{\varpi}}{\sum n}*\frac{|D|}{|j_{\varpi}+1|} \tag{4}$$

Where is the number of occurrences of the word ω in this case, which is the sum of the occurrences of all words in the case; Is the number of cases containing the word ω, and 1 is added to avoid the denominator being 0, which is the total number of cases in the case base. n_{ϖ} is the number of times the vocabulary ω appears in the case, $\sum n$ is the sum of the occurrences of all terms in the case; $|j_{\varpi}+1|$ is the number of cases containing the vocabulary ω, adding 1 is to avoid a denominator of 0, $|D|$ is the total number of cases in the case base.
Case retrieval reasoning: query past cases through key feature attributes, that is, retrieve case base. After vectorizing the extracted key feature attributes, the number of clustering centers is selected, and all cases in the case base are clustered by K-means according to the word vector, so as to find cases with the same feature attributes as the target case, that is, similar cases. The fault features of each similar case are converted into word vectors and input into the trained RBF neural network, and the similarity between the target case and each similar case is output at the output layer.
(C) case revision and update
Select fault cases with high similarity, determine the corresponding fault causes and solutions, and update the fault case base. According to the output results, the fault cases with high similarity are selected to locate the fault, find out the cause of the fault and its solution. If the same source case as the target case is retrieved, a definite solution can be

obtained and the target problem can be solved. Because the target case already has the same case, the target case can be discarded to avoid redundancy. If the source case similar to the target case is retrieved, the suggested solution of the target case is obtained by the solution of the similar case, and the suggested solution is modified according to the actual situation, and then the definitive solution is obtained, and the target case is saved as a new case in the case base. The above case correction is mainly based on the solution of the actual target case, which is mainly the process that technicians reason the failure according to their actual experience, the test results of technical instruments and the relevant technical principles of equipment, and correct the case after the actual failure problem is solved, so as to ensure the follow-up study of personnel and reference maintenance when similar failures are found, thus further improving the maintenance efficiency.

3 DESIGN APPLICATION BASED ON CBR

Productivity considers the problems in the whole manufacturing process, which includes manufacturability, assemblability and detectability. Manufacturability, assemblability and detectability mainly consider the technological ability of equipment and process equipment from the technical point of view, and see whether a product can be manufactured and assembled easily and can be detected. Besides the meaning of manufacturability, assemblability and detectability, producibility also includes whether the enterprise can meet the requirements in terms of equipment production capacity and personnel capacity when the products are produced in batches and at the required time of listing. Relying on CBR technology, this quality characteristic can be realized.
First of all, it can provide historical data reference. For example, a certain type of engine has excellent fuel efficiency under specific working conditions, which can be compared with the current fuel system design. If the key parameters are similar, it can predict the fuel efficiency potential. Secondly, it helps to comprehensively evaluate performance indicators, such as thrust, weight and durability, and can retrieve excellent cases and compare them. For example, specific materials and processes can reduce weight and increase durability, and if the current schemes are similar, it is expected to achieve good results. Furthermore, considering the cost factor, reviewing the cost composition and control strategy can predict the current cost, and learning from previous optimization measures can control the cost. In addition, assist in evaluating manufacturability, retrieve manufacturing problems and solutions of similar structures, prevent in advance, and ensure smooth production. Finally, reduce design risks, provide innovative case results, increase confidence in success, and promote cautious improvement in failure. During the construction of design case base, we can input the construction case base from six aspects: design object, design purpose, detailed parameters, problems, actual cost and actual effect. When designing and developing an engine, we search from five aspects: environmental requirements, performance requirements, target requirements, risk prevention and cost requirements, match relevant cases, and then modify the current design according to past cases. Application of CBR in designability can be seen in Figure 2.

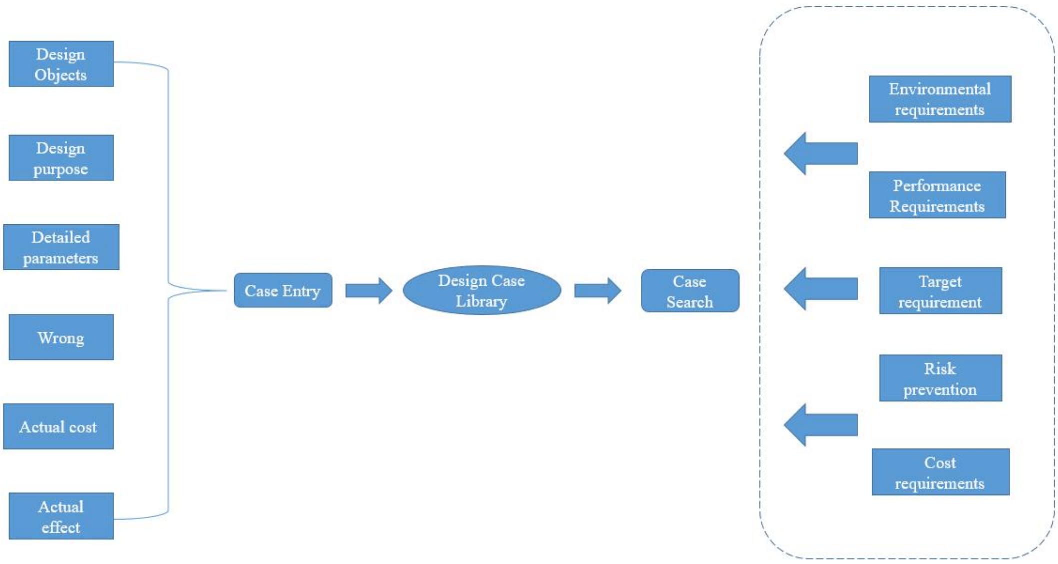

Figure 2 Application of CBR in Designability

4 QUALITY TRACEABILITY APPLICATION BASED ON CBR

Traceability means that every component, every process and raw material of military aero-engine can be clearly traced back to its source, production process and use. Once a quality problem occurs, the source and influence scope of the problem can be quickly and accurately located[7]. Depending on CBR technology, the process and parts can be traced back separately. First of all, CBR helps to trace the source and use of parts. Aero-engine is composed of many complex parts, each of which has its own specific supplier and production batch. Through CBR system, we can compare the information of parts used by the current engine with past cases. Secondly, CBR can trace and analyze the history of production technology. Different types of aero-engines may adopt similar production processes, but there may be differences in details. Using CBR, we can review the effects of similar processes under different conditions. Furthermore, CBR helps to trace the historical data of quality inspection. In the process of aero-engine production, strict quality inspection will be carried out many times. Through CBR, the current test results can be compared with the results of similar engines in the same test link in the past. If it is found that the current test results are similar to a case with quality problems, further investigation and analysis can be quickly started to ensure the quality of the engine. In addition, CBR can also trace the failure and maintenance history. When the engine breaks down in use and needs maintenance, CBR can provide the handling methods and maintenance records of similar failures in the past. Finally, CBR also plays a role in tracing the performance and changes of raw materials. The performance of raw materials used in aero-engines, such as special alloys, may be affected by factors such as production batch and processing technology[8]. Through CBR, we can compare the performance data of raw materials currently used with those in past cases, so as to better predict and control the performance and reliability of the engine. As shown in the figure 3 below, the traceability function can be realized through the case list database:

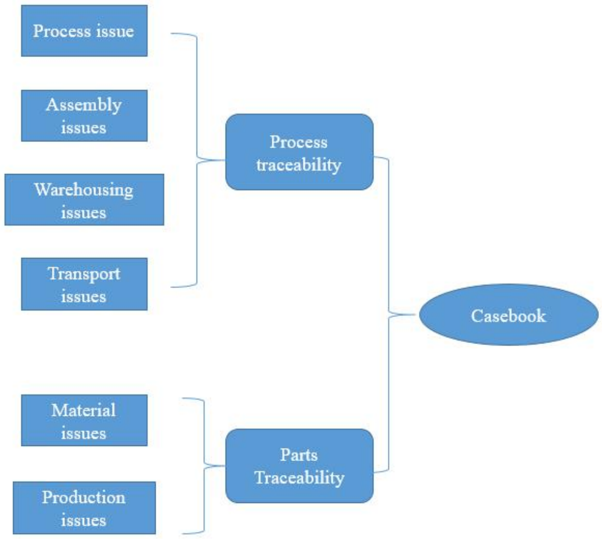

Figure 3 CBR Traceability Application

When building a case base, it should be entered from three parts: fault phenomenon, fault location and solution, as shown in Table 1:

Table 1 Case Entry Information Table

Fault phenomenon	Fault location	Knot solution
01 blade crack	Compressor blade	Strengthen raw material testing and manufacturing process control.
02 Turbine speed is unstable	turbine shaft	Check the wear of the shaft and repair or replace it.
03 insufficient air intake	air inlet	Clean the foreign body in the intake port and check the opening of the intake valve.
04 excessive engine vibration	Fan part	Balance the fan blades and check the installation and fixation.

5 SUMMARY

This paper aims to explore the application of case-based reasoning (CBR) in the manufacturability and traceability of aero-engines. As a representative of high-end manufacturing industry, the quality level of aero-engine is very important. In the production process, due to the variety of parts, complex production technology and many interference factors, it is necessary to carry out productive design in the research and development stage and realize effective monitoring and traceability of the whole process of product manufacturing[9]. The basic idea of CBR is to integrate historical successful cases into a case base to solve current problems. Its working steps include case collection, case reuse, case revision and learning record. In aero-engine production, the key technologies of CBR include case entry, case retrieval and case revision and update[10]. In productive application, CBR can provide historical data reference, compare current design with excellent cases, and predict fuel efficiency potential and performance effect; Consider the cost factor, estimate and control the cost; Assist to evaluate manufacturability and prevent production problems in advance; Reduce design risks and provide innovative case results. In the application of traceability, CBR is helpful to trace the source and use of parts, and compare the current parts information with past cases; Trace the history of production technology and analyze the effect of similar technology under different conditions; Trace the historical data of quality inspection and compare the current inspection results with past cases; Trace the history of faults and maintenance, and provide treatment methods and maintenance records for similar faults; Trace the performance and changes of raw materials to better predict and control the performance and reliability of the engine. With the help of CBR technology, it is helpful to realize the producibility and traceability of aero-engines and is of great significance to enhance the competitiveness of China's aviation industry in the international market.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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