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Modeling and Analysis of the Reliability of Machining Process of Diesel Engine Blocks Based on PFMECA

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ABSTRACT Due to its difficulty in maintenance, the diesel engine have special requirements on process reliability of the engine block, which is one of the most important and hard-to-machining components of the engine, and will directly affects the performance and service life of the engine. With continuous improvements to the engine quality, the process reliability of the engine block have become more and more important. However, the previous researches mainly focus on the reliability of products, machine tools, or cutting tools, while the researches on the reliability of machining process, which lead to unstable quality of the machined engine block, have been little discussed. Therefore, this paper proposes an integrated method to analyze the process reliability of DEB (Diesel Engine Blocks). First, the reliability model of the DEB machining process is established by using reliability block diagram method. The model is mainly concerned with the process reliability and error-free judgment probability of the key features of DEB, which is deduced by using the PFMECA (Process Failure Mode, Effects and Criticality Analysis) method. Then, the response surface and FEM method is used to establish a mathematical model for the key features and its key influencing factors, and the process reliability of the key features is evaluated by Monte Carlo simulation. The reliability of the machining process is evaluated by substituting the process reliability of the key features into the reliability model of the DEB machining process. The method is applied to evaluate the reliability of the machining process of a certain type of DEB and solves the problem that the actual machining data are insufficient for reliability evaluation.

INDEX TERMS Process reliability, PFMECA, FEM, Monte Carlo simulation.

I. INTRODUCTION

The diesel engine have high reliability requirements due to the harsh environment of its use. As the foundation for assembly of the engine, the processing quality of DEB is guarantee for a high-reliable engine. However, in practical, many uncertain factors, such as machine tool vibration, temperature and humidity changes, will influence the machining processes and lead to deviation between the processing quality and the expected. If the deviation is serious, it may even lead to the failure of DEB. At this point, it is particular important to improve the reliability of machining process of DEB.

The reliability of the machining process for a product refers to the ability to ensure that the processed product has a specified level of reliability under specified conditions for some time. In order to improve the process reliability, many researches have been reported. Zhang *et al.* [1] proposed a novel and effective system reliability evaluation method in terms of failure losses for manufacturing systems of job shop type, and use the failure losses based component importance measure for importance analysis of equipment. Ding and Zhang [2] proposed an efficient preventive maintenance policy in terms of failure effects analysis, and performed reliability evaluation and component importance measure based on failure effects analysis under the preventive maintenance policy. Chang and Lin [3]

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presented a fuzzy-based assessment model to evaluate system reliability of a labour-intensive manufacturing system with repair actions. Kharoufeh *et al.* [4] presented two stochastic failure models for the reliability evaluation of manufacturing equipment that degrades due to its complex operating environment. To realize an accurate prediction with the most recent data sets, Dong *et al.* [5] use the grey model to establish the reliability model, and applied the particle swarm optimization (PSO) algorithm further improve the prediction accuracy. He *et al.* [6] presented an approach to model the manufacturing system reliability dynamically based on their operation data of process quality and output data of product reliability, and introduced the product qualified probability to quantify the impacts of quality variation in manufacturing process on the reliability of manufacturing system. Chen *et al.* [7] proposed a way to determine the inherent formation and dependent enlarging process of the risk by considering quality variation propagation and functional failure dependency. It modeled from inherent risk and dependent risk on the basis of the risk formation chain. He *et al.* [8] established a multilayered model by part-level, componentlevel, system-level to model the reliability in the form of infant failure rate by quantifying holistic quality variations from manufacturing process for electromechanical products.

Besides the researches on manufacturing system reliability, the influence of ambient temperature and machining processes on the processing reliability have also been discussed. Qin *et al.* [9] established a man machine environment brittleness model of dynamic quality characteristics based on the brittleness theory of complex system to comprehensively and quantitatively analyse the influencing factors of dynamic quality characteristics in complex manufacturing processes. Diao *et al.* [10] proposed the weighted coupled network based quality control method to improve key features, and discussed the decoupling method based on small world optimization algorithm to analyze the status changes of key nodes accurately. If there are problems in the processing quality of the product or the processing reliability of the product is low, it is expensive to improve the manufacturing system. So, it is particularly important to analyze the processing technology of the product and evaluate the reliability of the processing process of the product accurately. Ge and Zhang [11] proposed a survival signature-based process optimization approach to improve the operational reliability of the manufacturing process. Loukil *et al.* [12] introduced variability in the estimation of the modal and cutting parameters in order to evaluate the instability probability of the machining operations and then the chatter reliability. Crookston *et al.* [13] used parametric and non-parametric analyses to examine potential differences in the WPC metrics of reliability for the two extrusion lines and estimated the process reliability. Lin *et al.* [14] proposed a Bayesian procedure to judge whether the process satisfies the preset quality reliability requirement. Based on state space model, Zhang *et al.* [15] built the process performance function which is used to describe the relations between the key product characters (KPC) of the machined part and

the key control characters (KCC) of multistage process in machining system. Lu *et al.* [16] studied the reliability of the technology of grinding process by discerning the potential causes, and regarded the product surface residual stress as the bridge between the grinding process parameters and product reliability to establish the grinding process reliability model. Lin [17] studied the Process incapability index based on multiple samples for normally distributed processes, and constructs a Bayesian approach to obtain upper bound of process incapability index to evaluate process performance. Dai *et al.* [18] presented a novel modelling method that draws upon a knowledge network of process scenarios based on the analytic network process (ANP), and developed a mathematical model and algorithm for calculating the reliability requirements of key characteristics with respect to different manufacturing process scenarios.

In conclusion, the previous researches mainly focused on the reliability of products, machine tools, or cutting tools, while the researches on the reliability of machining process, which lead to unstable quality of the machined engine block, had been little discussed.

Therefore, the process reliability model of DEB was established, and the key process and failure mode of DEB were discussed. The key influencing factors that have significant influence on machining were determined by finite element simulation. Finally, the reliability of DEB machining was calculated by Monte Carlo simulation. At last, the reliability of the machining process of a certain type of DEB was evaluated by using the method, and the problem that the actual machining data is not enough to support the reliability evaluation is solved.

II. ESTABLISHING A RELIABILITY MODEL FOR THE MACHINING PROCESS OF DEB

After the product is processed, it needs to pass the inspection before it can be put into use. This is because even if the product is well designed, it is rare to process raw materials or semi-finished products into finished products without quality changes. In the process of controlling the machining quality, the key feature method is often used to determine which excessive changes significantly affect the processing quality of products [19], and the essence of testing the quality of processed products is to test the quality of various features of products. It can be said that the processing reliability of products is reflected by the processing reliability of its various features. Therefore, when establishing a product processing process reliability model, first find out the features that have a significant impact on the product quality, and then analyze the relationship between the process reliability of these features and the process reliability of product to establish the reliability model of the machining process.

According to the processing requirements of DEB, if a certain feature or certain features of DEB cannot meet the requirements after processing, it is judged as a failure. Therefore, it is necessary to select a suitable reliability model to synthesize the process reliability of each feature.

FIGURE 2. Processing reliability analysis framework of DEB.

Commonly used reliability models include the series model, parallel model, series-parallel model, reliability model based on the strength-stress interference and the reliability upper and lower limit calculation model, etc., and the series model was selected according to the DEB processing fault judgment criterion. Assuming that DEB has *m* features, considering that there may be misjudgment in testing, the reliability block diagram of machining process of DEB is established as shown in Figure 1. The reliability model of the machining process of DEB is established according to the reliability block diagram [20], as shown in Eqs. 1:

$$
R = \prod_{i=1}^{m} \left[1 - (1 - P_i) \left(1 - P_j \right) \right] \tag{1}
$$

where P_i is the processing reliability of each feature, and P_j is the error-free judgment probability corresponding to each feature.

As DEB has many features that need to be processed, and the processing difficulty of each features is inconsistent, it is difficult to carry out detailed analysis of the process reliability of all features. Therefore, analyze and find out the features that are prone to faults in processing, and calculate the fault proportion of these features in DEB processing through statistical analysis. Assume that after analysis, it is determined that there are n key features affecting the DEB processing, and the reliability model of the machining process of DEB in Eqs. 1 is modified as shown in Eqs. 2:

$$
R = 1 - \left\{ 1 - \prod_{i=1}^{n} \left[1 - (1 - P_i) \left(1 - P_j \right) \right] \right\} \times a^{-1} \quad (2)
$$

where P_i is the processing reliability of these *n* features, P_j is the error-free judgment probability corresponding to each feature, and *a* is the proportion of faults caused by these *n* features to DEB processing failure.

Before using the reliability model for calculation, it is necessary to know the key features of DEB and their process reliability. Therefore, the key features of DEB and their process reliability should be analyzed and calculated next. The analysis steps are shown in Figure 2.

III. ANALYSIS OF KEY PROCESSES AND FAILURE MODES IN PROCESSING

To accurately find the key features of DEB, it is necessary to analyze the machining process of DEB. However, due to the complicated processing process of DEB, the detailed analysis of each process is a huge workload. Therefore, it is necessary to analyze the machining process of DEB to determine the key process, and then analyze the machining process of the key process in detail to determine the key features.

A. ANALYZING THE KEY PROCESSES IN THE MACHINING PROCESS

The processing flow of DEB can be mainly divided into casting molding, machining, inspecting and testing, etc. Each stage can be subdivided into multiple process links. The processing environment, clamping method, processing method, tolerance and accuracy requirements of each processing link are different. The three-dimensional simplified model of a certain type of DEB is shown in Figure 3. The main features are the top surface, bottom surface, crankshaft hole, camshaft hole, cylinder hole and so on.

FIGURE 4. Main processing links of DEB.

When selecting the key processing links, the following three angles need to be observed: there may be features in the process that have a greater impact on subsequent processing or on the final customer; there are features in the process that make it difficult to detect the processing quality; and there are features that are difficult to process. For the DEB, the main processing surface is the top surface, bottom surface, crankshaft hole, cylinder hole, and camshaft hole, etc. To ensure that the moving parts, such as the crankshaft, the connecting rod and the like, which are loaded into DEB, have sufficient clearance with the inner wall, the crankshaft holes and the cylinder holes at both ends are often used as a rough reference for machining. In addition, the crankshaft hole system and camshaft hole system of DEB have large span, so there are some difficulties in machining, and the machining quality of coaxiality and verticality is difficult to detect accurately. These reasons make the machining

process involving these features can be considered as a key process. The machining process of these features is shown in Figure. 4.

To fully consider the direct or indirect relationship between the key features of DEB and the various processes, it is necessary to compile the 'Parts-process Relationship Matrix' for the machining of DEB, as shown in Table 1.

It can be seen from Table 1 that the features of the DEB components are mainly reflected in the tolerance and accuracy requirements of the crankshaft hole, the cylinder hole, the camshaft hole and the top surface. Among them, the machining quality of coaxiality of each crankshaft hole, coaxiality of each camshaft hole and verticality of cylinder hole to crankshaft hole is difficult to guarantee and difficult to measure accurately. In addition, the final machining quality of DEB is guaranteed by finishing processing, so finishing processes involving many features should be selected as the

TABLE 1. Parts-process relationship matrix of DEB.

key processes, that is, process 10, process 11, and process 12 are selected as key processes, and failure modes and influence analysis are performed on the three processes.

B. ANALYSIS OF THE KEY FAILURE MODES OF DEB PROCESSING

In order to find the key features accurately, it is necessary to start from the aspects that the difficulty of feature processing, the probability of fault occurrence, the degree of fault influence and the difficulty of fault identification. Therefore, in order to determine the key features, the PFMECA method, which is commonly used in reliability analysis, is selected to analyze the machining faults of each feature in the key process processing. The essence of PFMECA is to determine all the possible failure modes and causes of each process during the production process, as well as all the influences on subsequent processes, components and equipment, and then determine the weak links in the process according to

the RPN (risk priority number) of the failure modes. Then, propose improvement measures to improve the reliability of products [21].

The purpose of this paper is to analyze the reliability of machining process of DEB. The PFMECA analysis is only used to find the key failure modes and the key failure causes. Therefore, no improvement measures are proposed in this paper.

To make the analysis results comprehensive and objective, it is necessary to list all possible causes when analyzing the failure modes of DEB processing and the causes of these failures. The description of the impact of each failure mode not only considers the impact of the failure mode on the next or subsequent processes but also the impact of the failure mode on the components and on the final diesel engine. The method used to judge the importance of each feature is the risk priority number (RPN) analysis method. This evaluation method is divided into three aspects: the grade of the severity

TABLE 2. PFMECA table of DEB.

degree of process fault, the grade of the probability degree of process fault occurrence and the grade of the undetectability degree of process fault. Each aspect is divided into 10 grades from 1 to 10. The greater the numerical value, the higher the degree of influence. The product of the three assessment grades is the value of RPN. The RPN reflects the possibility of the process failure mode and the severity of its consequences. The greater the risk sequence value, the greater the hazard of the process failure mode [22], which means that the feature of this failure mode is the key feature of the process.

As seen from the PFMECA table of DEB, there are two failure modes with high RPN values, which are respectively the ''coaxiality of each crankshaft was out of tolerance'' in process 10 and ''cylinder hole to crankshaft hole perpendicularity was out of tolerance'' in process 12. The consequences of these two failure modes are serious too. Therefore, the features of these two failures are taken as the key features of DEB.

The reliability model of the machining process for a certain type of DEB in this paper is as follows:

$$
R = 1 - \{1 - [1 - (1 - P_{\Phi}) (1 - P_k)]
$$

$$
\times [1 - (1 - P_{\perp}) (1 - P_q)]\} \times b^{-1}
$$
 (3)

where P_{Φ} is the crankshaft hole coaxiality processing reliability, P_k is the crankshaft hole coaxiality without error judgment probability, *P*⊥ is the cylinder hole to crankshaft hole verticality processing reliability, P_q is the cylinder hole to crankshaft hole verticality without error judgment probability, and *b* is the proportion of the coaxiality deviation of the crankshaft hole and the verticality deviation of the cylinder hole to the crankshaft hole in the machining failure of DEB.

IV. PROCESSING RELIABILITY ANALYSIS OF KEY FEATURES

The process reliability of key features is calculated by statistical approach, which means a large amount of data is needed for analysis. However, due to the high cost and long period of DEB processing, the practical data is insufficient. Thus, a large amount of data is generated by simulation to replace the actual data for calculation.

A. ANALYSIS OF KEY INFLUENCING FACTORS

To obtain the simulation data, it is necessary to find the mathematical model of key features. However, the actual machining process is complex and changeable, and there are too many influencing factors, so it is impossible to establish the exact mathematical model of machining quality of key features at present. So, this paper takes a compromise: establishing an approximate mathematical model of key features.

In order to make the approximate model simple in structure and high in accuracy, it is necessary to find out the factors that have a significant influence on the machining quality of key features. According to the results of the PFMECA analysis, the failure causes with a large risk priority number of key

FIGURE 5. Boring simulation model.

failure modes are improper environmental temperature and improper selection of process parameters. However, the analysis results of PFMECA are subjective, and the specific influence degree is unknown. To accurately explore the influence of the environmental temperature and various process parameters on key features, this paper adopts the method of the orthogonal test design combined with a mean analysis to carry out a finite element analysis on the machining quality of a boring crankshaft hole.

1) FINITE ELEMENT MODELLING OF THE CUTTING PROCESS

The Deform-3D software is used to analyze the crankshaft hole boring process. Select the 3D tool model that was established in UG, export it in.STL format, then import it into Deform-3d. The workpiece model intercepts the outer portion of the material near the tool. The tool material is WC hard alloy. The geometric parameters of the tool are: anterior angle -7° , edge inclination angle -7° , rear knife angle -7° , main declination angle 90°, declination angle 30°, and the radius of the tool nose is 0.3965 mm. After the tool model is established, the workpiece is formed with the tool and constitutes a simulation model, as shown in Figure 5. The tool divides 25,000 meshes in a relative manner: the workpiece mesh is divided in absolute terms, the minimum cell size of the mesh is 30% of the workpiece feed, and the maximum and minimum cell size ratio of the control mesh is 7.

When simulating boring in Deform-3D, the non-working surface of the workpiece is constrained, and the node speed of the non-working surface is set to 0; that is, the workpiece is fixed, and the tool moves relative to the workpiece. Metal cutting is the process of elastoplastic deformation of the workpiece. According to the contact relationship between the tool and the workpiece, the tool is set to a rigid body in Deform-3D, the workpiece is a soft body, and the friction type is set to shear friction.

According to different parameter variables of the workpiece during the cutting process, there are two principles of chip separation criteria: the principle of geometric separation and the principle of physical separation. The principle of geometric separation is to compare the magnitude of the local deformation of the workpiece to determine whether the chip is generated; the principle of physical separation through

FIGURE 6. Clamping load constraint and cutting load application.

the physical parameters of certain materials have reached a critical value to determine whether there is separation. In this paper, the principle of physical separation is adopted according to the cutting requirement. When the stress value of the working part of the tool and the workpiece exceeds the material fracture limit value of 0.1 MPa during the cutting process, the workpiece mesh node is broken, and a chip is generated [23].

Various mathematical models are often used to represent the flow stress data in the range of temperature and strain rate in cutting simulation. The constitutive models of commonly used metal cutting models are: the Zener-Holloman constitutive model, Bodner-Partom constitutive relation model, constitutive equation in the form of power function, interpolation constitutive equation and Johnson-Cook (J-C) constitutive equation. Among them, the J-C constitutive model is applicable to various crystal structures in its simple form and is, therefore, widely used [24]. The equation is:

$$
\bar{\sigma} = \left[A + B\left(\varepsilon\right)^n\right] \left[1 + C\ln\left(\frac{\dot{\varepsilon}}{\dot{\varepsilon}_0}\right)\right] \left[1 - \left(\frac{T - T_0}{T_{melt} - T_0}\right)^m\right] \tag{4}
$$

where *A* is the yield stress of the material, *B* is the strain hardening constant, *C* is the strain rate enhancement coefficient of the material, *n* reflects the strain hardening effect, m reflects the heat softening effect, T is the deformation temperature, T_0 is room temperature, and *Tmelt* is the material melting point temperature. The connecting rod material is ductile iron QT 500-7, according to its performance to establish the relevant parameter model. Table 3 shows the relevant mechanical parameters of QT 500-7.

2) FINITE ELEMENT SIMULATION OF DEFORMATION

Finite element software HyperMesh was used to mesh the DEB. To increase the accuracy of the calculation, the hexahedral mesh was divided for the crankshaft hole and the density of the local mesh was increased, while the other positions were divided into tetrahedral meshes, as shown in Figure 6. Then, the divided grid files were imported into ABAQUS software. Then, the model grid was divided, and the material parameters, elastic modulus, Poisson's ratio,

density and thermal expansion coefficient of the DEB were all defined. Considering that the clamping and self-weight have a certain influence on the processing quality, the six degrees of freedom were limited at four positions on the bottom of the DEB, and the clamping pressure was applied to 57.8 MPa. Gravitational acceleration was set in the positive direction of the Y-axis to apply its own gravity load. After the above work was completed, the boring force and the boring heat obtained from Deform-3d were applied to the clamped workpiece in the form of a static load.

3) EVALUATION OF SIMULATION RESULTS

Figure.7 is the original curves of the cutting force and the cutting heat when cutting speed v_c = 200 r/min, feed rate $f = 0.4$ mm/r, depth of cut $a_p = 0.5$ mm, ambient temperature $T = 20^{\circ}$ C. Figure 8 shows the deformation and displacement cloud diagram of the crankshaft hole obtained by simulation under the same parameters. It can be seen from Figure 8 that there is a difference in the deformation degree of each position of the crankshaft hole, and the maximum value can reach 0.03381 mm. It can be inferred that the center line of the

FIGURE 7. Simulation results of Deform-3D cutting. (a) Boring temperature curve. (b) Main cutting force Fy curve.

FIGURE 8. Deformation and displacement diagram of the DEB crankshaft hole.

crankshaft hole is offset. Obviously, in the actual processing, due to the influence of blank casting quality and other factors, the deviation degree of center line of each crankshaft hole is not consistent, and the coaxiality of the whole crankshaft hole system changes. Suppose that if the cylinder hole processing quality perfectly meets the design requirements, the change of center line of the crankshaft hole will also lead to the change of the verticality of the cylinder hole to the crankshaft hole. What's more, not all cylinder hole processing quality can perfectly meet the design requirements. So, the verticality of the cylinder hole to the crankshaft hole has also changed differently.

4) ORTHOGONAL TEST DESIGN AND ANALYSIS

Based on the finite element simulation method, four factors, the cutting speed, cutting depth, feed rate and ambient temperature, were taken as independent variables, and the maximum deformation displacement of crankshaft hole was taken as dependent variables [25]. The $L9(3^4)$ orthogonal test of four factors and three levels was designed. The results of the orthogonal test are shown in Table 4.

In order to study the influence of these four factors on machining deformation of crankshaft hole, the simulation test

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results in Table 4 were analyzed by the mean value analysis method. To visually indicate the degree of influence of these four factors, the orthogonal test data were input into the data analysis software Minitab15 to perform a mean analysis, and the mean curve was obtained, as shown in Figure 9.

It can be seen from Figure 8 that the cutting speed and the cutting depth have a large influence on the deformation of the crankshaft hole, the feed rate has a certain influence on the deformation of the crankshaft hole, and the change of ambient temperature has little influence on the deformation of the crankshaft hole. This seems to mean that the key influencing factors of the processing of the crankshaft hole only have both the cutting speed and the cutting depth, but this is only a result of the simulation of the machining of workpiece.

Since only the initial temperatures of the tool and workpiece were set during the boring simulation, the machining deformation caused by the change of the ambient temperature of the boring lathe was not considered. Fanjie Luo and Danlu Song used a certain milling machine headstock as the research object. They established a temperature field and thermal deformation under different ambient temperatures by using the finite element method. The influence of different ambient temperatures on the front end of the spindle was analyzed, and the results show that when the ambient temperature

TABLE 4. Orthogonal test design and deformation displacement results.

Generate random numbers

changes from 20 ◦C to 32 ◦C, the thermal deformation of the front end of the spindle changes from 0.052 mm to 0.187 mm [26]. It can be seen that the change of ambient temperature has a strong influence on the machining accuracy of the machine tool. Therefore, this paper chooses the ambient temperature, cutting speed and cutting depth as the key influencing factors that affect the deformation of crankshaft holes.

B. RESPONSE SURFACE MODELING

To establish the mathematical model between the key features and the key influencing factors, the response surface method is used for modeling [27]. The basic idea of the response surface method is to construct an approximate linear polynomial that can express the function of an implicit function through an experimental design [28]. It is clear that the mathematical model of the key feature is non-linear, so the threefactor second-order response surface model is selected, and its general form is:

$$
Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_1^2 + \beta_5 x_2^2
$$

+ $\beta_6 x_3^2 + \beta_7 x_1 x_2 + \beta_8 x_1 x_3 + \beta_9 x_2 x_3 + \varepsilon$ (5)

FIGURE 11. Parameter distribution diagram.

In this paper, the response surface model of the key feature of DEB can be expressed as:

$$
Y = \beta_0 + \beta_1 v + \beta_2 a_p + \beta_3 T + \beta_4 v^2 + \beta_5 a_p^2
$$

+ $\beta_6 T^2 + \beta_7 v a_p + \beta_8 v T + \beta_9 a_p T + \varepsilon$ (6)

where ν is the cutting speed, a_p is the cutting depth, T is the ambient temperature, and ε is the random error term.

The above response surface model can also be represented as a matrix:

$$
Y = X_{10 \times n} \beta + \varepsilon \tag{7}
$$

where *n* is the number of tests;

$$
X = \begin{bmatrix} 1 & v_1 & a_{p_1} & T_1 & v_1^2 & a_{p_1}^2 & T_1^2 & v_1 a_{p_1} & v_1 T_1 & a_{p_1} T_1 \\ 1 & v_2 & a_{p_2} & T_2 & v_2^2 & a_{p_2}^2 & T_2^2 & v_2 a_{p_2} & v_2 T_2 & a_{p_2} T_2 \\ \vdots & \vdots \\ 1 & v_n & a_{p_n} & T_n & v_n^2 & a_{p_n}^2 & T_n^2 & v_n a_{p_n} & v_n T_n & a_{p_n} T_n \end{bmatrix}
$$

$$
Y = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix}; \quad \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_9 \end{bmatrix}; \quad \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}
$$

The key to establishing the response surface model is to solve the value of the coefficient , and the least squares estimator of the coefficient β is: $\beta = (X'X)^{-1}X'Y$. After the coefficient is calculated, a goodness of fit test is required. The closer the goodness of fit is to 1, the higher the degree of fit is [29]. Generally, the goodness of fit reaches 0.8, which indicates that the approximate model can be used. If there is a problem of insufficient goodness of fit, it is necessary to consider increasing the amount of data or checking whether there are outliers in the existing data.

C. CALCULATING THE RELIABILITY OF CRITICAL FEATURE PROCESSING

In order to obtain enough data to carry out probability statistical analysis on the process reliability of key features,

Monte Carlo simulation method is selected. The essence of the Monte Carlo method is that after sampling each random variable, the random number is input into the mathematical model for calculation. After enough independent calculation, the probability characteristics of the function can be determined [30]

In the actual machining process, the cutting speed, the cutting depth and the ambient temperature are not a constant value due to the influence of current, voltage, vibration and other factors. They change in a certain fluctuation range. In processing, the fluctuation of these key factors may lead to the change of processing quality. Therefore, the influence of parameter fluctuation should be considered when evaluating the process reliability of key features.

Before sampling each process parameter, it is necessary to clarify the distribution law of each variable. It is assumed by the central limit theorem that each parameter obeys an independent normal distribution during processing. Therefore, it is necessary to test whether the measured values of each parameter obey the normal distribution.

It is assumed that the fluctuation amplitude of the cutting speed v , the cutting depth a_p , and the ambient temperature *T* are $\pm a$ (m / min), $\pm b$ (mm), $\pm c$ (°C). Under a certain set of parameters (v, a_p, T) , the steps to calculate the process reliability of the coaxiality of the crankshaft hole or the perpendicularity of the cylinder hole to the crankshaft hole are shown in Figure 10. Because of the parameters obey the normal distribution, the number of random numbers that are generated in the fluctuation interval of different parameter values may vary greatly, and the number of random numbers in some intervals may not meet the requirements of probability statistics. Therefore, after generating random numbers, all the random numbers located in the parameter fluctuation interval, namely located in $[v - a, v + a]$, $[a_p - b, a_p + b]$, and $[T - c, T + c]$, are extracted. As shown in Figure 11, the fluctuation interval of each parameter is regarded as the statistical population, and the probability distribution of each parameter within its fluctuation interval is also regarded as a

TABLE 5. Orthogonal test design table and test results.

normal distribution. In the figure, μ is the population mean and δ is the fluctuation range.

The extracted parameter values were taken as sample data to calculate the mean value and variance of the fluctuation interval. Then, random numbers were taken for each parameter again, and these random numbers were brought into the response surface model for calculation. The probability density distribution curve of the key features was drawn based on the simulation results. As shown in Figure 12, if the qualified interval of the feature is known, the process reliability of a key feature under a certain set of parameters can be obtained by calculating the area between the regions in the probability density distribution.

V. CASE ANALYSIS

In this paper, taking a certain type of DEB as an example, the key features are the coaxiality of crankshaft hole and the verticality of the cylinder hole to the crankshaft hole, and the reliability model of machining process of DEB is established accordingly. The key influencing factors are the

FIGURE 12. Calculating the reliability of key feature processing.

cutting speed, the cutting depth and the ambient temperature. When using the response surface method to fit the mathematical model between the key feature and the key influencing factors, 25 groups of tests are designed by orthogonal test method.

When conducting the orthogonal test, the order of implementation of the test needs to be randomized, that is, the order

FIGURE 13. Probability density map. (a) Coaxiality of crankshaft hole. (b) Verticality of cylinder hole to the crankshaft hole.

of the standard test numbers needs to be disrupted. The purpose of randomization is not to reduce the test error itself, but to prevent the occurrence of some unknown events that may affect the response variables. In order to make the test results objective and clear, the original order of standard test number should be arranged after the test.

According to the repetition principle of the test design, it is necessary to carry out repeated tests in the orthogonal test. The purpose of setting up repeated tests is to estimate and reduce the test error, so as to overcome the influence of individual differences, operational errors and various accidental factors. After obtaining the results of repeated tests and eliminating the possible outliers, the average value of the test results is written into the orthogonal test table arranged in accordance with the original standard test number order. The orthogonal test table after arranging and the test results are shown in Table 5.

After testing the distribution law of each parameter in the above table, it was found that each parameter obeys an independent normal distribution, and these distribution forms were *v* ~ N(200, 35.355²), a_p ~ N(0.4, 0.072²), and $T \sim N(20, 3.608^2)$.

Based on the test results in Table 5, the response surface model between the coaxiality of the crankshaft hole and the key influencing factors was established, as shown in Eqs. 8:

$$
\Phi = (1.547 + 0.134 \times v + 11.539 \times s + 2.002
$$

×T + 9.518 × s² - 0.014 × T² + 0.119
×v × s - 0.004 × v × t) × 10⁻³ (8)

The response surface model between the verticality of cylinder hole to crankshaft hole and the key influencing factors are established as shown in Eqs. 9:

$$
\perp = (-23.338 + 0.266 \times v + 10.762 \times s + 2.027
$$

×T + 12.992 × S² - 0.02 × T² + 0.047 × v × s
-0.004 × v × T + 0.691 × s × T) × 10⁻³ (9)

It has been verified that the goodness of fit \mathbb{R}^2 of the response surface model of the coaxiality of the crankshaft hole was 0.8622, with a high degree of fitting. The response

surface model can better describe the relationship between the key parameters and the coaxiality of the crankshaft hole in the processing process. The goodness of fit \mathbb{R}^2 of the verticality of cylinder hole to crankshaft hole was 0.9737, which had a high degree of fitting. The response surface model can well describe the relationship between the key parameters and the verticality of cylinder hole to crankshaft hole in the processing process.

According to the processing requirements of DEB, when the coaxiality of crankshaft hole $\Phi > 0.06$ mm, the verticality of cylinder hole to crankshaft hole \perp > 0.05 mm, a fault occurs. Through investigation, it was found that the fluctuation range of cutting speed *v*, cutting depth *ap*, and ambient temperature *T* were \pm 5 (m/min), \pm 0.02 (mm/r), and ± 1 (\degree C), respectively. When the cutting speed was 180r/min, the cutting depth was 0.4 mm, and the ambient temperature was 23° C, after 10,000 random tests, the probability density distribution of the coaxiality of the crankshaft hole was obtained as shown in Figure 13a. Under the condition that the coaxiality error-free judgment probability was 90%, the process reliability of the coaxiality of the crankshaft hole was 90.82%; when the cutting speed was 160 r/min, the cutting depth was 0.5 mm and the ambient temperature was 20° C. After 10,000 random tests, the probability density distribution of the verticality of cylinder hole to crankshaft hole was obtained, as shown in Figure 13b. Under the condition that the verticality error-free judgment probability was 90%, the process reliability of the verticality of cylinder hole to crankshaft hole was 86.42%.

To calculate the proportion of failure caused by key features in DEB processing failure, 150 failures of previous DEB machining were investigated, and the investigation results are shown in Figure 14.

According to the calculation, the two failure modes, the coaxiality out-of-tolerance of crankshaft hole and verticality out-of-tolerance of the cylinder hole to the crankshaft hole, account for 86.667% of the machining failure of DEB. The failure ratio was substituted into the machining process reliability model showed in Eqs. 2, and the process reliability of DEB is calculated as 97.388%.

FIGURE 14. Investigation on the processing failure of DEB.

VI. CONCLUSION

This paper established a reliability model of machining process of DEB by using reliability block diagram method. The key features of DEB and their influencing factors were deduced by using the PFMECA and FEM method. The important conclusions are:

1) the coaxiality of the crankshaft hole and the verticality of cylinder hole to crankshaft hole are the key features of diesel engine block.

2) cutting speed, cutting depth and ambient temperature had significant influence on the coaxiality of the crankshaft hole and the verticality of the cylinder hole to the crankshaft hole.

3) When the crankshaft hole is machined under the conditions that the cutting speed was 180 r/min, the cutting depth was 0.4 mm and the ambient temperature was 23° C in process 10, and the cylinder hole is machined under the conditions that the cutting speed was 160 r/min, the cutting depth was 0.5 mm and the ambient temperature was 20° C in process 12, the reliability of machining process of DEB is 97.388%. The evaluation results show that DEB has high process reliability and can ensure the processing quality of DEB under this process condition.

The ultimate aim of studying process reliability is to improve the processing quality of products. The research content of this paper is limited to the calculation of the machining process reliability of the DEB, and there is no specific research on how to improve the quality of processing. In the future, how to improve the processing technology to improve machining process reliability should be studied. Besides, in the PFMECA analysis of the DEB, the evaluation method adopted is the evaluation of the traditional expert panel, and there is a serious subjective tendency. In the future, more scientific and advanced methods should be used to enumerate failure modes and failure causes, and more objective methods should be adopted to judge the impact degree.

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