Multi-objective optimization of main bearing assembly structure based on improved NSGA-II

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Abstract
Multi-objective optimization of the main bearing assembly structure entails a high computational cost; moreover, the experimental measurement of the main-bearing-hole out-of-roundness has the problem of poor accuracy and inadequate repeatability. To address these issues, an improved NSGA-II algorithm based on the fixed-sized candidate set adaptive random testing (FSCS-ART) algorithm and an adaptive strategy is proposed, and a more accurate method for measuring out-of-roundness based on the compensation method is developed. Accordingly, a mathematical model and a parametric model are established for optimization. Finally, the optimal design scheme is obtained by solving with the improved NSGA-II algorithm. The results show that the proposed out-of-roundness measurement method has a high accuracy, with <5% error. The improved NSGA-II algorithm exhibits a better solution convergence compared with the original algorithm does. The optimized solution of the improved NSGA-II algorithm has a higher fitness when the two algorithms evolve to the same generation in the late stage, and the distribution of the Pareto optimal of the improved algorithm solution is closer to the Pareto frontier. After optimization, the stresses at the danger areas of the engine block and bearing cap are reduced by 13.67% and 6.71%, respectively. The out-of-roundness of the main bearing hole is reduced by 14.13%, and the maximum contact pressure on the dangerous contact surface is reduced by 14.08%. This study makes a significant contribution to the design of internal combustion engines because it facilitates the development of high-power diesel engines by optimizing the reliability of the main bearing assembly structure.

Keywords
improved NSGA-II, main bearing assembly structure, multi-objective optimization, out-of-roundness, reliability analysis
INTRODUCTION

With the increasing development of the automobile industry, to meet the requirements of high mobility, improving the power of diesel engines is of immense significance.\(^1,2\) The power of diesel engines is improved by increasing the speed and average effective pressure. However, a series of reliability problems arise when the speed and average effective pressure are significantly increased.\(^3\)

The main bearing assembly structure is the main load-bearing structure of a diesel engine that is mainly composed of an engine block, bearing cap, bearing bush, crankshaft, and a number of corresponding bolts. With the increasing power of diesel engines, the working load of the main bearing assembly structure increases significantly. In addition, owing to the limitation of the design space of the main bearing assembly structure, typical parts such as the engine block and the bearing cap under high working loads are prone to stress concentration in few areas, and the out-of-round deformation of the main bearing hole is substantial. Therefore, it is particularly important to optimize the reliability of the main bearing assembly structure for high-power diesel engines. In recent years, an increasing number of scholars have focused on analyzing the failure models of the main bearing assembly structure and have achieved remarkable results. The optimized design of the main bearing assembly structure was realized to a certain extent, and the working reliability of the main bearing assembly structure was improved.\(^4,5\) However, the optimization of the reliability of the main bearing assembly structure mainly focuses on the reliability indexes of its key components. This could lead to trade-offs between the optimization objectives of various parts, that is, the optimization of few objectives could cause the deterioration of other objectives.\(^6\) Therefore, it is necessary to start at the level of the main bearing assembly structure system. The multi-objective optimization of the overall reliability performance of the main bearing assembly structure needs to be conducted by comprehensively considering the reliability indexes of the main bearing assembly structure.

The overall performance of the main bearing assembly structure is mainly reflected in four aspects: whether the strength of each component meets the design requirements, whether the out-of-round deformation of the main bearing hole is within a reasonable range, whether the contact pressure of each contact surface meets the contact limit of the material, and whether the lightweight design is considered.\(^7\) For the multi-objective optimization of the main bearing assembly structure, the four indexes of strength, deformation, contact, and weight as the optimization targets must be considered. There are two main methods for the multi-objective optimization of the main bearing assembly structure. One approach is to use the approximate model to proxy the finite element calculation process of the main bearing assembly structure, and subsequently use the optimization algorithm to iterate the approximate model. Another approach is to directly use the finite element calculation model of the main bearing assembly structure to perform iterative calculations in the optimization algorithm. If an approximate model is used to proxy the finite element calculation process, the determination of the approximate model requires a large amount of finite element simulation data for support. Moreover, the objective functions and basic random variables may be highly nonlinear in most cases. It is difficult to obtain the numerical value of the objective function with a higher precision using the first method.\(^8\) Therefore, the multi-objective optimization of the main bearing assembly structure is more suitable for the method of iteration in the optimization algorithm that directly employs the finite element model.

1.1 Related work on NSGA-II

For multi-objective optimization of the main bearing assembly structure, a highly effective multi-objective optimization algorithm is necessary. Inspired by nature, modern metaheuristic algorithms have been developed to deal with complicated optimization problems,\(^9,10\) such as elephant herding optimization (EHO),\(^11\) monarch butterfly optimization (MBO),\(^12\) earthworm optimization algorithm (EWO),\(^13\) moth search (MS) algorithm,\(^14\) and genetic algorithm (GA).\(^15\) Multi-objective evolutionary algorithms (MOEAs) based on metaheuristic algorithms, such as NSGA,\(^16\) NSGA-II,\(^17\) MOEA/D,\(^18\) and NSGA-III,\(^19\) have been extensively developed and improved to solve multi-objective optimization problems (MOPs). Yi et al\(^20,21\) proposed an improved NSGA-II algorithm based on an adaptive mutation operator for Big Data optimization problems in 2018. As one of the most classic multi-objective optimization algorithms, NSGA-II has been widely employed to solve MOPs and realistic problems owing to its excellent performance.\(^22,23\) Li et al\(^24\) researched the multi-objective energy management for Atkinson cycle engine and series hybrid electric vehicle based on NSGA-II in 2021. However, NSGA-II still has certain limitations compared with other multi-objective optimization algorithms. On the one hand, the dominated sorting of the algorithm in NSGA-II is performed on a mixed population that is twice the size of the parent population; thus, the computational cost of NSGA-II is twice that of most algorithms. On the other hand, in the later stage of the algorithm, when individuals exceeding the number of new populations belong to the first dominating set of the mixed population,
some solutions that are with smaller crowding distance but are Pareto optimal solutions may give way to non-Pareto optimal solutions but dominating solutions. This will degrade the distribution of Pareto optimal solutions.

So, the improvement of NSGA-II can generally be significantly improved in two directions. First, to increase the computational convergence speed of the NSGA-II algorithm, an adaptive algorithm is introduced in NSGA-II, such that the evolution of the population individual changes as the algorithm progresses. Dai et al proposed an improved NSGA-II algorithm based on an adaptive elite retention scale strategy. The change in the scale of the elite retention in the early stage of the evolution increased the diversity of solutions, while the change in the scale of the elite retention in the late stage enhanced the convergence of the algorithm.28 Yin et al29 proposed an improved NSGA-II based on the adaptive variation step size according to the upper and lower boundaries of decision variables to enhance the ability to search the space and achieve a faster solution convergence. Second, to ensure the diversity of the population and avoid reaching the local optimal solution during the optimization search process, the population initialization method or genetic method of NSGA-II can be improved to ensure the distribution of the optimal solution in the entire search space. Kong et al30 proposed an enhanced NSGA-II based on the mixed-integer coding method and the arithmetic crossover operator to improve the global search ability and maintain the diversity of the population. To make the initial population individual distribution more uniform, Xiao et al proposed a population initialization method that divided the value range of each one-dimensional variable in the decision space into several subregions. They used the roulette algorithm and the method of changing the selection probability to generate decision variables.31 Although scholars have made significant breakthroughs in the improvement of NSGA-II, it is difficult to balance the convergence speed of the algorithm with the diversity of the population according to the No Free Lunch Theorem. It is necessary to make a certain trade-off according to specific problems. So, an improved NSGA-II suitable for the multi-objective optimization problem of the main bearing assembly structure, balancing the convergence speed and population diversity, still need to be researched.

1.2 Related work of out-of-roundness measurement

Using the optimization method of iterating, the finite element calculation process of the main bearing assembly structure in the optimization algorithm requires the establishment of a parametric finite element model of the main bearing assembly structure and experimental verification of its reliability indicators. The out-of-round deformation of the main bearing hole is an important reference standard for evaluating the reliability of the main bearing assembly structure. The out-of-roundness of the main bearing hole is generally adopted as an evaluation index. In the experimental verification of the parametric finite element model of the main bearing assembly structure, the measurement of the out-of-roundness is generally performed using an INCOMETER profile-measuring instrument.32 However, there are two main problems encountered in the measurement of the out-of-roundness of the main bearing hole. On one hand, INCOMETER is an accurate measuring instrument, and its measurement accuracy can reach 1 μm. Machining accuracy errors may cause errors in the out-of-roundness measurements of the main bearing hole. On the other hand, the diesel engines used for measurement are generally test diesel engines that have been operated for a considerable period of time. This results in a certain degree of abrasion or irreversible deformation of the main bearing holes and causes the out-of-roundness to be nonzero under unloaded conditions. Thus, the accuracy of the out-of-roundness of the main bearing hole under load conditions is even more difficult to guarantee. Therefore, the experimental method for the measurement of the out-of-roundness of the main bearing hole remains to be studied.

1.3 Research contents

In this paper, to ensure the diversity of the population and increase the convergence speed in the multi-objective optimization of the main bearing assembly structure, an improved NSGA-II algorithm is proposed based on the fixed-sized candidate set adaptive random testing (FSCS-ART) population initialization method, and an adaptive strategy is introduced into the improved NSGA-II algorithm to control the probability of crossover and mutation in the genetic process. Moreover, to address the poor accuracy and inadequate repeatability of experimental measurement of the out-of-roundness of the main bearing hole, a novel method of measuring the out-of-roundness based on the compensation method is proposed. Using these methods, multi-objective optimization of the main bearing assembly structure is achieved.

The remainder of this paper is structured as follows. In Section 2, the multi-objective optimization mathematical model and finite element model of the main bearing assembly structure are established. In Section 3, the calculation accuracy of the finite element model is experimentally
verified. In Section 4, the improved NSGA-II based on the FSCS-ART algorithm and the adaptive strategy is introduced in detail. In Section 5, the final optimization results of the main bearing assembly structure are presented. Section 6 provides a summary of the paper. The multi-objective optimization process for the main bearing assembly structure is shown in Figure 1.

2 | ESTABLISHMENTS OF MATHEMATICAL MODEL AND FINITE ELEMENT MODEL

The establishment of a multi-objective optimization model of the main bearing assembly structure of a high-power diesel engine mainly includes two aspects: the establishment of a multi-objective optimization mathematical model of the main bearing assembly structure and the establishment of a parametric finite element model of the main bearing assembly structure.

2.1 | Mathematical model establishment

2.1.1 | Design variables determination

The structure diagram of the single partition board model of the main bearing assembly structure for a certain type of high-power diesel engine is shown in Figure 2. Based on the research and analysis of scholars on the main bearings of diesel engines, the design parameters that may affect the strength, deformation, contact, and weight of the main bearing assembly structure are selected. Combined with the numerical calculation of the main bearing assembly structure, the key design parameters of the main bearing assembly structure are extracted as design variables, including the structural size parameters, assembly parameters, and load parameters. The value range of each design variable is determined according to the limit of the design parameters, ensuring that the stress, deformation, and contact pressure of the structure are within a reasonable design range. The design variables and their value ranges are shown in Table 1.

FIGURE 1 Multi-objective optimization process of the main bearing assembly structure
The design variables can be defined as \( x_1, x_2, x_3, x_4, x_5, x_6, \) and \( x_7 \), as shown in Table 1. Considering each design variable as an element, a vector \( X \) of the design variables is generated. \( X \) can be expressed as
\[ X = (x_1, x_2, x_3, x_4, x_5, x_6, x_7)^T. \] (1)

2.1.2 | Objective functions
determination and dimensionless processing

(1) Strength objective functions.

The strength evaluation of the main bearing assembly structure mainly investigates the stress concentration at the strength danger areas of the typical component parts, and its index is the value of the stress. The engine block and bearing cap are the typical components of the main bearing assembly structure. Under load conditions, the two typical components are prone to stress concentration. Through the finite element calculation and analysis, it can be seen that the stresses at the root of the vertical rib on the side wall of the engine block and the front end of the bolt hole of the bearing cap are relatively large, and the strength reliabilities at the two positions are poor, as shown in Figure 3. Therefore, the stresses at the two positions are considered as the strength objective function of the engine block and the strength objective function of the bearing cap, respectively. To eliminate the errors in the optimization calculation results caused by the large numerical difference between the objective functions, based on the existing research, the dimensionless calculation formula of the strength objective function is introduced as follows:
\[ \Delta \xi = \log \left( \frac{\xi_i}{\xi_{0,i}} \right), \] (2)
where \( \xi_i \) is the minimum strength safety factor of the \( i \)-th component in the assembly structure, \( \xi_{0,i} \) is the required limit for the strength safety factor of the \( i \)-th component. The material of the engine block is cast aluminum, and the

![Structure diagram of the single partition board model of the main bearing assembly structure](image)

| Design variables | Maximum value | Minimum value |
|------------------|---------------|---------------|
| \( x_1 \) | Proportional coefficient of the pretightening force of horizontal bolt and vertical bolt | 0.45 | 1.00 |
| \( x_2 \) | Assembly clearance between the engine block and the bearing cap (mm) | 0.05 | 0.15 |
| \( x_3 \) | Pretightening force of the vertical bolt (kN) | 100 | 250 |
| \( x_4 \) | Interference of bearing bush (mm) | 0.12 | 0.20 |
| \( x_5 \) | Thickness of rib on side wall of the engine block (mm) | 30.0 | 50.0 |
| \( x_6 \) | Thickness of the bearing cap (mm) | 36.0 | 44.0 |
| \( x_7 \) | Thickness of the engine block partition board (mm) | 40.0 | 48.0 |
The tensile limit of the material is 250 MPa. The material of the bearing cap is steel, and the tensile limit of this material is 980 MPa. The minimum safety factor limit $\xi_{01}$ is set to 1.2. The above parameters are substituted in Equation (2). The dimensionless strength objective functions of the engine block and bearing cap can be expressed as

$$F_1(X) = \log \left( \frac{250}{1.2 \sigma_1} \right) ,$$

$$F_2(X) = \log \left( \frac{980}{1.2 \sigma_2} \right) ,$$

where $\sigma_1$ is the stress at the danger area of the engine block, and $\sigma_2$ is the stress at the danger area of the bearing cap.

(2) Deformation objective function.

The deformation evaluation of the main bearing assembly structure focuses on the out-of-round deformation of the main bearing hole. The evaluation index is the out-of-roundness of the main bearing hole. The smaller the out-of-roundness, the better the deformation reliability of the main bearing assembly structure. Therefore, the out-of-roundness of the main bearing hole is employed as the deformation objective function of the multi-objective optimization design. In the optimization iteration process, the node coordinates of the main bearing hole under the main bearing load condition are extracted by writing the post-processing script of the finite element calculation results. The node coordinates are fitted, and the out-of-roundness is calculated based on the least-squares circle method.\[35\]

A dimensionless calculation formula for the deformation objective function is introduced as follows:

$$\Delta \varphi_\alpha = \log \left( \frac{\varphi_0}{\varphi} \right) ,$$

(5)

where $\varphi_0$ is the required limit for the out-of-roundness of the main bearing hole, and its value is a constant. $\varphi$ is the out-of-roundness of the main bearing hole. According to the actual engineering requirements of this type of diesel engine, the limit of the out-of-roundness of the main bearing hole is 0.12 mm. The dimensionless deformation objective function of the multi-objective optimization of the main bearing assembly structure is determined as follows:

$$F_3(X) = \log \left( \frac{0.12}{\varphi} \right) ,$$

(6)

(3) Contact objective function.

The evaluation of the contact performance of the main bearing assembly structure mainly considers the contact pressure of each contact surface, and the evaluation index is the maximum contact pressure of the dangerous contact surface of the assembly structure. The analysis of the finite element calculation results of the main bearing assembly structure shows that the contact pressure of the contact surface between the engine block and the bearing cap is relatively large, and its contact reliability is poor, as shown in Figure 4. The maximum contact pressure of the surface is considered as the contact objective function. Considering the dimensionless calculation of the contact objective function, the formula is expressed as follows:

$$\Delta \gamma = \log \left( \frac{\gamma_0}{\gamma} \right) ,$$

(7)

where $\gamma_0$ is the limit of the contact pressure of the dangerous contact surface that is a constant. $\gamma$ is the maximum contact pressure of the contact surface between the engine block and the bearing cap. The limit contact pressure of the engine block material is 380 MPa. The dimensionless contact...
objective function for the multi-objective optimization of the main bearing assembly structure is defined as follows:

$$F_4(X) = \log \left( \frac{380}{\gamma} \right). \quad (8)$$

(4) Weight objective function

The weight of the main bearing assembly structure is one of the key indicators of the overall performance of the main bearing assembly structure. Considering the lightweight design of the main bearing assembly structure, the mass of the single partition board model of the main bearing assembly structure is considered as the weight objective function. The formula for calculating the dimensionless weight objective function of the main bearing assembly structure is as follows:

$$\Delta M = \log \left( \frac{m_0}{m} \right). \quad (9)$$

where $m_0$ is the mass of the single partition board model of the main bearing assembly structure before optimization that is a constant. $m$ is the mass of the optimized single partition board model of the main bearing assembly structure. According to the finite element calculation results of the main bearing assembly structure, the mass before optimization is 75.01 kg. The dimensionless weight objective function of the multi-objective optimization of the main bearing assembly structure is defined as

$$F_5(X) = \log \left( \frac{75.01}{m} \right). \quad (10)$$

2.1.3 Constraint conditions determination

According to the limit of the strength, deformation, and contact of the main bearing structure, a strength safety factor $>1.2$, at the strength danger areas of typical components, is regarded as the strength constraint condition. The out-of-roundness of the main bearing hole $<0.12$ mm is considered as the deformation constraint condition, and the maximum contact pressure of the contact surface between the engine block and the bearing cap less than the contact limit of the engine block material is employed as the contact constraint condition. The increase in weight after optimization cannot exceed 3%, is used as the weight constraint condition. The constraint conditions for the multi-objective optimization of the main bearing assembly structure are defined as follows:

$$g_1(X) = \frac{250}{1.2\sigma_1} - 1 > 0, \quad (11)$$

$$g_2(X) = \frac{980}{1.2\sigma_2} - 1 > 0, \quad (12)$$

$$g_3(X) = \frac{0.12}{\varphi} - 1 > 0, \quad (13)$$

$$g_4(X) = \frac{380}{\gamma} - 1 > 0, \quad (14)$$

$$g_5(X) = \frac{m}{75.01} - 1 < 3\%. \quad (15)$$

2.1.4 Mathematical model determination

Aiming at the multi-objective optimization of the main bearing assembly structure, the key design parameters of the main bearing assembly structure are considered as the design variables. The dimensionless indexes that characterize the performance of the strength, deformation, contact, and weight are considered as the objective functions. The constraint conditions are that all the reliability indexes meet the allowable requirements. Accordingly, a mathematical model for the multi-objective optimization of the main bearing assembly structure is established. The maximum value of each objective function is solved to achieve a comprehensive optimization of the reliability indexes. The final multi-objective optimization mathematical model of the main bearing assembly structure is as follows:

$$\begin{align*}
F_1(X) &= \log \left( \frac{250}{1.2\sigma_1} \right), \\
F_2(X) &= \log \left( \frac{980}{1.2\sigma_2} \right), \\
F_3(X) &= \log \left( \frac{0.12}{\varphi} \right), \\
F_4(X) &= \log \left( \frac{380}{\gamma} \right), \\
F_5(X) &= \log \left( \frac{75.01}{m} \right).
\end{align*}$$

Maximize

$$X = (x_1, x_2, x_3, x_4, x_5, x_6, x_7)^T,$$  \quad (17)

subject to

$$\begin{align*}
g_1(X) &= \frac{250}{1.2\sigma_1} - 1 > 0, \\
g_2(X) &= \frac{980}{1.2\sigma_2} - 1 > 0, \\
g_3(X) &= \frac{0.12}{\varphi} - 1 > 0, \\
g_4(X) &= \frac{380}{\gamma} - 1 > 0, \\
g_5(X) &= \frac{m}{75.01} - 1 < 3\%.
\end{align*}$$  \quad (18)
where $F_i(X)$, $i = 1, 2, 3, 4, 5$ are the objective functions of the multi-objective optimization of the main bearing assembly structure. $x_i$, $i = 1, 2, 3, 4, 5, 6, 7$ are the design variables in multi-objective optimization. $g_l(X)$, $l = 1, 2, 3, 4, 5$ are the constraint conditions of multi-objective optimization.

### 2.2 Parametric finite element model establishment

Abaqus software was used for the finite element calculation of the main bearing assembly structure. The main framework of the software is the Python programming language. A writing script program based on Python can be used to control the Abaqus kernel to complete various operations on the finite element model. According to the definition of design variables in the multi-objective optimization in Section 2.1.1, combined with the finite element method, the geometric model of the main bearing assembly structure is parametrically modeled based on the secondary development of the Abaqus software. To ensure that the meshing can be automatically performed when the structural size changes during the optimization iteration process, the meshing of each component is parameterized according to the geometric characteristics of each component. The contact, constraints, boundary conditions, and loads of the main bearing assembly structure are set in the form of parameters by writing the script. The flow chart of the parametric modeling of the main bearing assembly structure based on the finite element method is shown in Figure 5. The parametric finite element model of the main bearing assembly structure is shown in Figure 6.

The contact surface of the parametric finite element model adopts the "surface-to-surface" standard contact method. The assembly of the side walls of the engine block and bearing cap adopts a clearance assembly. The assembly of the bearing bush and the main bearing hole adopts an interference assembly. The assembly of the bearing bush and crankshaft adopts a clearance assembly. In addition, the shadow surface and its symmetry plane in the front view of the engine block only release the freedom of displacement in the direction perpendicular to the paper surface, as shown in Figure 7. The top plane of the cylinder, as seen from direction $A$, releases the freedom of displacement in all directions, while the top plane of the cylinder on the other side, as seen from direction $B$, releases the freedom of displacement and rotation in all directions. According to the actual working conditions of the model researched in this paper, it is determined that the pretightening force of a single vertical bolt is 200 kN, the pretightening force of a single horizontal bolt is 98 kN, the initial assembly interference of the main bearing bush is 0.16 mm, and the initial assembly clearance between the engine block and the bearing cap is 0.1 mm. The relatively severe main bearing force in one working cycle of this type of diesel engine is taken as the calculated load value. The component of the force in the vertical direction is $-78,365$ N, and the component of the force in the horizontal direction is $-195,769$ N.

### 3 EXPERIMENTAL VERIFICATION OF PARAMETRIC MODEL

The experimental verification of the parametric finite element model of the main bearing assembly structure mainly includes the verification of three reliability indicators, namely strength, contact, and deformation. The main specifications of the experimental instruments and their uncertainties are listed in Table 2.

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**FIGURE 5** Flow chart of parametric modeling of the main bearing assembly structure
3.1 Verification methods for strength and contact

(1) Strength verification method.

In the strength verification method of the main bearing assembly structure, the stress of the strength danger areas is measured using strain gauges and subsequently, compared with the numerical calculation data of the corresponding position. According to the analysis of the strength danger areas in Section 2.1.2, the strength danger areas of the bearing cap are inside the assembly structure. It is difficult to measure the position using strain gauges when the model is assembled. Therefore, the stress of the strength danger area of the engine block is considered as the evaluation index of the verification scheme in this study. Four BX series $4 \times 4 \text{mm}^2$ resistance strain gauges are selected and placed on both sides of the roots of the side walls of the engine block, as shown in Figure 8. Resistance strain gauges are used as the resistance on the measuring bridge. When the main bearing assembly structure is loaded, the measured bridge output voltage is transmitted to the amplifier through the conversion circuit and finally transmitted to the computer to read the response strain value.

(2) Contact verification method.

In the contact verification method of the main bearing assembly structure, the maximum contact pressure of the dangerous contact surface is measured using pressure-sensitive paper and thereafter compared with the numerical calculation result. According to the analysis of the dangerous contact surface, the verification index of the contact performance is determined to be the maximum contact pressure of the contact surface between the engine block and the bearing cap. The HHS model pressure-sensitive paper is selected for the experiment based on the numerical value of the contact pressure. The pressure-sensitive papers are cut to place them between the engine block and the bearing cap, as shown in Figure 9. When the main bearing assembly structure is loaded, the pressure-sensitive papers undergo a color change owing to the contact pressure. The colored pressure-sensitive papers are compared with the standard color card and the value of the maximum contact pressure is read.

3.2 Verification method for deformation

For the deformation verification of the main bearing assembly structure, the out-of-roundness of the main
bearing hole is measured using an INCOMETER contour measuring instrument, as shown in Figure 10. During the measurement process, the measurement parameters, including the measurement diameter, device clamping diameter, and coordinates of the measured axial section, need to be set up in advance. During the measurement, the measuring stylus with a ruby touches the surface of the measured component. The structure composed of the measuring stylus and spring can adapt to small changes in the measured surface. According to the cross-sectional coordinates of the measured circular hole set in advance, the motor on the screw shaft drives the measuring stylus to the specified position. Thereafter, the measuring stylus completes the measurement of the different axial cross-sections of the measured circular hole. The measuring stylus outputs an electronic signal according to the small change in the measured surface that is transmitted to the control box via the control cable, and finally to the computer. The computer terminal can directly read the deformation of the measured bearing hole section in different angle directions in the form of polar coordinates. Because the measuring instrument needs to reach deep into the main bearing hole to measure the out-of-roundness, the experimental verification target is the out-of-roundness of the main bearing hole under bolt load without the assembling of the crankshaft, as shown in Figure 11.

Aiming at the problems of poor measurement accuracy and nonrepeatability in measuring the out-of-roundness of the main bearing hole using the INCOMETER, a method is proposed wherein the deformation of the unloaded main bearing hole is first extracted, and subsequently the deformation is used to correct the loaded main bearing hole measurement data. The core idea of this method is to measure the deformation of the unloaded main bearing hole in advance and consider the inverse number of the deformation. Thereafter, the inverse number of the unloaded deformation is added to the deformation of the main bearing hole after loading. The purpose of this calculation method was to ensure that the main bearing hole is an ideal circle when it is not loaded. The specific methods used are as follows:

Considering a certain type of high-power diesel engine as the measurement object, the experimental engine has been in operation for a period of time, and the inner surface of the main bearing hole shows a certain degree of abrasion or irreversible deformation. First, the measurement data of a certain axial section of the main bearing hole in the unloaded state are extracted, as shown in Figure 12. It can be seen from the figure that the main bearing hole is not an ideal circle in the unloaded state on the axial section, and there is deformation in all angular directions. Suppose the polar coordinates of the measuring points of the main bearing hole of the axial section are \( \Phi_i \left( \theta_i, r_i \right) \), where \( \theta_i \) is the angle formed by the \( 0^\circ \) ray and the straight line, determined by the \( i \)-th measuring point in the counterclockwise direction and the origin, \( r_i \) represents the deformation of the \( i \)-th measuring point. Second, the measurement data of the main bearing hole with the same axial section under load are extracted. Suppose that the polar coordinates of the measuring points of the main bearing hole of the axial section under load are \( \Phi_{0,i} \left( \theta_i, r_{0,i} \right) \), the deformation of the main bearing hole under load after correction can be expressed as \( \Phi_i \left( \theta_i, r_{0,i} - r_i \right) \). The initial diameter of the main bearing hole in this model is 150 mm. The radius \( R_i \) of the main bearing hole after being loaded can be expressed as

\[
R_i = 75 + \left( r_{0,i} - r_i \right) \cdot 10^{-3}. \tag{19}
\]

The polar coordinates \( \left( \theta_i, R_i \right) \) of the main bearing hole are converted to rectangular coordinates \( \left( x_i, y_i \right) \), and thereafter, the out-of-roundness of the main bearing hole under load is solved based on the least-squares circle method.

To verify the correctness of the proposed data processing method for the main bearing hole measurement data, the out-of-roundness of the main bearing hole was measured for the experimental engine without operation. To avoid errors in the verification process, the other measurement conditions and measurement targets for the two measurements are same. Considering the center of the central axial section of the main bearing hole as the origin, a comparison of the different axial-section
out-of-roundness of the nonoperating experimental engine and the operated experimental engine is shown in Figure 13. It can be seen from the figure that the selected cross-sections are distributed on the front and back sides of the main bearing hole. This is because there is an oil injection hole in the middle of the main bearing hole, and the measuring stylus must avoid the position of the oil injection hole. It can be seen from the changing trend of the curves that the measured cross-section close to the middle section of the main bearing hole has a higher degree of out-of-roundness. This is because the middle section of the main bearing hole is distributed with bolt holes that causes the rigidity of the middle part of the bearing hole to be slightly lower. The out-of-roundness of the main bearing hole of the nonoperating engine under the bolt pretightening state is slightly different from the value of the main bearing hole after the correction of the operated engine, and the error is within 5%. This shows that the data processing method of the main bearing hole measurement data proposed in this paper is effective and feasible. It is worth noting that the out-of-roundness of the main bearing hole in the figure is small compared with the out-of-roundness calculated in the following part of this manuscript. This is because the out-of-roundness in the figure only considers the influence of the bolt pretightening force on the out-of-round deformation of the main bearing hole, but does not consider the influence of the crankshaft load on it.

3.3 | Experimental verification results

Based on the research on the experimental verification method of strength, deformation, and contact, the stress in the engine block danger area, the maximum contact pressure of the contact surface between the engine block and the bearing cap, and the out-of-roundness of the main bearing hole are experimentally verified. Among them, the section with an axial coordinate of 12 mm is selected as the reference section to verify the out-of-roundness of the main bearing hole. Comparing the finite element simulation calculation results of the main bearing assembly structure with the experimental measurement results, it can be found that the difference between the simulation calculation results and the experimental measurement results is extremely small, and the error range does not exceed 6%, as shown in Figure 14. This error range can satisfy the design requirements of the main bearing assembly structure in actual engineering applications and prove the calculation accuracy of the parameterized finite element model established in this study.

4 | IMPROVED NSGA-II ALGORITHM

For the multi-objective optimization of the main bearing assembly structure, the original NSGA-II algorithm still has few limitations. Owing to the high time cost of calculating the objective functions via the finite element
method for the main bearing assembly structure, it is necessary to improve the convergence speed of the original NSGA-II algorithm in full measure while ensuring population diversity. Therefore, an improved NSGA-II algorithm for the multi-objective optimization of the main bearing assembly structure is proposed in this paper. A flow chart of the improved NSGA-II algorithm is shown in Figure 15.

4.1 | Population initialization method based on FSCS-ART

The distance-based adaptive random testing (D-Art) algorithm was the earliest ART algorithm proposed.\textsuperscript{36,37} The core idea of distance-based adaptive random testing is to first generate a certain number of candidate test cases. Thereafter, the distances between each test case in the
candidate test case and the executed test cases are calculated. Finally, the candidate test case with the maximum value of the shortest distances is considered as the next executed test case. D-ART is one of the most effective ART testing methods, while the fixed-sized candidate set ART (FSCS-ART) algorithm is one of the most classic algorithms in a series of D-ART.

In view of the current problems in the multi-objective optimization of the main bearing assembly structure, to increase the diversity of the population and avoid reaching the local optimal solution during the optimization process, this study introduces the FSCS-ART algorithm to NSGA-II to initialize the population. The specific method is as follows. First, \( k \) candidate individuals are randomly generated, and a set of candidate individuals \( C = \{ c_1, c_2, \ldots, c_k \} \) is generated. Thereafter, the shortest distance between each candidate individual \( c_j, j = 1, 2, \ldots, k \), and all the individuals that have been included in the initial population \( S = \{ s_1, s_2, \ldots, s_q \} \) is determined, where \( q \) indicates the number of individuals in the current initial population. Finally, the candidate with the maximum value of the shortest distance is selected as the next individual to be included in the initial population. The mathematical formula can be expressed as

\[
\text{mindist} \ (c_b, S_i) \geq \text{mindist} \ (c_m, S_i), \forall c_b, c_m \in C, \ (20)
\]

where \( i = 1, 2, \ldots, |S|, |S| \) represents the number of individuals in the current initialized population \( |S| \), \( \text{dist} \ (a, b) \) represents the distance between individuals \( a \) and \( b \) in the hyperdimensional space of design variables. The pseudo code of NSGA-II improved the population initialization method based on the FSCS-ART algorithm, as shown in Table 3.

### 4.2 Crossover and mutation based on adaptive strategy

In the existing NSGA-II algorithm, the parent individuals inherit offspring individuals through crossover and mutation, and the probabilities of crossover and mutation are constant. Aiming at the multi-objective optimization of the main bearing assembly structure, to increase the convergence speed of NSGA-II, an adaptive genetic strategy is introduced in NSGA-II. The evolution process of the population is divided into the early stage and the late stage according to the setting stage condition (evolution generation). In the early stage, to ensure the diversity of the population and avoid the optimization from reaching the local optimal solution, the population undergoes genetic evolution by the original NSGA-II algorithm, in which the probabilities of crossover and mutation are constant. In the late stage, the population evolves with adaptive crossover and mutation probabilities to increase the convergence speed of the algorithm.

According to the research on adaptive algorithms, the distance between an individual and the Pareto front or the origin is a typical evaluation index used to access individual fitness. Based on the characteristics of the multi-objective optimization of the main bearing assembly structure, the distances between the individuals and the origin of the hyperdimensional space of the objective function are used as the evaluation indexes of individual fitness. It can be expressed as

\[
dis \ (X) = \sqrt{\sum_{i=1}^{n} F_i^2 \ (X)}, \ (21)
\]
where \( \text{dis}(X) \) represents the distance between the individual and the origin in the hyperdimensional space of the objective function. \( n \) is the number of objective functions for the multi-objective optimization of the main bearing assembly structure. Thereafter, the individual fitness function can be expressed as

**FIGURE 15** Flow chart of the improved NSGA-II algorithm
Algorithm 1 Population initialization method based on FSCS-ART

| Step | Description |
|------|-------------|
| 1.   | Set $S = \{\}$ and $C = \{\}$. |
| 2.   | Randomly generate $q$ population individuals according to uniform distribution, and generate the candidate individual set $S$. |
| 3.   | **while** $(q + 1 > pop$, where pop is the population size.) **do** |
| 4.   | Randomly generate $k$ population individuals according to uniform distribution, and generate the candidate individual set $C$. |
| 5.   | **for** each candidate individual $c_j \in C$, where $j = 1, 2, \ldots$, **do** |
| 6.   | Calculate the shortest distance $d_j$ between $s_i \in S$ and $c_j$. |
| 7.   | **end_for** |
| 8.   | Find $c_b \in C$ such that $d_b \geq d_j$, where $j = 1, 2, \ldots$. |
| 9.   | Set $s_{p+1} = c_b$. |
| 10.  | Set $S = \{s_1, s_2, \ldots, s_{p+1}\}$. |
| 11.  | **end_while** |
| 12.  | Output initial population $S = \{s_1, s_2, \ldots, s_{pop}\}$. |

\[
Fit(X) = \frac{1}{1 + D - \text{dis}(X)}, \tag{22}
\]

where $Fit(X)$ represents the fitness of an individual. The maximum value of $\text{dis}(X)$ in each generation is considered as the value of $D$ for controlling the value range of $Fit(X)$. According to the calculation of individual fitness, the probabilities of adaptive crossover and mutation can be calculated. The calculation formulae are as follows:

\[
p_c = \begin{cases} 
  k_1 f_c \leq f_{avg} & \frac{k_1 (f_{max} - f_c)}{f_{max} - f_{avg}}, f_c > f_{avg} \\
  k_2 \left( f_{max} - f_m \right) & f_m > f_{avg} 
\end{cases}, \tag{23}
\]

\[
p_m = \begin{cases} 
  k_1 f_c \leq f_{avg} & \frac{k_2}{f_{max} - f_{avg}}, f_c > f_{avg} \\
  k_2 \left( f_{max} - f_m \right) & f_m > f_{avg} 
\end{cases}, \tag{24}
\]

where $p_c$ and $p_m$ are the probabilities of adaptive crossover and mutation, respectively. $k_1$ and $k_2$ are two constants that are related to the crossover and mutation probabilities in the original NSGA-II algorithm. $f_c$ is the greater fitness value of the two individuals to be crossed. $f_m$ is the fitness value of the mutated individual. $f_{max}$ is the maximum fitness of the individuals in the current generation. $f_{avg}$ is the average fitness of the individuals in the current generation. The calculation method of $f_{avg}$ can be expressed as $f_{avg} = \frac{1}{N} \sum_{i=1}^{N} Fit(X)$, where $N$ is the number of individuals in the population. The pseudocode for calculating crossover and mutation probabilities based on the adaptive strategy is presented in Table 4.

5 | RESULTS AND DISCUSSION

For the multi-objective optimization of the main bearing assembly structure, the improved NSGA-II algorithm adopts a binary encoding method and an initial population method based on the FSCS-ART algorithm. The binary crossover is selected as the crossover method in the algorithm, and the polynomial mutation is employed as the mutation method. In addition, the size of the population for the multi-objective optimization of the main bearing assembly structure is set to 12. Evolutionary generation is set to 50. The initial crossover probability is set to 0.9, and the initial mutation probability is set to 0.1. According to the empirical calculation of the multi-objective optimization for the main bearing assembly structure, when the threshold value of the evolution generation distinguishing the early and late stages is set to 24, the algorithm has the best convergence effect, and the distribution of the optimized solution is relatively uniform. The computational environment included the following: an Intel Xeon Gold 6145 CPU, 128 GB RAM, the Windows 10 operating system, and MATLAB R2017a.

5.1 | Optimization results

Multi-objective optimization problems are different from the previous optimization problems that contain only a single objective. The solution to this type of problem is not a single optimal value. The result of a multi-objective optimization problem is a set of trade-offs between a set of multiple conflicting objectives. They are called the Pareto optimal solution set or nondominated solution set. The mathematical model of the multi-objective optimization of
Algorithm 2 Calculation method of adaptive probabilities of crossover and mutation

1. if \( i > v \), where \( u \) is the current evolution generation, \( v \) is the generation threshold that distinguishes the early stage and the late stage of evolution.

2. Set \( f_{\text{avg}} = 0 \), \( f_{\text{max}} = 0 \).

3. for individual \( X_j \), where \( j = 1, 2, \ldots, pc \), \( pc \) is the population size.

4. Calculate the value \( F_i (X_j) \) of the objective functions of each individual, where \( i \) is the number of objective functions.

5. Calculate the distance \( dis (X_j) \) between each individual and the origin in the hyperdimensional space of the objective function.

6. Calculate the fitness \( \text{Fit} (X_j) \) of each individual.

7. end_for

8. Calculate the average fitness \( f_{\text{avg}} \) of the current generation.

9. Calculate the maximum fitness \( f_{\text{max}} \) of the current generation.

10. Randomly select two individuals \( X_{i1} \) and \( X_{i2} \) in the parent population to be crossed.

11. Calculate \( \text{Fit} (X_{i1}) \) and \( \text{Fit} (X_{i2}) \).

12. if \( \text{Fit} (X_{i1}) > \text{Fit} (X_{i2}) \)

13. \( f_c = \text{Fit} (X_{i1}) \)

14. else

15. \( f_c = \text{Fit} (X_{i2}) \)

16. if \( f_c \leq f_{\text{avg}} \)

17. Crossover probability \( p_c = k_c \), where \( k_c \) is the crossover probability used in the early stage of NSGA-II that is a constant.

18. else

19. Crossover probability \( p_c = \frac{k_c(f_{\text{max}} - f_c)}{f_{\text{max}} - f_{\text{avg}}} \)

20. Randomly select an individual \( X_m \) in the parent population to be mutated.

21. Calculate \( \text{Fit} (X_m) \) and let \( f_m = \text{Fit} (X_m) \).

22. if \( f_m \leq f_{\text{avg}} \)

23. Mutation probability \( p_m = k_m \), where \( k_m \) is the mutation probability used in the early stage of NSGA-II that is a constant.

24. else

25. Mutation probability \( p_m = \frac{k_m(f_{\text{max}} - f_m)}{f_{\text{max}} - f_{\text{avg}}} \)

26. end_if

the main bearing assembly structure is solved based on the improved NSGA-II algorithm. The Pareto optimal solution set of the multi-objective optimization is obtained, as shown in Table 5. In the table, \( x_1 \) represents the proportional coefficient of the pretightening force of the horizontal and vertical bolts. \( x_2 \) represents the assembly clearance between the engine block and the bearing cap. \( x_3 \) represents the pretightening force of the vertical bolt. \( x_4 \) represents the interference of bearing bush. \( x_5 \) represents the thickness of the ribs on the side wall of the engine block. \( x_6 \) represents the thickness of the bearing cap. \( x_7 \) represents the thickness of the engine-block partition board. \( F_1, F_2, F_3, F_4, \) and \( F_5 \) are the strength objective function of the engine block, strength objective function of the bearing cap, deformation objective function, contact objective function, and weight objective function, respectively.

For the selection of the optimization design scheme for main bearing assembly structures, the order of the optimization objectives must be determined first according to the failure mode of the main bearing assembly structure under a high working load. Thereafter, the optimization design scheme of the main bearing assembly structure can be chosen based on the order of the optimization objectives. Through numerical calculations and experimental researches, it was found that the failure of the main bearing assembly structure was mainly caused by the out-of-round deformation of the main bearing hole. Therefore, the deformation of the main bearing assembly
structure is determined as the first optimization objective. The strength, contact, and weight are the second, third, and fourth optimization objectives, respectively. It can be seen from the table that the two best design schemes for the deformation objective function are shown in Scheme 1 and Scheme 2. The difference in the deformation objective function between the two is extremely small that can be ignored in practical engineering problems. Comparing the other optimization objectives of the two, it can be found that the strength, contact, and weight objective functions of Scheme 1 are better than those of Scheme 2. Therefore, it is more reasonable to consider Scheme 1 as the optimal design scheme for the main bearing assembly structure.

5.2 | Fitness analysis

In the process of multi-objective optimization of the main bearing assembly structure, the fitness of each individual is extracted, and the average fitness and maximum fitness of each generation are calculated. To illustrate the advancement of the improved NSGA-II algorithm, the original NSGA-II algorithm is used to optimize the main bearing assembly structure, and the fitness of each generation is accordingly calculated. The improved NSGA-II data and the original NSGA-II data are compared, as shown in Figure 16. It can be seen from the figure that the average fitness of the individuals increases rapidly in the early stage, irrespective of whether the improved NSGA-II algorithm or the original NSGA-II algorithm is employed, while the increasing trends of the two in the late stage gradually slow down. This finding shows that the threshold value chosen in this study to distinguish between the early and late stages of evolution is reasonable. Comparing the three curves in the figure, it can be seen that with the increase in generation, the average fitness curves of the improved NSGA-II and the original NSGA-II population gradually move closer to the maximum fitness curve. This reflects the gradual convergence of the optimization solution in the iterative

| No. | $x_1$ | $x_2$ | $x_3$ | $x_4$ | $x_5$ | $x_6$ | $F_1$ | $F_2$ | $F_3$ | $F_4$ | $F_5$
|-----|------|------|------|------|------|------|------|------|------|------|------|
| 1   | 0.74 | 0.104| 210 407.3 | 0.184| 32.15 | 42.91 | 45.77 | 0.232 | 0.782 | 0.278 | 0.330 | 0.019 |
| 2   | 0.74 | 0.091| 225 807.7 | 0.182| 32.49 | 43.84 | 46.37 | 0.230 | 0.779 | 0.283 | 0.329 | 0.017 |
| 3   | 0.45 | 0.073| 177 299.9 | 0.176| 38.68 | 36.03 | 41.75 | 0.379 | 0.729 | 0.175 | 0.352 | 0.038 |
| 4   | 0.74 | 0.106| 150 594.0 | 0.176| 32.68 | 42.77 | 40.80 | 0.198 | 0.879 | 0.156 | 0.512 | 0.025 |
| 5   | 0.46 | 0.054| 151 358.4 | 0.200| 38.77 | 42.74 | 40.80 | 0.335 | 0.864 | 0.156 | 0.561 | 0.024 |
| 6   | 0.45 | 0.139| 158 629.1 | 0.176| 38.79 | 36.05 | 40.80 | 0.275 | 0.752 | 0.119 | 0.406 | 0.039 |
| 7   | 0.69 | 0.104| 200 207.8 | 0.181| 32.66 | 36.51 | 46.06 | 0.240 | 0.714 | 0.222 | 0.299 | 0.033 |
| 8   | 0.66 | 0.108| 168 631.3 | 0.182| 32.49 | 43.89 | 45.18 | 0.159 | 0.834 | 0.214 | 0.469 | 0.017 |

![Fitness comparison between the improved NSGA-II and the original NSGA-II algorithms](image)
calculation processes of the two optimization algorithms. Comparing the improved NSGA-II average fitness curve with the original NSGA-II average fitness curve, it can be found that the average fitness change trends of the two in the early stage of evolution are basically the same. However, in the late stage of evolution, owing to the influence of adaptive probabilities of crossover and mutation, the average fitness of the improved NSGA-II is significantly faster than the original NSGA-II average fitness in approaching the maximum fitness curve. This shows that the improved NSGA-II in the late stage has an improved solution convergence efficiency.

In addition, it is worth noting that when the evolution proceeds to the 50th generation, the difference between the average fitness of the improved NSGA-II algorithm and the maximum fitness of the population is extremely small. This difference is negligible in actual engineering applications. However, there is an obvious difference between the average fitness of the original NSGA-II and the maximum fitness. This phenomenon shows that when the improved NSGA-II and original NSGA-II algorithms evolve to the same generation in the late stage of the algorithm, the optimized solution of the improved NSGA-II algorithm has a higher fitness. To support this viewpoint, the average objective function values of the Pareto optimal solution set of the improved NSGA-II and original NSGA-II algorithms are extracted, and the difference between the two is shown in Figure 17. As shown in the figure, the mean values of the strength, deformation, contact, and weight objective functions of the Pareto optimal solution set calculated by the improved NSGA-II algorithm are slightly larger than those calculated by the original NSGA-II algorithm. This proves that the distribution of the Pareto optimal solution calculated by the improved NSGA-II algorithm is closer to the Pareto frontier.

5.3 | Comparison of optimized scheme and original scheme

The values of the design parameters of the main bearing assembly structure before and after optimization are compared according to the selected optimization design scheme of the main bearing assembly structure in Section 4.1, as shown in Table 6. The optimized finite element model of the main bearing assembly structure is established by referring to the optimized design scheme in the table. The strength, deformation, contact, and weight reliability indexes of the optimized model of the main bearing assembly structure are calculated and compared with those of the original model. To show the difference between the reliability indicators before and after optimization more intuitively, a radar chart is introduced. The reliability indexes before and after optimization are represented by two different closed polylines, as shown in Figure 18. The closer the endpoint of the polyline is to the center of the pentagon, the smaller the corresponding index and the better the reliability, and vice versa.

In terms of strength, the stress at the strength danger area of the engine block of the optimized model is 123.87 MPa, while the stress of the original model is 143.48 MPa. The stress of the engine block is reduced by 13.67% after the optimization. The stress at the strength danger area of the bearing cap of the optimized model is 137.50 MPa, while the stress in this position of the original model is 147.39 MPa, and the stress of the bearing cap is
reduced by 6.71% compared with that before optimization. For deformation, the out-of-roundness of the main bearing hole after optimization is 0.0632 mm, while the out-of-roundness of the main bearing hole of the original model is 0.0736 mm. After optimization, the out-of-roundness of the main bearing hole is reduced by 14.13%. In terms of contact, the optimized maximum contact pressure of the contact surface between the engine block and the bearing cap is 177.44 MPa that is significantly less than the maximum contact pressure of 206.51 MPa before optimization. The optimized maximum contact pressure decreased by 14.08% compared with that in the original model. For weight, the mass of the single partition board model of the main bearing assembly structure before optimization is 75.01 kg, and the mass after optimization is 76.56 kg. After optimization, the mass of the main bearing assembly structure is slightly increased, but the increase is only 2% that meets the design requirements of the main bearing assembly structure in practical engineering.

6 | CONCLUSION

This study focuses on multi-objective optimization based on the reliability indexes of the main bearing assembly structure, such as strength, deformation, contact, and weight. By analyzing the structural characteristics and failure modes of the main bearing assembly structure, a mathematical model for multi-objective optimization and a parametric finite element model of the main bearing assembly structure are established, and the accuracy of the parametric finite element model is verified based on the experimental verification method proposed in this paper. In addition, in view of the computational efficiency problems

| Design parameters                                      | Initial value | Optimal value |
|--------------------------------------------------------|---------------|---------------|
| Proportional coefficient of the pretightening force of | 0.49          | 0.74          |
| horizontal and vertical bolts                          |               |               |
| Assembly clearance between the engine block and the    | 0.1           | 0.104         |
| bearing cap (mm)                                       |               |               |
| Pretightening force of vertical bolt (kN)              | 200           | 210.41        |
| Interference of bearing bush (mm)                      | 0.16          | 0.184         |
| Thickness of ribs on side wall of the engine block     | 30            | 32.15         |
| Thickness of the bearing cap (mm)                      | 40            | 42.91         |
| Thickness of the engine block partition board (mm)     | 44            | 45.77         |

FIGURE 18 Comparison of reliability indexes of main bearing assembly structure before and after optimization
encountered during the current multi-objective optimization of the main bearing assembly structure, an improved NSGA-II multi-objective optimization algorithm based on the adaptive strategy is proposed, and an ART-based population initialization method is introduced in the improved algorithm. Based on the improved NSGA-II algorithm, the mathematical model of the multi-objective optimization for the main bearing assembly structure is solved, and the optimization result is obtained. Thereafter, by comparing the individual fitness of the improved NSGA-II and original NSGA-II algorithms, the performance of the two is evaluated. Finally, according to the selection criteria of the optimal design scheme, the optimal design scheme of the main bearing assembly structure is determined. The finite element model of the main bearing assembly structure is reconstructed. The reliability indexes before and after optimization are compared. The main conclusions are as follows.

1. The method of measuring the out-of-roundness of the main bearing hole based on the compensation method proposed in this paper can effectively improve the measurement accuracy of the out-of-roundness of the main bearing hole and overcome the poor repeatability of the out-of-roundness measurement. By comparing the data of the operated engine measured based on this method with the measured data of the nonoperating engine, the error between the two is not more than 5% that demonstrates the correctness of the measurement method.

2. Compared with the original NSGA-II algorithm, the improved NSGA-II algorithm proposed has an improved convergence of the optimized solution. In the early stage of evolution, the convergence trends of the two optimized solutions are basically the same, while the optimized solution of the improved NSGA-II algorithm in the late stage converge significantly faster. Furthermore, when the improved NSGA-II and the original NSGA-II algorithms evolve to the same generation in the late stage, the optimized solution of the improved NSGA-II algorithm has a higher fitness, and the distribution of the Pareto optimal solution is closer to the Pareto frontier.

3. Through the multi-objective optimization of the reliability indexes of the main bearing assembly structure, comparing the optimized model and the original model, it is found that the stress of the engine block is reduced by 13.67%, the stress of the bearing cap is reduced by 6.71%, the out-of-roundness of the main bearing hole is reduced by 14.13%, and the maximum contact pressure of the dangerous contact surface is reduced by 14.08%. Although the weight of the main bearing assembly structure increases slightly after optimization, the increase rate is only 2% that meets the design requirements of practical engineering. The overall improvements in the reliability indexes indicate the effectiveness of the multi-objective optimization design for the main bearing assembly structure described in this paper.

The limitations of this study are as follows. The mathematical model of the multi-objective optimization of the main bearing assembly structure is only considered to be solved using the improved NSGA-II. Apart from the improved NSGA-II proposed herein, some of the most representative computational intelligence algorithms can be employed for multi-objective optimization of the main bearing assembly structure, such as monarch butterfly optimization (MBO), earthworm optimization algorithm (EWA), elephant herding optimization (EHO), moth search (MS) algorithm, slime mold algorithm (SMA), and Harris hawks optimization (HHO). Additionally, the single main bearing model is used as the parametric finite element model; thus, the reliability of multiple main bearings under dynamic load could not be researched in this study.

Thus, in further studies, other optimization algorithms such as MBO, EWA, EHO, and SMA can be employed for multi-objective optimization of the main bearing assembly structure. Additionally, the overall model of a diesel engine can be employed to study the multi-objective optimization of the main bearing assembly structure; this will allow for fully considering the consistency of the out-of-round deformation among the multiple main bearings of the diesel engine. Moreover, mainly static analysis of the main bearing assembly structure was conducted in this study. Hence, reliability optimization of the main bearing assembly structure under dynamic load will be considered in future.

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