

RESEARCH ARTICLE

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Structure optimization design of gasket test rig based on response surface model

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Abstract. In order to enhance the temperature regulation response speed of the gasket test rig and reduce the hysteresis of the temperature control system, structural optimization is implemented in the hardware part of the test rig. Firstly, a multi-physical field coupling method is employed for comprehensive performance testing of high-temperature and high-pressure gaskets, establishing a heat-fluid-solid coupling simulation and analysis model based on ANSYS. Then, internal temperature distribution of the gasket test device is calculated considering initial and boundary conditions. Next, data is collected using Latin hypercube sampling method, and optimal structural parameter combinations are determined through a multi-objective optimization approach utilizing response surface method and improved genetic algorithm. Finally, collected data is further utilized with response surface method and improved genetic algorithm multi-objective optimization technique to obtain optimal structural parameter combinations for the gasket test device which are verified by heat-fluid-solid coupling simulation. The temperatures tested before and after optimization are analyzed for comparison purposes. The results demonstrate that optimized gasket test rig significantly enhances its temperature control performance.

Keywords: Structure optimization / gasket test rig / finite element analysis / response surface / advanced genetic algorithm / temperature control

1 Introduction

Gasket Test Rig (GTR) is utilized for the purpose of conducting mechanical characterization tests on gasket materials [1–3]. With the development of petrochemical plants and novel gasket materials, the service environment of the gasket is developing toward high temperature and pressure. Gaskets are important sealing components that determine the performance of pressure-bearing equipment [4]. However, the quality of the products and testing methods are not fully adapted to the level of development of the equipment, resulting in an increasing number of cases due to seal failure during long service at high temperatures. This has led to a demand for developing a comprehensive high temperature and pressure test rig for related gaskets.

Literature [5] monitored the amount of deformation by three displacement transducers located at different positions during the hot seal test, and this measurement method increased the accuracy of the measurement. Sawa [6] investigated the sealing performance of large diameter

bolted joints at elevated temperatures, where internal pressure changes were monitored by pressure transducers and strain gauges attached to the bolt rods were used to monitor axial bolt forces. However, this test setup leaves little space for the heater to heat up to 200 °C. Jeya and Bouzid [7] utilized the Universal Gasket Rig (UGR) can achieve temperature conditions up to 450 °C, but the electro-ceramic band heater it uses is ineffective in temperature control and temperature retention and is not suitable for higher temperature test conditions. Literature [8] developed a high-temperature gasket comprehensive performance testing machine, and conducted compression resilience, creep relaxation, and sealing performance tests for a variety of gaskets, achieving very good test results, but it carries out the test temperature does not exceed 500 °C. Ouzid and Das [9,10] evaluated the high temperature performance of flexible graphite gaskets in service environments by using a High-temperature Aged Leakage Relaxation (HALR) fixture, which is mainly used to evaluate various types of gaskets in the range of 430–550 °C. However, the designed fixture cannot provide large loads and is not suitable for gasket performance testing in high pressure environments. Wang Yulong [11] designed a

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high-temperature sealing gasket performance testing device, its heating device using resistance disc to achieve, heat insulation screen and pressure plate filled with insulation cotton material for insulation, can achieve room temperature to 500°C range of temperature control.

Although the above methods have achieved some results in the structural design of the gasket test rig, they have not fully considered test conditions under high temperature conditions. In order to further improve the temperature regulation response speed of the gasket test rig and reduce the hysteresis of the temperature control system. In this paper, the thermal-fluid-solid coupling simulation model of the gasket test rig is established by ANSYS, and the optimal structural parameter combinations press plate (HP), the height of the heat shield (HS), and the height of the gasket contact board (HC) are obtained by the multi-objective optimization method of the response surface method and the improved genetic algorithm, and the reliability analyses are carried out with the help of finite element software. Finally, the temperature test of the gasket test rig before and after optimization are compared and analyzed with examples.

2 Finite element model of gasket test rig

The research object of this paper is a set of comprehensive performance gasket test rig. The gasket test rig is based on the electric pressure tester as the main platform, including cold plate, heat insulation plate, heating plate and pressure plate. Driven by a motor and a hot plate, the test bench can perform compression recovery, creep and stress relaxation tests up to a maximum temperature of 600°C and a maximum pressure of 20 MPa. A cold plate is placed under the indenter of the motorized pressure tester to avoid high temperatures. An insulating plate made of mica was used to avoid heat loss from the heated plate to the cold plate and the surroundings. Heating of the gasket is achieved by means of two resistance heating plates placed close to the press head. The test measures both creep and compression resilience of the gasket material under high compression loads. Three optical encoders (OE) are used to monitor axial displacement or thickness changes of the gasket. Temperature is monitored by thermocouples inserted in the middle plane of the platen and connected to a computer via a data acquisition and control system. The physical object is shown in Figure 1.

2.1 Establishment of finite element model

The components involved in heat transfer calculations and key performance tests in the test set are modelled with the gasket placement plane as the symmetry plane, and the structure of the upper and lower parts of the test set is the same, so only the upper part is taken to carry out the heat transfer analysis in order to reduce the workload caused by repeated calculations. The upper half of the model contains the cold plate, insulation plate, heat plate and press plate. The geometrical model parameters are shown in Table 1.



Fig. 1. Gasket test rig.

Table 1. Geometrical model parameters.

Part name	Diameter/mm	Height/mm
Cold plate	210	55
Insulation plate	210	20
Heat plate	210	40
Press plate	210	50

A SolidWorks 3D model is built according to the design of the gasket test rig, to simulate the distribution of the temperature field, as shown in Figure 2. The fluid domain model, as shown in Figure 3.

2.2 Grid division

A tetrahedral mesh is used for the chilled water tray, fluid domain and platen components, a hexahedral mesh is used for the insulation plate and heating plate, and the mesh is refined by controlling the number of parts at the boundary lines of the fluid domain at the entrances and bends, and at the entrances and exits of the water cooler tray. The model is set up according to the above settings, and the resulting mesh has an average mesh mass of 0.853 and an average mesh skewness of less than 0.2. Figure 4 shows the mesh of the solid domain and the fluid domain.

2.3 Materials models

The material characterization is important for defining its deformation behavior and thermal performance under loading and elevated temperature. The cold plate is made of steel (SS316L), the heat shield is made of mica, and the heat plate and press plate are made of K465. As a kind of high-temperature alloy, K465 is widely used in aerospace and has high temperature strength and good heat resistance and corrosion resistance [12]. The thermophysical properties of SS316L, mica and K465 are listed in Table 2.

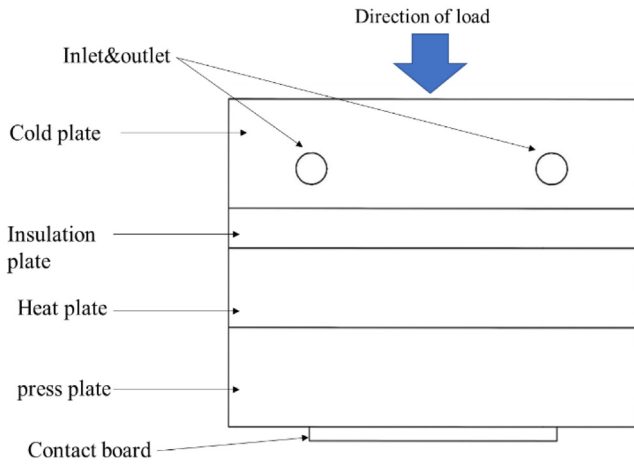


Fig. 2. Schematic diagram of gasket test rig model.

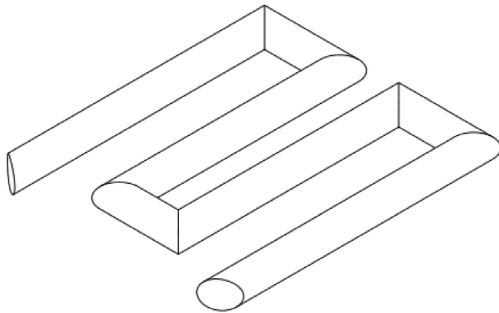


Fig. 3. Fluid domain model.

2.4 Boundary condition

In this study, the boundary conditions are specified as follows:

- The initial temperature of the test rig is set as 34 °C.
- The compressibility of cooling water is not considered, and the inlet and backflow are stable at a temperature of 10 °C and a velocity of 1.54 m/s according to the cooling requirements.
- The heat convection between the test rig boundary and air is stable, and the environment temperature oscillation is not considered.

2.5 Discussion of simulation results

The model with the initial and boundary conditions is solved iteratively using ANSYS Fluent [13], considering the k- ϵ turbulence model and the SIMPLEC algorithm.

Figure 5 shows the temperature distribution along the vertical direction of the gasket test rig after 6000 s. The temperature of the surface of the press plate and heat plate is within the same color scale. It can be observed that the maximum temperature of the press plate and heat plate is 608 °C. The temperature of the area between the heat plate and heat shield appears lower than 548 °C because of heat conduction. Compared to the lower surface, the upper surface of heat shield is 400 °C lower, proving the heat shield's excellent insulation performance.



(a) Solid domain



(b) Fluid domain

Fig. 4. Meshing results.

Table 2. Material properties of test rig.

Material	Density/ (kg/m^3)	Specific heat ($J/kg.K$)	Conductivity $W/(m.K)$
Stainless steel (316L)	7930	588	22.2
Mica	3200	880	4.0
K465	8314	622	22.7

3 Structural optimization of gasket device based on response surface methodology and improved genetic algorithm

The experiments are based on validation using probabilistic and statistical tools [14]. When carrying out the structural optimization of the gasket test rig, it is necessary to consider both the mechanical properties of the device under large loads and the temperature oscillation, so the problem is considered a multi-objective optimization problem to ensure that the test rig resists deformation as much as possible when optimizing the temperature response efficiency of the gasket test rig.

3.1 Modelling response surfaces

3.1.1 Optimization variable

Fluent cannot express the complete interference factors, such as unstable output power of the heat plate in the simulation process, so it cannot directly measure the response efficiency of the temperature control system, but the temperature difference between the heat plate and the thermocouple can reflect the control efficiency of the temperature control system. The smaller the temperature difference, the faster the temperature adjustment

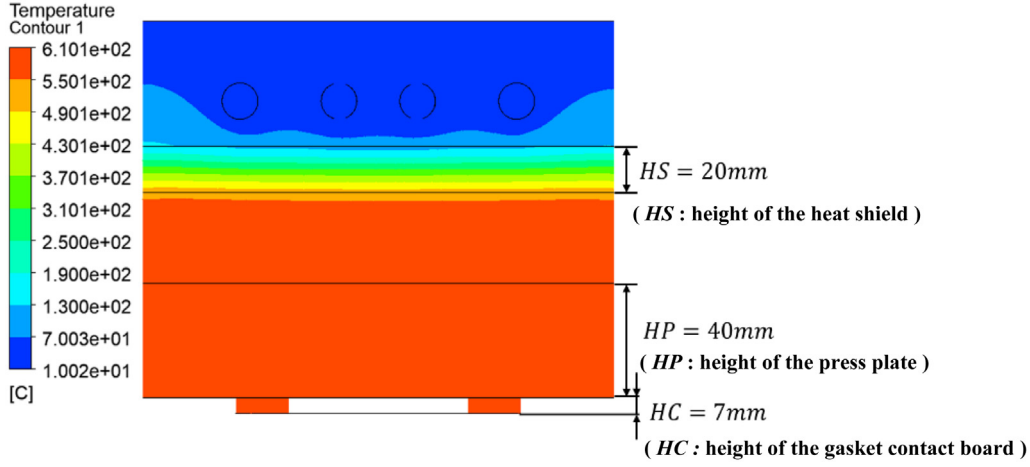


Fig. 5. Contour of vertical plane.

Table 3. The ranges of structure parameters.

Parameter	Max	Min
HS (mm)	30	10
HP (mm)	50	20
HC (mm)	14	2

when the temperature of the heat plate changes. At the same time, the total volume of the gasket test rig reflects the ability of the gasket test rig to resist deformation in a high temperature and pressure environment.

In this study, the height of the press plate (HP), the height of the heat shield (HS), and the height of the gasket contact board (HC) are selected as three input parameter variables. Two parameters of the gasket test rig, the temperature difference (ΔT) and volume (V), are selected as the output response. ΔT is the temperature oscillation range, the difference between the maximum value and the minimum value. V is the total volume of the gasket test rig, excluding the volume of the cold plate. The ranges of design variables are shown in Table 3.

In order to construct an accurate response surface model, an appropriate experimental design method is required to obtain the exact relationship between the design variables and the response values with minimum sample points. Latin hypercube sampling (LHS) [15] is selected as the experimental design method. As a type of stratified Monte Carlo Sampling, Latin hypercube sampling can divide the design variables into several equal parts uniformly without duplication, thus enabling full coverage of the range of design variables and effective study of the influence of each design variable on the response values in the design space.

3.1.2 Establishment of response surface model

The response surface method is a statistical analysis method based on the design of experiments for modelling and analyzing multivariate problems [16,17]. The principle of the method is to create a hypersurface in a certain way to

make the implicit function explicit when the actual function values of some points around a point are known. In the region around that point, this approximate surface can be used instead of the actual function for calculations. A standard multivariate second-order response surface model is shown in equation (1):

$$y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_{i < j}^k \beta_{ij} x_i x_j + \varepsilon \quad (1)$$

where $\beta_0, \beta_i, \beta_{ii}, \beta_{ij}$ are the coefficients to be determined, x_i, x_j are design variable, ε is the approximation error, and the range is determined according to the required accuracy.

By the method of Latin hypercube sampling, 25 sampling points are determined. The temperature difference and volume of the 25 samples are obtained from Fluent, as shown in Table 4.

3.1.3 Verification of response surface model

The fitting accuracy of the constructed response surface model can be evaluated based on the evaluation coefficient R^2 , as shown in equation (2):

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_l)^2}{\sum_{i=1}^n (y_i - \bar{y}_l)^2}, \quad (2)$$

Where $\hat{y}_l$ is the prediction value; $\bar{y}_l$ is the mean of the true response value; y_i is the sample point true response value.

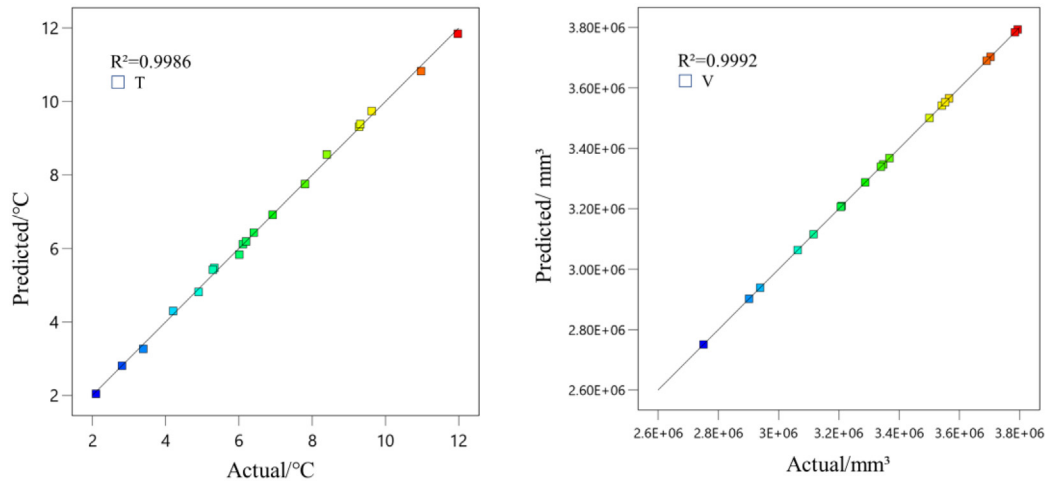
The closer the value of R^2 is to 1, the better the fitting effect. The comparison of predicted values and simulated values are shown in Figure 6. The agreement between predicted values and simulated values is great [18].

3.2 Improved genetic algorithm

In this paper, based on the classical genetic algorithm, the mathematical model, the coding and decoding method and the operational setup parameters are determined. Mathematical model, coding and solving method and operation parameters are determined, in order to improve the iterative speed of the optimal solution process and the

Table 4. Response values of each group of samples.

No.	HS (mm)	HP (mm)	HC (mm)	$\Delta T(^{\circ}\text{C})$	$\Delta V(\text{cm}^3)$
1	12.80	28.52	9.82	4.20	2890.17
2	19.20	47.70	12.12	6.41	3793.28
3	21.59	43.59	8.11	8.40	3703.11
4	27.28	37.67	7.44	10.97	3690.03
5	11.73	49.18	6.31	9.28	3541.54
6	10.56	40.66	6.72	5.33	3209.22
7	22.53	39.38	4.90	7.81	3565.39
8	24.21	32.54	13.69	5.37	3453.89
9	15.30	21.28	13.06	6.11	2750.83
10	28.57	24.83	7.07	9.31	3287.36
11	14.19	45.34	10.61	14.04	3526.61
12	16.66	27.70	2.40	4.21	2938.75
13	17.23	36.62	12.82	6.20	3346.86
14	25.33	23.78	4.06	3.35	3115.86
15	11.04	31.79	4.53	4.90	2902.05
16	27.62	20.08	11.58	3.83	3124.48
17	12.44	29.45	11.92	4.54	2925.95
18	18.52	30.72	9.08	5.00	3158.70
19	26.72	33.64	3.42	9.63	3500.43
20	24.95	27.04	2.84	3.39	3206.25
21	20.04	46.88	10.82	6.92	3784.05
22	29.21	38.53	3.67	16.83	3757.83
23	20.44	34.98	8.43	5.29	3367.68
24	13.48	41.78	5.43	11.98	3339.23
25	15.94	44.58	9.53	6.01	3552.63

**Fig. 6.** Comparison of actual and predicted values.

accuracy of the optimal solution, the classic iteration speed and the accuracy of the optimal solution, the classical genetic algorithm is improved to compensate for the difficulty in finding the optimal solution. In order to improve the iteration speed and accuracy of the optimal solution, the classical genetic algorithm is improved to make up for its tendency to fall into local optimality when finding the optimal solution.

3.2.1 Improvements in adaptive crossover, variational operators

Since the excellent individuals in the population at the early stage of evolution have large fitness values, the crossover rate and variation rate are relatively low, and the search is easy to fall into local convergence [19]. To address this problem, under the premise of retaining

high fitness individuals, the number of individuals near the average fitness should be increased to form a stable population, so the S-shaped growth curve function is introduced as an adaptive adjustment curve for crossover rate and mutation rate. The upper and lower segments of the S-shaped growth curve change gently, and the middle segment changes rapidly and nearly linearly. The adaptive genetic operators constructed in this paper are shown in equations (3) and (4):

$$P_c = \begin{cases} \frac{P_{m_{\max}}}{(e^{f_{\max}} - e^{f_{\min}})}, & f \leq f_{\max} \\ \frac{(e^{f_{\max}} - e^{f_{\min}})P_{m_{\max}}}{(e^{f_{\max}} - e^{f_{\min}})P_{m_{\max}} + (e^{f_{\min}} - e^{f_{\max}})P_{m_{\min}}}, & f > f_{\max} \end{cases} \quad (3)$$

$$P_m = \begin{cases} \frac{P_{m_{\max}}}{(e^{f_{\max}} - e^{f_{\min}})}, & f \leq f_{\max} \\ \frac{(e^{f_{\max}} - e^{f_{\min}})P_{m_{\max}}}{(e^{f_{\max}} - e^{f_{\min}})P_{m_{\max}} + (e^{f_{\min}} - e^{f_{\max}})P_{m_{\min}}}, & f > f_{\max} \end{cases} \quad (4)$$

Where: P_c is the crossover probability; P_m is the mutation probability; $f_{\max}$ is the maximum value of fitness in each generation; $f_{\min}$ is the average value of fitness in the population in each generation; f is the fitness value of the individual to be mutated; $P_{c_{\min}}$, $P_{c_{\max}}$ are the minimum and maximum value of crossover probability respectively; $P_{m_{\min}}$, $P_{m_{\max}}$ are the minimum and maximum values of the variance probability.

3.2.2 Improving the fitness function

Genetic algorithms use the fitness function to evaluate the degree of individual superiority and inferiority, and the effectiveness of the fitness function in evaluating the individual characteristics of the population determines the search direction and evolutionary ability of the algorithm [20]. In this paper, the fitness function of classical genetic algorithm is improved by using small habitat operation, which ensures the diversification of the solution process and makes the optimal solution stable and reliable at the same time. The small habitat operation is derived from the sharing function [21], and the closeness of the relationship between individuals of the population is represented by the sharing function $S(d_{ij})$, where d_{ij} is some kind of relationship between two bodies.

Let $d_1(s_i, x_j)$ be the Hemming distance, $d_2(s_i, x_j)$ be the fitness distance of individual i, j . σ_1, σ_2 , represent the radius of the niche, then the sharing function can be expressed as equation (5):

$$S(d_{ij}) = \begin{cases} 1 - d_1(x_i, x_j)/\sigma_1 & d_1(x_i, x_j) < \sigma_1, \sigma_2(x_i, x_j) \geq \sigma_2 \\ 1 - d_1(x_i, x_j)/\sigma_2 & d_1(x_i, x_j) \geq \sigma_1, d_2(x_i, x_j) < \sigma_2 \\ 1 - d_1(x_i, x_j)d_2(x_i, x_j)/\sigma_1\sigma_2 & d_1(x_i, x_j) < \sigma_1, d_2(x_i, x_j) < \sigma_2 \\ 0 & \text{other conditions} \end{cases} \quad (5)$$

The fitness function of an individual adjusted to the sharing function obtained from the small habitat operation is equation (6):

$$F'_i(x) = \frac{F_i x}{\sum_{j=1}^M S(d_{ij})} \quad (6)$$

where $F_i x$ is the individual fitness function before sharing; $F'_i(x)$ is the individual fitness function after sharing; M is the number of evolutionary generations.

After the above improvements, the genetic algorithm can be improved in local search capability, population diversity generalization performance and search direction to a certain extent. ability, the generalization performance of population diversity and the search direction can be improved to some extent. The improved genetic algorithm can improve the local search ability, population diversity generalization performance and search direction to a certain extent, which can make the optimization solving process run stably. The basic steps of optimization using the improved genetic algorithm are as follows:

- Determine the basic parameters of the genetic algorithm.
- Perform basic variance calculations for the genetic algorithm.
- Initialize the algorithm chromosome set.
- Judge the initial conditions and recalculate if the conditions are not met.
- Calculate the objective function value and the basic fitness function according to the current situation.
- Improve the calculation of the results of the fifth step, using the adaptive variation rate to improve the variation operator and the small habitat operation to improve the fitness function.
- If the optimal conditions are met, terminate the iteration, otherwise derive a new population and iterate the calculation again until the optimal appears.

Figure 7 shows the solution process of the improved genetic algorithm.

3.3 Multi-objective optimization

The mathematic model of multi-objective problem can be expressed as equation (7):

Objective: Minimize $T(HS, HP, HC)$

$$\begin{aligned} & \text{Maximize } V(HS, HP, HC) \\ & \text{Subject to: } 10 \leq HS \leq 30, \\ & 20 \leq HP \leq 50, 2 \leq HC \leq 14 \end{aligned} \quad (7)$$

Fifty groups of initial samples are generated, and the subsequent iterations are made up of a population of 50 groups of samples. Three samples with the highest fitness are selected as candidate points after 80 iterations. The Pareto optimized solution set is calculated and obtained by the improved genetic algorithm, and the Pareto-optimal front is shown in Table 5. It can be referred that the large decrease in HP and HC are the main reasons for the changes in the response values of the optimization objective.

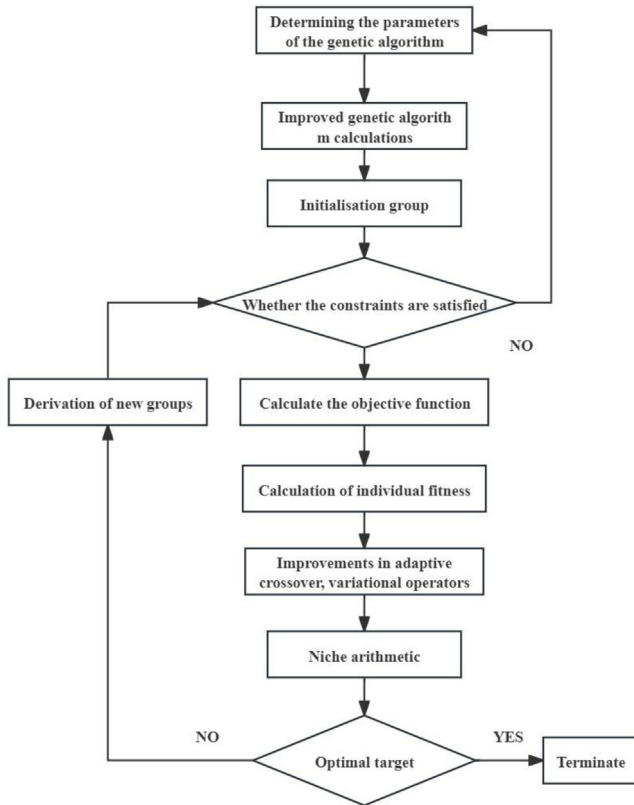


Fig. 7. Improved genetic algorithm solution process.

According to the principle of the smallest temperature difference value, the parameters of group 1 can be selected as the optimized value. But its HP is too small to resist deformation under large load, increasing the difficulty of installing the optical encoders. Therefore, group 2 is selected as the optimal solution. As shown in Table 6.

The optimal solution is revised to facilitate the manufacturing and installation of the equipment. According to the revised values of the optimized design parameters, the effectiveness of the optimization is verified by establishing a new finite element model and temperature field analysis.

The predicted values and corresponding simulated results are listed in Table 7. The optimization result of temperature difference is less error with the simulation result. The temperature difference is reduced by 41.13% compared with the initial parameters, and the volume increased by 2.39%, which effectively improves the temperature control performance of the gasket test rig.

4 Optimization validation

The press plate and heat shield are manufactured according to the optimized parameters. The optimized gasket test rig is shown in Figure 8. It can be observed from Figure 8 that the height of press plate and gasket contact board were sharply reduced.

Table 5. Optimization of design candidates.

Design variables	Group 1	Group 2	Group 3
HS (mm)	25.33	24.65	18.93
HP (mm)	23.78	28.61	32.66
HC (mm)	4.06	2.11	6.48
$\Delta T(^{\circ}C)$	2.81	3.12	3.52
$\Delta V(cm^3)$	3115.9	3244.8	3220.3

Table 6. Design variables comparison before and after optimization.

Design variables	Before optimization	After optimization	Revised value
HS(mm)	10.00	24.65	24.50
HP(mm)	40.00	28.61	28.50
HC(mm)	7.00	2.11	2.00

Improving the responsiveness of the temperature control system can reduce steady-state temperature oscillations. The better the responsiveness of the temperature control system, the smaller the temperature oscillation range and overshoot of the controlled object.

By conducting gasket test under temperature of 500 °C and 600 °C, the temperature overshoot and the temperature oscillations in steady-state conditions are recorded by thermocouple and data collection system. The results after optimization are compared to those before optimization.

The record of oscillation started from the temperature entered steady-state oscillation phase which the temperature variation is much smaller than the overshoot phase.

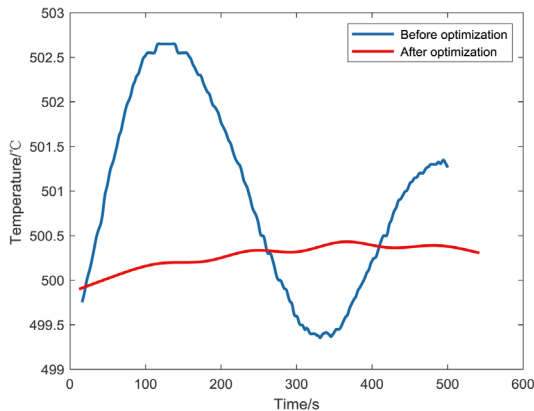
4.1 Comparison of before and after optimization of 500 °C temperature rise

Comparison of 500 °C temperature rise curve of the gasket test rig before and after optimization are shown in Figures 9 and 10.

In terms of overshoot, it can be observed that the maximum temperature reached 500.45 °C, which exceeds the set value by 0.11%. Compared with the temperature rise before optimization, the fallback temperature is less than 0.5 °C, and soon entered the steady-state phase. The overshoot is reduced by 2.2 °C, which highly improves the substantial adjustments in the overshoot phase. It is important to point out the steady-state temperature oscillation in the interval of [499.9, 500.45]. The range is 0.55 °C, 1.45 °C lower than before optimization, and the trend shows steady and consistent oscillation, indicating a predictable pattern to the temperature variations. as shown in Table 8.

Table 7. Optimization results comparison.

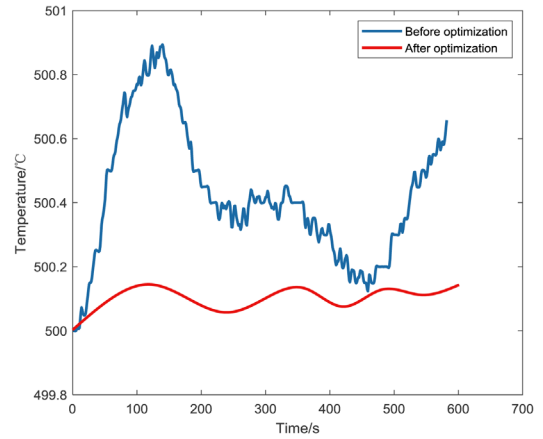
Optimization objectives	Before optimization	After optimization	Simulated value	Percentage change
$\Delta T(^{\circ}\text{C})$	5.30	3.12	3.08	-41.13%
$\Delta V(\text{cm}^3)$	3169.13	3244.8	3244.8	2.39%

**Fig. 8.** Optimized gasket test rig.**Fig. 9.** Temperature overshoot comparison (500 °C).

4.2 Comparison of before and after optimization of 600 °C temperature rise

Comparison of 600 °C temperature rise curve of gasket test rig before and after optimization are shown in Figures 11 and 12.

Due to the output power limitation of the heat plate, the optimization on overshoot of the test under the temperature of 600 °C is not significant. However, in Figure 12, the lower temperature limit of fallback in the phase of overshoot is greatly optimized. Similarly, during the steady state phase, the temperature rarely exceeded the setting temperature. Once the temperature reaches 599.6 °C, it starts dynamic balance. This shows that the optimized heat transfer path was more in line with the design requirements, so the temperature exhibits continuous fluctuations within a relatively stable range, indicating

**Fig. 10.** Temperature oscillation comparison (500 °C).

a consistent oscillation pattern. The optimized temperature oscillation is located in the [599.9, 600.2] interval, the range is 0.3 °C. As shown in Table 9.

5 Conclusion

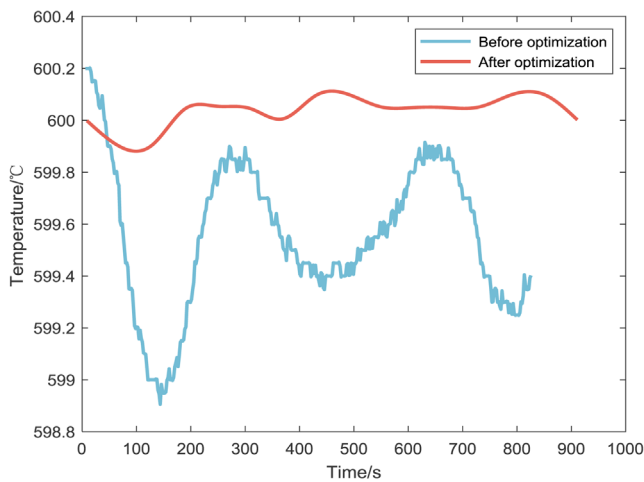
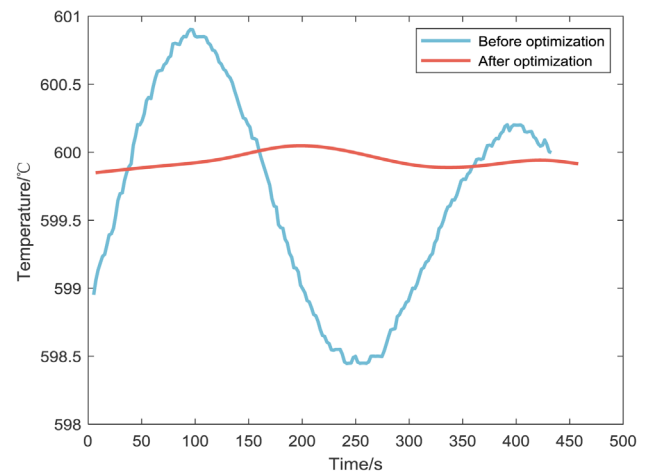
In this paper, multi-objective optimization of the structure of the gasket test rig is carried out to improve the response speed of the temperature control system, which is of some significance in guiding and reference for the optimal design of gasket test rigs under high temperature and high pressure conditions in the future.

The research conclusions are as follows:

- Based on the response surface model and improved genetic algorithm, a multi-objective optimal design of the structure of the gasket test rig was carried out. In the response surface model, the coefficient of determination R^2 between the predicted values of the response surface model and the results obtained by numerical calculation is greater than 0.9, which indicates that the fit between the response surface model and the Fluent simulation values is high. At the same time, the effectiveness of the optimization effect is verified by finite element model and temperature field analysis based on the heights of the pressure plate, heat insulation plate and gasket contact plate obtained through the improved genetic algorithm.
- The structural parameters of the optimized gasket test rig are investigated, and testing the performance of an optimized gasket test rig. The results show that the optimized gasket test rig has excellent temperature control performance. By testing the gasket test rig at 500 °C and 600 °C, the results show that the fluctuation range is kept below 0.11% and the temperature oscillation range is kept below 0.55 °C.

Table 8. Test comparison (500 °C).

Parameter name	Before optimization	After optimization	Range of variation
Maximum temperature/°C	502.65	500.45	−2.2
Volatility ratio	0.40%	0.11%	−0.29%
Interval of temperature oscillation/°C	[499.35,501.35]	[499.9,500.45]	—
Range of temperature oscillation/°C	2	0.55	−1.45

**Fig. 11.** Temperature overshoot comparison (600 °C).**Fig. 12.** Temperature oscillation comparison (600 °C).**Table 9.** Test comparison (600 °C).

Parameter name	Before optimization	After optimization	Range of variation
Maximum temperature/°C	600.9	600.2	−0.7
Volatility ratio	0.22%	0.05%	−0.17%
Interval of temperature oscillation/°C	[598.9,600.2]	[599.9,600.2]	—
Range of temperature oscillation/°C	1.3	0.3	−1

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Conflict of Interest

We declare that there is no conflict of interest in this paper.

Data availability statement

The data that have been used are confidential.

Author contribution statement

Writing-original draft: Quan Wang, Jiayan Chen. writing-review and editing: Zhenyu Zhang, Lu Wang.

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