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# Optimization of preparation process parameters for light closed cell structure of coal gangue based foam ceramic

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**SUMMARY:** *To address the multi-parameter collaborative regulation required for preparing coal gangue-based foam ceramics with a light closed-cell structure, this study used a coal gangue–diatomite composite system. The mass ratio of coal gangue to diatomite was fixed at 7:3, the holding time was 30 min, and the additions of potassium feldspar and magnesium oxide were 10% and 5%, respectively. Silicon carbide content, sodium phosphate content, and sintering temperature were selected as the core process variables to construct an orthogonal experimental dataset and parameter coding scheme. Combined with a multi-index normalization method, total porosity, closed-pore ratio, bulk density, compressive strength, and thermal conductivity were jointly evaluated. The results show that silicon carbide content had the strongest influence on structure formation, followed by sintering temperature, while sodium phosphate continuously regulated pore stability. Under the optimal condition of 1.5% silicon carbide, 3% sodium phosphate, and 1200 °C sintering temperature, the sample achieved a total porosity of 86.65%, a closed-pore ratio of 83.33%, a bulk density of 0.3532 g/cm3, a compressive strength of 3.19 MPa, and a thermal conductivity of 0.096 W/(m·K). The proposed framework provides a reusable computational basis for process design and coordinated performance evaluation of coal gangue-based foam ceramics.*

*Povzetek: a članek predlaga metodo optimizacije priprave lahke zaprto-celične penaste keramike na osnovi premogove jalovine v sistemu jalovina–diatomejska zemlja. Poskusi kažejo, da je optimalna kombinacija parametrov 1,5 % SiC, 3 % natrijevega fosfata in temperatura sintranja 1200 °C. Pri teh pogojih skupna poroznost doseže 86,65 %, delež zaprtih por 83,33 %, prostorninska gostota znaša 0,3532 g/cm3, tlačna trdnost 3,19 MPa, toplotna prevodnost pa 0,096 W/(m·K). Rezultati kažejo, da ta metoda zagotavlja zanesljivo osnovo za optimizacijo procesa priprave lahkih zaprto-celičnih struktur.*

***KEYWORDS:*** *Coal gangue based foam ceramic; Computer modeling; Process parameter optimization*

## 1 Introduction

Under the background of solid waste resource utilization and energy-saving material upgrading, coal gangue based foam ceramics have attracted attention due to the stable source of raw

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materials and outstanding heat insulation potential. On the one hand, building insulation scenarios require materials to maintain high obturator ratio and strength at low bulk density. On the other hand, the firing energy consumption, raw material fluctuation and pore structure dispersion also improve the parameter control accuracy requirements. In order to adapt to the trend from empirical preparation to quantitative design, the computational analysis of process parameters has become one of the important directions in the research of this kind of materials.

In recent years, data modeling and intelligent optimization methods have brought new research paths for ceramic foam process analysis. The computational method can be used to organize experimental data, identify key variables and screen parameter combinations. It can also serve for hole structure prediction, performance correlation analysis and optimal scheme judgment. Using parameter coding and multi-index normalization method, the influence degree of different process variables on total porosity, closed porosity, bulk density and thermal conductivity can be compared.

In recent years, domestic and foreign scholars have carried out many studies on the preparation of coal gangue based ceramic foam. For example, Li X et al. [1] prepared high obturator rate coal gangue based foam ceramics and analyzed the thermal insulation application performance. Ren P et al. [2] used SiC as foaming agent to construct the preparation path of coal gangue based ceramic foam, and discussed the corresponding relationship between foaming components and thermal properties. Dai L et al. [3] developed a coal gangue based ceramic foam forming method based on water spraying granulation and particle accumulation, which expanded the control idea of raw material organization on pore structure evolution. Related studies provide a basis for parameter optimization.

The purpose of this study is to enhance the controllability of the formation of light closed cell structure of coal gangue based ceramic foam through the calculation and analysis of process parameters and combination optimization. The specific research contents include: 1) establish the process parameter expression mode of coal gangue - diatomite system; Secondly, the parameter coding and index mapping are used to realize the collaborative analysis of total porosity, obturator porosity, volume density, compressive strength and thermal conductivity. 3) Complete the combined screening of silicon carbide content, sodium phosphate content and sintering temperature; 4) The corresponding performances of obturator structures and comprehensive properties under different parameter combinations were analyzed.

The purpose of this study is to provide a parameter optimization scheme with data support for the process design of coal gangue based ceramic foam, and to promote the preparation process from empirical judgment to quantitative judgment. At the same time, it provides a reference for the application of the calculation method in solid waste-based ceramic materials. In this paper, parameter coding, orthogonal experimental data organization and multi-index collaborative evaluation are integrated into the same analysis framework, and the consistency and comparability of process results are enhanced.

# 2 Literature Review

## 2.1 Research progress on preparation of light closed cell structure of coal gangue based foam ceramic

The research on the preparation of light closed cell structure of coal gangue based foam ceramics is changing from the pure utilization of solid waste to the technical path of synerging raw materials, pore structure regulation and performance calculation. The relevant results not only broaden the utilization range of coal gangue in light heat insulation materials, but also provide a clear experimental basis for subsequent process parameter modeling, performance prediction and combination optimization.

The following are some representative research advances in the field of light closed cell structure preparation of coal gangue based foam ceramics: Fu F et al. [4] prepared high added value light glass ceramics based on phosphorus tailings and coal gangue, indicating that coal gangue has good component adaptability and structure formation ability in the construction of low-density heat insulation materials. Liu L et al. [5] studied the preparation process, crystallization kinetics and heavy metal stability behavior of steel slag and coal gangue solid waste glass ceramics, and proposed that the stability of the internal structure of materials can be improved by means of crystallization adjustment. Wang Y et al. [6] constructed a reaction-bonded silicon carbide ceramic membrane for coal gangue sintered at low temperature, indicating that the silicon-aluminum system involving coal gangue could take into account both porous structure formation and mechanical maintenance. Liu K et al. [7] prepared the microfiltration porous ceramic membrane based on coal gangue and loess, and verified the feasibility of the system in pore structure control and application adaptation. Chen F et al. [8] developed high-strength microporous mullite refractory based on low-grade bauxite and coal gangue, which further expanded the application level of coal gangue in high-temperature microporous structural materials. Lei Y et al. [9] proposed a pore structure optimization method oriented to the cooperative balance between thermal and mechanical properties of ceramic foams, and pointed out that there was a close correlation between pore size distribution, pore wall integrity and obturator ratio.

The above research has been continuously deepened from raw material composition, structure construction to performance coordination, so that the preparation of coal gangue based ceramic foam gradually has a research foundation combining parameter coding, structural characterization and calculation analysis, and also provides stable support for the subsequent establishment of process parameter database and intelligent optimization. On this basis, the collaborative control of lightweight, closed pore and heat insulation properties began to shift from empirical comparison to quantitative analysis based on sample organization, variable mapping and index linkage. This change promoted the research on preparation of coal gangue-based ceramic foam from empirical regulation to the analysis path combining data modeling, parameter calculation and performance prediction.

## 2.2 Research on data modeling of preparation process parameters and performance characterization method

The research on parameter data modeling and performance characterization of the preparation process of gangue based ceramic foam is shifting from single index testing to parameter-structure-performance collaborative analysis. The relevant methods not only serve for the quantitative comparison of firing regime and foaming process, but also provide a more stable analysis basis for the computational expression, performance prediction and combination optimization of lightweight closed cell structures. Dong Y et al. [10] studied the preparation process of granite waste and red mud bearing foam ceramics, and proposed that the pore structure and bulk density could be adjusted linkage by raw material ratio and firing conditions. Zhou H et al. [11] prepared foam glass ceramics based on waste glass and high-titanium blast furnace slag, and completed material characterization analysis, indicating that the adjustment of molten components has a direct effect on foams behavior and structural stability.

Zhang J et al. [12] proposed the preparation path of hierarchical porous glass ceramics based on alkali excitation and crystallization process, so that the pore structure formation and phase transformation process can be analyzed under a unified characterization framework.

Zhang J et al. [13] studied the method of preparing glass ceramic foam from fly ash from waste incineration, and discussed the foaming characteristics and the formation mechanism of hierarchical pores, which enhanced the process cognition of pore evolution behavior. Pandey V et al. [14] constructed the morphology and thermomechanical characterization system of lightweight silica foam under the reaction formation thermal foamy process, which provided a more detailed evaluation basis for lightweight control and thermal response analysis. Siddika A et al. [15] reviewed the parameters, properties and challenges in the powder sintering and gel pouring methods of waste glass foam materials, further indicating that the preparation process research is extending to parameter correlation, data sorting and comprehensive evaluation.

The above studies promoted the preparation analysis of foamed ceramics from empirical judgment to quantitative path based on sample organization, variable mapping and performance characterization, and also provided a methodological basis for establishing process parameter database, carrying out performance modeling and introducing intelligent optimization for lightweight closed cell structure of coal gangue based foamed ceramics. On this basis, the linkage relationship between total porosity, obturator, bulk density, compressive strength and thermal conductivity began to have the condition of computable expression, which also provided the basis for subsequent parameter coding, multi-index normalization and performance prediction model construction.

## 2.3 Application research of intelligent optimization algorithm in foam ceramic process control

The application research of intelligent optimization algorithm in ceramic foam process control is shifting from empirical screening to collaborative development of parameter calculation, performance prediction and combination optimization. The relevant methods not only improve the quantitative level of foaming system, firing system and pore structure control, but also provide a clearer calculation path for the preparation of light closed cell structure of coal gangue based ceramic foam. This method also compresses the range of the test, makes the parameter selection process more focused, makes the results comparison and combination judgment clearer, and enhances the stability of the setting. Optimization of process parameters is an important application of intelligent optimization algorithm in the research of ceramic foam. Wang H et al. [16] used a variety of solid wastes to prepare foam glass ceramics, indicating that raw material collaborative design and process control can realize structure formation and performance improvement under the same analysis framework. Liu T et al. [17] studied the preparation process of self-bubbling glass ceramics under the condition of multi-solid waste collaborative treatment, and analyzed the structure-performance relationship and spontaneous bubbling behavior, and proposed that process characterization could be used to strengthen the identification of pore structure evolution. Liang J et al. [18] used the grey system theory to study the corresponding relationship between firing regime and foam ceramic properties, so that the correlation between temperature, time and material indicators could be calculated. Cooperative control of structural properties is another important application of intelligent optimization algorithms in the research of ceramic foam technology. Shi X et al. [19] used multi-solid waste to prepare and characterize foam glass ceramics, and further showed that there was a continuous mapping relationship between the changes in raw material composition, foaming behavior and final structure. Fu F et al. [20] prepared lightweight ceramic foam by adjusting the sintering time and heating rate, and proposed that the firing rhythm adjustment could simultaneously act on the formation of pore wall, bulk density and thermal insulation performance. The above studies show that the process control of ceramic foam has gradually formed the analysis basis of combining sample organization, variable mapping and performance prediction, and parameter coding, multi-index normalization and result regression have also begun to enter the process evaluation process. This change provides a clear method support for parameter selection and comprehensive performance optimization in the preparation of light closed cell structure of coal gangue based foam ceramics, and also makes the expression of process results more consistent, comparable and application extensible.

## 2.4 Shortcomings of existing research and directions for improvement

The research on the preparation of lightweight obturator structure of coal gangue based foam ceramics forms the technical basis for the coordination of raw materials, foaming regulation and firing optimization. However, there is still room for the existing results to be tightened in the aspects of parameter linkage expression, quantification of obturator holding capacity and unified judgment. Most of the related studies can explain the single-class additive, single-group firing system or performance change rule, and the coupling relationship between lightweight, closed pore, strength retention and thermal insulation response has been reflected, but the experimental samples, process variables and performance labels are rarely treated in the same calculation framework. Dong Y et al. [21] used CaO to adjust the pore structure of granite waste foam ceramics, indicating that the modifier could affect the pore size distribution and structural stability. Fu F et al. [22] studied the foaming mechanism and properties of ceramic foaming in Sio2-Al2O3-Cao system under different foaming agents, and proposed that the change of foaming components would act synchronously on gas release, pore wall formation and thermal response. Wang L P et al. [23] used silicon cutting waste as foaming agent to prepare foaming glass, indicating that the replacement of foaming source can change the structure formation path. Li C et al. [24] studied the preparation process of fly ash and chromium slag glass ceramics, and showed that component adaptation and phase transition control in the solid waste system had an impact on the final structure.

As shown in Table 1, the existing research mainly focuses on additive regulation, foaming mechanism, solid waste substitution and firing control, which can effectively support the structure design of foam ceramics, but is still weak in multi-parameter collaborative calculation.

*Table 1: Emphasis and further extension of existing research.*

| Reference | Main Method | Material System | Key Result | Further Extension Direction |
|---|---|---|---|---|
| Dong Y et al. [21] | CaO modification | Granite waste foam ceramic | The pore structure was optimized | Introduce coupled variable modeling |
| Fu F et al. [22] | Comparison of different foaming agents | Si–Al–Ca foam ceramic system | Differences in foaming mechanisms were revealed | Establish a multi-index evaluation model |
| Wang L. P. et al. [23] | Preparation using alternative foaming agents | Waste glass foam glass | The foaming-source pathway was improved | Strengthen parameter encoding representation |
| Li C et al. [24] | Synergistic crystallization using solid wastes | Fly ash–chromium slag glass-ceramics | Structural stability was enhanced | Extend performance prediction analysis |

From the research progress, existing methods can identify the influence of key process variables on pore structure and performance, but there is still a lack of unified processing chain for continuous mapping between variables, comparable expression between samples, and automatic selection of optimal combinations. For the preparation of light closed cell structure of coal gangue based ceramic foam, silicon carbide content, additive content, sintering temperature and insulation system are not independent effects. The above process variables will jointly affect the liquid phase viscosity, gas escape rate, hole wall bonding state and closed cell proportion retention ability. Therefore, it is more suitable to introduce parameter coding, multi-index normalization, result regression and combination optimization methods in subsequent research, so that the experimental data can serve for performance prediction and process judgment, and enhance the calculation consistency between different process plans. This improvement direction is more suitable for the writing requirements of technical journals on data modeling, structure analysis and reusability of results.

# 3 Design and implementation of intelligent optimization model for process parameters of coal gangue based ceramic foam preparation

## 3.1 Preparation process of coal gangue based ceramic foam and analysis of parameter variables

The starting point of preparation is the input of coal gangue, diatomite, potassium feldspar, magnesium oxide, silicon carbide and sodium phosphate. Coal gangue provides silica-aluminum skeleton and determines the basic sintering activity, diatomite regulates the lightweight characteristics and pore formation potential, potassium feldspar promotes the formation of liquid phase, magnesium oxide enhances the stability of high temperature structure, silicon carbide assumes the function of foaming source, sodium phosphate participates in melt regulation and bubble stability. After grinding, sieving and weighing, the raw material enters the mixing stage. The ball milling uniformity, particle gradation and water content state will affect the molding compactness, and affect the gas expansion path and the continuity of the hole wall.

The formed body undergoes the synchronous evolution of foaming activation and sintering curing during the heating process. When the temperature increases, the silicon carbide reacts with the oxygen in the system and releases gas. The viscosity of the molten phase changes with the content of the auxiliary and the temperature. If the gas release rate and the melt encapsulation capacity are in the matching interval, the bubbles can remain independent after expansion, and then form a closed cell structure. If foaming is too fast and the viscosity is insufficient, the pore wall is easy to break and induce the increase of connected pores. If the viscosity is too high and the gas release is insufficient, the pore expansion is limited and the bulk density will increase. Therefore, the silicon carbide content, sodium phosphate content, sintering temperature and holding time are the key control quantities that determine the pore size distribution, obturator ratio and strength retention.

From the perspective of model input, the variables in this study are divided into four categories: raw material ratio variables, foaming variables, firing variables and process state variables. The raw material ratio variable includes the proportion of gangue and diatomite and the content of auxiliary components, the foaming variable corresponds to the content of silicon carbide, the firing variable includes the peak temperature and holding time, and the process state variable includes the body mass, moisture content and particle size interval. In order to serve intelligent optimization, each variable needs to be encoded, normalized and aligned with labels to form a sample matrix. Total porosity, obturator porosity, bulk density, compressive strength and thermal conductivity are recorded at the output end, thus incorporating lightweight, obturator and load-bearing capacity into the evaluation system.

The preparation of coal gangue based ceramic foam is not a simple series of several experimental steps, but a dynamic process of continuous coupling of raw material reaction, gas release, liquid phase formation, hole wall curing and performance output. This section carries out analysis from two levels of process chain and variable structure, aiming to clarify which parameters enter the optimization model, which response indexes assume the evaluation function, and establish the data interface for parameter optimization and result regression, as shown in Figure 1.

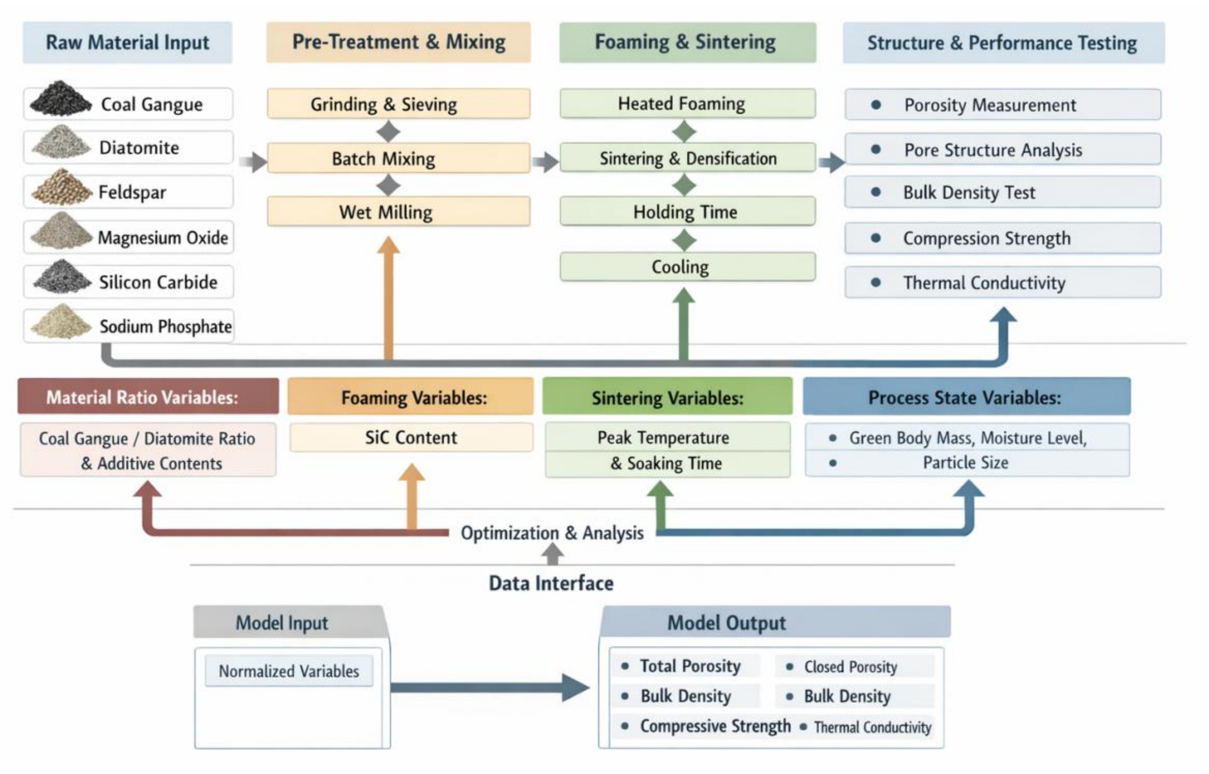


*Figure 1: The preparation process of coal gangue based ceramic foam and the analysis framework of parameter variables.*

Figure 1 shows the preparation process of coal gangue based ceramic foam and the analysis framework of parameter variables. The framework takes raw material input as the starting point, takes pretreatment, mixture forming, foaming sintering and structure inspection as the main line, connects process data, structure data and performance data of each stage in series, and forms input-output mapping relationship at the end, which can be called by the model. After this process, the experimental process is transformed into a computable and iterative parameter analysis chain, which provides support for the intelligent optimization model to identify the optimal process combination.

## 3.2 Construction of optimization model for preparation process parameters

### 3.2.1 Model architecture

In the preparation process parameter optimization model construction, this paper adopts the parameter intelligent optimization architecture oriented to the multivariate coupling process. In this architecture, the preparation of coal gangue based ceramic foam is no longer regarded as a simple comparison of several isolated test sites, but the composition of raw materials, foaming behavior, firing response and performance output are integrated into the same data mapping chain, so that the input variables, hidden characteristics and evaluation results can be continuously transmitted in a unified model. The model is composed of a parameter input layer, a feature coding layer, a coupling calculation layer and a performance output layer. The input layer accepts variables such as silicon carbide content, sodium phosphate content, sintering temperature, holding time and raw material ratio. The feature coding layer is responsible for eliminating dimensional differences and extracting process characteristics. The output layer completes the synchronous prediction of total porosity, obturator porosity, bulk density, compressive strength and thermal conductivity. After processing in this way, the experimental process is transformed into a computable, comparable, and regressible parameter flow.

In order to intuitively illustrate the overall composition of the intelligent optimization model for the parameters of the preparation process of coal gangue based ceramic foam, the connection relationship between parameter input, feature coding, coupling calculation and performance output is organized as FIG. 2. The left part of the figure is the input layer of process parameters, including the ratio of gangue and diatomite, the content of silicon carbide, the content of sodium phosphate, the sintering temperature and the holding time. The middle part is the process of parameter normalization, feature extraction and coupling calculation, which is used to characterize the nonlinear correlation between the foaming reaction, liquid phase generation and pore wall curing. The right side is the performance output layer, which outputs indicators such as total porosity, obturator porosity, volume density, compressive strength and thermal conductivity, and further forms a comprehensive evaluation value. The figure is not only used to show the data flow between each layer of the model, but also provides a unified structural expression for subsequent algorithm search, weight adjustment and identification of optimal parameter combination.

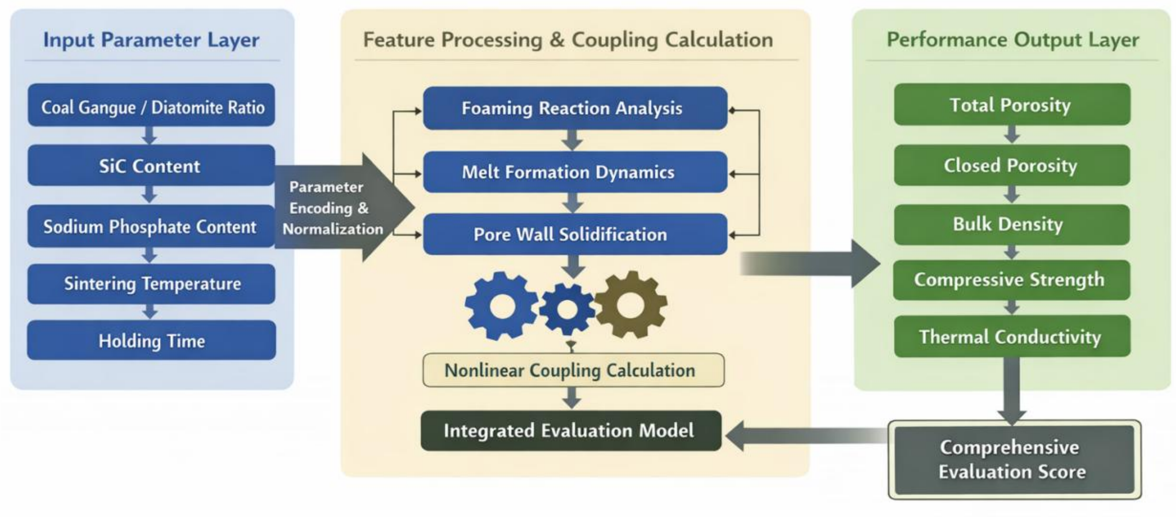


*Figure 2: Model architecture for intelligent optimization of process parameters in the preparation of coal gangue based ceramic foam.*

In order to express the input organization of process parameters in the model, the core variables of a single group of samples are first defined as parameter vectors, as shown in Equation (1):

$$x_i = [a_i, b_i, T_i] \tag{1}$$

Among them, $a_i$ represents the content of silicon carbide, $b_i$ represents the content of sodium phosphate, $T_i$ represents the sintering temperature, the holding time is fixed at 30 min, the mass ratio of coal gangue to dicelite is fixed at 7：3, and the addition of potassium feldspar and magnesium oxide is fixed at 10% and 5%, respectively. The above conditions are written into the sample setting as the experimental boundary, and do not participate in the parameter search of this round. Equation (1) is used to define the input space of the model and organize the core process variables involved in the optimization into unified sample nodes, so that different experimental combinations can enter the same computational framework.

In order to eliminate the dimensional differences between different variables and enhance the stability of the subsequent feature extraction process, the input parameters are normalized in this paper, and the expression is shown in Equation (2):

$$z_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{2}$$

Here, $x_{min}$ and $x_{max}$ represent the minimum and maximum values of each variable in the sample set, and $z_i$ represents the normalized parameter vector. The function of equation (2) is to compress variables of different dimensions into a consistent interval, avoid feature deviation caused by order of magnitude differences among temperature, time and dosage, and thus provide stable input for subsequent weight learning and feature extraction.

After parameter standardization, the model further extracts the features of the coupling relationship between process variables through the hidden layer, and its calculation form is shown in Equation (3):

$$h_i = \sigma(W_1 z_i + b_1) \tag{3}$$

Here, $W_1$ represents the weight matrix from the input layer to the hidden layer, $b_1$ represents the bias term, $\sigma$ represents the nonlinear activation function, and $h_i$ represents the feature representation of the sample in the coupling space. Equation (3) is used to extract the nonlinear connection between raw material reaction, gas release, liquid phase formation and pore wall curing, so that the formation characteristics of lightweight closed cell structures can be recognized and retained by the model.

In order to realize the comprehensive evaluation of lightweight, closed hole, bearing capacity and heat insulation performance, this paper constructs a unified objective function, which is defined as shown in Equation (4) :

$$F_i = \alpha P_i + \beta C_i + \gamma S_i - \delta D_i - \varepsilon K_i \tag{4}$$

where $P_i$ represents total porosity, $C_i$ represents obturator porosity, $S_i$ represents compressive strength, $D_i$ represents volume density, $K_i$ represents thermal conductivity, and $\alpha$, $\beta$, $\gamma$, $\delta$, $\varepsilon$ are index weights. Equation (4) is used to integrate lightweight, pore closure, bearing capacity and thermal insulation performance into a unified optimization goal, so as to complete the comprehensive sorting and optimization judgment of parameter combinations.

From the perspective of model operation logic, Equation (1) is responsible for the completion of process variable expression, Equation (2) is responsible for the completion of sample standardization processing, Equation (3) is responsible for the extraction of process coupling characteristics, and Equation (4) is responsible for the output of comprehensive evaluation results. After the process of this framework, the raw material setting, firing control and performance indicators in the preparation of coal gangue-based ceramic foam are no longer dispersed, but organized as a parameter-feature-result chain that can be directly input into the model. The architecture not only retains the physical meaning in the material process, but also provides a unified interface for subsequent algorithm description, parameter search and optimal combination identification, so that the preparation process optimization can be turned from empirical judgment to data-driven computational analysis.

### 3.2.2 Description of the algorithm

In the process of preparing parameter optimization solution, this paper uses parameter coding, surrogate prediction and multi-objective search to run the algorithm in concert. The algorithm is suitable for the scene of limited variable dimension, obvious nonlinear performance response and the co-existence of target constraints in the preparation of light closed cell structure of coal gangu-based ceramic foam. It can complete the parameter search, performance estimation and optimal combination judgment under the condition of controllable sample size.

Step 1: In the initialization phase of the algorithm, in order to ensure the coverage of the search space, this paper randomly generates initial candidate samples according to the upper and lower bounds of the parameters, and its expression is shown in Equation (5):

$$X_i^{(0)} = X_{min} + \rho_i \odot (X_{max} - X_{min}) \tag{5}$$

where $X_i^{(0)}$ represents the i-th initial candidate process combination, $X_{min}$ and $X_{max}$ represent the lower and upper bounds of each parameter respectively, $\rho_i$ represents a random vector whose value ranges within [0,1], and $\odot$ represents the multiplication of corresponding elements. Equation (5) is used to generate initial samples that satisfy the boundary constraints, so that the parameter search covers different formulations and firing intervals from the beginning.

Step 2: After the candidate samples are generated, the algorithm estimates the multi-performance output of each process combination through the surrogate prediction module, whose expression is shown in Equation (6):

$$\hat{Y}_i = G\left(X_i^{(k)}; \Theta\right) = \left[\hat{P}_i, \hat{C}_i, \hat{D}_i, \hat{S}_i, \hat{K}_i\right] \tag{6}$$

Here, $G(\cdot)$ represents the surrogate prediction model, $\Theta$ represents the model parameters, $X_i^{(k)}$ represents the i-th candidate sample in the KTH iteration, $\hat{P}_i$, $\hat{C}_i$, $\hat{D}_i$, $\hat{S}_i$ and $\hat{K}_i$ represent the predicted total porosity, predicted obturator, predicted volume density, predicted compressive strength and predicted thermal conductivity, respectively. Equation (6) is used to directly map the input parameters into the multi-objective performance output, thereby reducing the number of blind trials.

Step 3: In order to enhance the convergence ability and local correction ability in the search process, this paper adopts an adaptive update strategy for the candidate solution, whose expression is shown in Equation (7):

$$X_i^{(k+1)} = X_i^{(k)} + \lambda_k \left(X_{best}^{(k)} - X_i^{(k)}\right) + \eta_k \Delta_i^{(k)} \tag{7}$$

Here, $X_i^{(k+1)}$ represents the updated candidate parameter combination, $X_{best}^{(k)}$ represents the current best sample in round k, $\lambda_k$ represents the convergence weight, $\eta_k$ represents the perturbation weight, and $\Delta_i^{(k)}$ represents the random perturbation vector. Equation (7) is used to enhance the local optimization ability while maintaining the global search ability, so that the process combination gradually shrinkates to the more optimal region.

Step 4: In order to ensure that the search results meet the basic performance boundaries of the preparation of lightweight closed cell structures at the same time, this paper adds the feasibility constraint judgment function in the iteration process, and its expression is shown in Equation (8):

$$Q_i = 1(\widehat{P}_i \geq P_0) \cdot 1(\widehat{C}_i \geq C_0) \cdot 1(\widehat{S}_i \geq S_0) \cdot 1(\widehat{D}_i \leq D_0) \cdot 1(\widehat{K}_i \leq K_0) \tag{8}$$

Here, $Q_i$ represents the feasibility mark of the $i$-th candidate process combination, and $1(\cdot)$ represents the indicative function, which takes the value 1 if the condition holds, and 0 otherwise. $\widehat{P}_i$, $\widehat{C}_i$, $\widehat{S}_i$, $\widehat{D}_i$ and $\widehat{K}_i$ denote predicted total porosity, predicted obturator porosity, predicted compressive strength, predicted volume density and predicted thermal conductivity, respectively. $P_0$, $C_0$, $S_0$, $D_0$, and $K_0$ represent the target thresholds for each performance metric, respectively. Equation (8) is used to screen out candidate samples that do not meet the requirements of lightweight, pore closure, strength preservation and thermal insulation, so that the subsequent search is always carried out within the effective parameter region.

Step 5: Candidate update and convergence determination. The algorithm retains the dominant samples and generates new candidate solutions, and the update form is shown in Equation (9):

$$X_i^{new} = X_i + \lambda(X_i^{best} - X_i) + \mu\Delta_i \tag{9}$$

Here, $X_i^{new}$ represents the updated parameter combination, $X_i^{best}$ represents the current optimal sample, $\Delta_i$ represents the perturbation vector, and $\lambda$ and $\mu$ represent the convergence coefficient and perturbation coefficient, respectively. The prediction error is calculated after each round of updating, and the loss function is shown in Equation (10).

$$L = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{10}$$

Here, $\hat{y}_i$ represents the predicted value, $y_i$ represents the measured value, and $n$ represents the number of samples. When the loss decreased steadily and the optimal fitness was no longer significantly improved, the algorithm output the optimal process combination and completed the parameter iteration.

In conclusion, the intelligent parameter optimization algorithm constructed in this paper is not an isolated search for a single process variable, but organizes the raw material ratio, foaming reaction, firing regime and performance output into a continuous iterative calculation chain. After parameter coding, feature extraction, fitness evaluation, candidate update and loss convergence judgment, the model can maintain good search stability and result identification ability under the condition of limited samples, and the synergistic relationship between total porosity, obturator, volume density, compressive strength and thermal conductivity can be unified expression.

## 3.3 Parameter optimization strategy

### 3.3.1 Setting of raw material boundary under fixed matrix composition

The raw material boundary setting under the fixed matrix composition is based on the stable matching relationship between the gangue matrix composition, the light adjustment component and the foaming auxiliary component. The goal is to provide consistent raw material conditions for the subsequent cooperative regulation of foaming and firing under the premise of ensuring the stability of the blank forming and the continuity of the firing reaction. Combined with the above experimental Settings, this paper fixed the mass ratio of gangue to diatomite as 7：3, fixed the addition of potassium feldspar and magnesium oxide as 10% and 5%, respectively, and wrote the above conditions into the experimental system as a unified boundary for sample construction and parameter search. The reason for this treatment is that coal gangue is responsible for providing silica-aluminum skeleton and basic sintering activity, diatomite is responsible for lightweight regulation and pore generation support function, potassium feldspar is used to promote liquid phase formation, magnesium oxide is used to enhance high temperature structure stability, and several components have formed a relatively clear division of labor in the current system. If the ratio of raw material, dosage of foaming agent, content of auxiliary agent and sintering temperature continue to be loosened at the same time in this round of research, it will not only expand the search space, but also weaken the ability of three-factor three-level orthogonal design to identify the strength of key variables. Therefore, this paper does not optimize the raw material ratio independently, but takes the fixed matrix composition as the preconstraint of process parameter optimization, so that the changes of SiC content, sodium phosphate content and sintering temperature can be compared and evaluated under the uniform raw material background. After this process, the interference caused by the fluctuation of raw material composition on pore structure judgment, performance mapping and result regression is controlled, and the comparability between samples is also stronger, thus providing stable input conditions for subsequent comprehensive performance constrained optimization and optimal process combination identification.

### 3.3.2 Cooperative regulation strategy of foaming and firing

The cooperative regulation strategy of foaming and firing is based on the matching relationship between gas release rate, melt viscosity change and pore wall curing rhythm, and the goal is to maintain the synchronization of pore expansion and obturator maintenance during the heating process. This strategy is particularly critical for the formation of light closed cell structure of coal gangue based foam ceramic, which can ensure the foaming strength and stabilize the firing process. Its core consists of two steps: (1) Collaborative parameter setting: Under the condition that the mass ratio of gangue to diatomite was fixed at 7：3, the holding time was fixed at 30 min, and the addition amount of potassium feldspar and magnesium oxide was fixed at 10% and 5%, respectively, SiC content, sodium phosphate content and sintering temperature were selected as the collaborative control variables, and a three-factor and three-level orthogonal optimization scheme was constructed to provide a parameter combination basis for subsequent experimental evaluation. (2) Firing rhythm control: The foaming agent reaction interval and temperature evolution interval are written into the model update chain, and the matching state between the foaming window and the firing window is continuously corrected through parameter coding, stage determination and sample regression, so that the gas generation, liquid encapsulation and pore wall closure are coordinated, thus providing a stable input for the subsequent performance constraint optimization of lightweight closed cell structures. The strategy does not output the optimal combination in advance, but limits the parameter screening to the effective interval that can be foaming, sinter and closed pore, and enhances the calculation consistency, control continuity and process repeatability between different batches of samples. At the same time, the results of collaborative regulation can also be used as a priori basis for the next round of sample screening, compressing the invalid test firing range, and reducing the degree of interference and cumulative error caused by temperature fluctuation and parameter deviation on structure determination.

#### 3.3.3 Optimization strategy of lightweight closed-cell structure performance constraints

The performance constrained optimization strategy of lightweight obturator structures is centered on the collaborative balance among total porosity, obturator ratio, bulk density, compressive strength and thermal conductivity. The goal is to eliminate structural instability samples and retain candidate combinations with better comprehensive performance in the parameter search process. This strategy is particularly critical for the preparation of coal gangue based ceramic foam, which can make the lightweight, closed pore and strength maintain in the same calculation chain to complete the judgment. The core of the model consists of two steps: (1) Performance threshold constraints: According to the requirements of the target material, the lower limits of total porosity, obturator and compressive strength are set, and the upper limits of volume density and thermal conductivity are set. These boundaries are written into the sample screening rules, so that the parameter combinations that do not meet the constraints are automatically eliminated in the iteration process of the model. (2) Ranking of comprehensive indexes: normalization calculation and weight synthesis are continued for the candidate samples determined by constraints, and the combinations with the characteristics of light volume, high obturator, low thermal conductivity and structural stability are preferentially retained. The strategy does not regard the improvement of a single index as the final goal, but makes the comparison of different process samples under a unified judgment standard through performance constraints, result regression and multi-index linkage evaluation, and provides a more stable calculation basis for subsequent experimental verification and optimal scheme output. At the same time, the performance constraint results can reverse correct the parameter update direction, reduce the repetition of high porosity and low strength samples and low density and high thermal conductivity samples in the search space, and enhance the convergence speed of the model, the comparability of the samples and the repeatability of the process optimization results.

# 4 Experimental Evaluation

## 4.1 The dataset

In the study of preparation process optimization of light closed cell structure of coal gangue based foam ceramic, data set construction directly relates model training effect and parameter determination accuracy. To ensure the computability and repeatability of the experimental evaluation, a data set oriented to process parameter optimization is constructed in this paper. The data set takes the burning samples of gangue-diatomite system as the core object, covering the links of raw material ratio, foaming agent addition, auxiliary agent adjustment, firing system and performance output, which can more completely reflect the variable relationship in the formation of lightweight closed cell structure.

Data sources include orthogonal experiment records, parallel sample test results, and firing process monitoring data. The original samples were from the three-factor three-level process combination, the mass ratio of fixed gangue to diatomite was 7：3, the addition of potassium feldspar and magnesium oxide was 10% and 5%, respectively, and the samples were collected around SiC content, sodium phosphate content and sintering temperature. Total porosity, obturator porosity, bulk density, compressive strength and thermal conductivity were recorded for each group of samples, while process information such as furnace temperature curve, insulation stage and weighing error were supplemented.

In the preprocessing stage, the original data are processed by outlier removal, missing item correction, parameter coding, normalization and label alignment, and the continuous process variables and performance indicators are organized into a unified sample matrix. The input contains SiC content, sodium phosphate content, sintering temperature, holding time and raw material Settings, and the output corresponding to the total porosity, obturator ratio, volume density, compressive strength and thermal conductivity.

In order to enhance the sample representativity, this paper adds repeat burning and parallel detection data to the original orthogonal samples, and hierarchically divides them according to the training set, validation set and test set. The data set not only retains the process fluctuation under the test conditions, but also maintains the continuity of the parameter distribution and the stability of the performance label, which can provide a reliable basis and verification for the subsequent model convergence and optimal process identification.

## 4.2 Experimental Design

The aim of this study is to evaluate the effectiveness, stability and repeatability of the optimization model of process parameters for the preparation of lightweight closed cell structures of coal gangue based ceramic foam through a combination of orthogonal experiments and computational analysis. The goal of the experiment is to construct a standardized parameter combination for the model to call under the condition of fixed matrix system and auxiliary components, and complete the subsequent performance prediction and combination judgment through a unified sample organization method. In the experiment, total porosity, obturator porosity, bulk density, compressive strength and thermal conductivity are used as subsequent evaluation indexes, but only parameter design, factor setting and implementation process are explained in this section.

The experimental design used a three-factor three-level orthogonal scheme. In terms of fixed conditions, the mass ratio of gangue to diatomite was set as 7：3, the holding time was fixed as 30 min, and the addition of potassium feldspar and magnesium oxide was fixed as 10% and 5%, respectively. On this basis, SiC content, sodium phosphate content and sintering temperature were selected as the three core experimental factors, and three levels were set for each factor. Without considering the interaction between factors, $L9(3^3)$ orthogonal table was used to organize the test combination. In this way, the experiment scale can be controlled while the distribution of parameters is balanced, and a clearer input boundary can be provided for subsequent data modeling.

In the implementation process, the experimental parameter input, sample coding, data normalization and label sorting are completed in the Python environment. NumPy and pandas are mainly used for data processing, and the random seed is kept fixed to ensure the consistency of the experimental organization and model training process. Table 2 presents the orthogonal experimental factor level Settings adopted in this study.

*Table 2: Table of orthogonal test factors.*

| Level | A (SiC) / % | B (Sodium Phosphate) / % | C (Sintering Temperature) /°C |
|---|---|---|---|
| 1 | 1.0 | 2.5 | 1190 |
| 2 | 1.5 | 3.0 | 1200 |
| 3 | 2.0 | 3.5 | 1210 |

## 4.3 Experimental Results

The results of orthogonal test samples show that the pore structure response of coal gangue based ceramic foam varies significantly under different process combinations, and the total porosity fluctuates between 61.85% and 84.97%, which indicates that there is a strong synergistic effect between the dosage of foaming agent, the content of auxiliary agent and the sintering temperature. With the change of parameter combinations, the samples show clear differences in pore expansion degree, pore wall continuity and structure retention ability, and the boundary between the optimal combination and the non-optimal combination is relatively clear.

Table 3 lists the total porosity results of the nine groups of samples under different process conditions. It can be seen that the pore structure of the samples is quite different under different parameter combinations, and the total porosity is distributed between 61.85% and 84.97%, indicating that SiC content, sodium phosphate content and sintering temperature have direct effects on the foaming process and pore wall formation.

*Table 3: Results of the orthogonal test.*

| No. | A (SiC) / % | B (Sodium Phosphate) / % | C (Sintering Temperature) / °C | Total Porosity / % |
|---|---|---|---|---|
| 1 | 1.0 | 2.5 | 1190 | 72.35 |
| 2 | 1.0 | 3.0 | 1200 | 76.89 |
| 3 | 1.0 | 3.5 | 1210 | 70.57 |
| 4 | 1.5 | 2.5 | 1200 | 84.97 |
| 5 | 1.5 | 3.0 | 1210 | 82.69 |
| 6 | 1.5 | 3.5 | 1190 | 78.59 |
| 7 | 2.0 | 2.5 | 1210 | 68.93 |
| 8 | 2.0 | 3.0 | 1190 | 65.67 |
| 9 | 2.0 | 3.5 | 1200 | 61.85 |

It can be seen from Table 3 that the total porosity of the fourth group is the highest, reaching 84.97%, and the fifth and sixth groups are 82.69% and 78.59%, respectively, all at a high level. The total porosity of the samples in groups 8 and 9 is relatively low. The overall trend shows that when the SiC content increases from 1.0% to 1.5%, the foaming reaction is enhanced, and a more coordinated matching relationship is formed between the gas release and melt encapsulation in the system, so the pore expansion is more sufficient. When SiC continued to increase to 2.0%, the continuity of the pore wall was weakened, the local bubble coalescence and rupture increased, and the total porosity decreased. Although the sodium phosphate content and sintering temperature did not show the same dominant effect as SiC, the changes in different groups have shown a regulating effect on bubble stability and structure retention.

In order to further judge the strength of the effect of each factor on the total porosity, the range analysis of the orthogonal results is carried out, and the results are shown in Table 4.

*Table 4: Analysis of the results of the orthogonal test.*

| Level | A (SiC) / % | B (Sodium Phosphate) / % | C (Sintering Temperature) / °C |
|---|---|---|---|
| K1 | 197.141 | 216.22 | 208.65 |
| K2 | 248.25 | 226.76 | 228.92 |
| K3 | 214.99 | 217.40 | 222.81 |
| $\bar{K}1$ | 65.71 | 72.07 | 69.55 |
| $\bar{K}2$ | 82.75 | 75.08 | 76.31 |
| $\bar{K}3$ | 71.66 | 72.47 | 74.27 |
| R | 17.04 | 3.26 | 6.76 |

Table 4 shows that the corresponding range value of factor A is 17.04, which is the largest among the three, indicating that SiC content is the dominant factor affecting the change of total porosity. The corresponding range value of C factor is 6.76, which indicates that the sintering temperature has a strong effect on the pore structure development and stability. The corresponding range value of factor B is 3.26, indicating that sodium phosphate content has a relatively slow effect on the total porosity, but it is still involved in the regulation of melt flow state and bubble retention capacity. According to the law of range size, the order of influence of three factors on the total porosity is: SiC content > sintering temperature > sodium phosphate content. According to the mean results of each factor, A2, B2 and C2 levels all showed better responses, so A2B2C2 was selected as the preferred process combination in the subsequent verification stage. This shows that under the current gangue base system, moderate amount of foaming agent, moderate additive addition and moderate sintering temperature are more conducive to forming a structural state with sufficient pore expansion and stable pore walls.

On the basis of orthogonal screening, this paper prepared samples according to A2B2C2 combination and tested their full performance, and the results are shown in Table 5.

*Table 5: Performance of the samples fired by the optimal scheme.*

| Sample ID | Total Porosity / % | Closed Porosity / % | Bulk Density / (g·cm-3) | Compressive Strength / MPa | Thermal Conductivity / [W/(m·K)] |
|---|---|---|---|---|---|
| A2B2C2 | 86.65 | 83.33 | 0.3532 | 3.19 | 0.096 |

It can be seen from Table 5 that the total porosity of the sample prepared under the condition of A2B2C2 reaches 86.65%, the obturator ratio reaches 83.33%, the volume density decreases to 0.3532 g·cm-3, the compressive strength reaches 3.19 MPa, and the thermal conductivity reaches 0.096 W/(m·K). This result shows that the parameter combination obtained after orthogonal screening can not only promote pore expansion, but also maintain a high ratio of closed pores, so that the material still has good mechanical support ability and heat insulation performance on the basis of lightweight. In terms of the corresponding relationship between parameters, structure and properties, the process combination formed a coordinated matching state between the foam-gas generation, the molten phase encapsulation ability and the pore wall curing rhythm, so that it could simultaneously obtain higher porosity, higher obturator and lower thermal conductivity, without a significant decrease in compressive strength caused by too thin pore walls.

In order to supplement the structural basis of the obturator ratio results of the optimized process samples, the obturator and connected pore distributions of A2B2C2 samples in different pore sizes were statistically analyzed, and the results are shown in Figure 3.

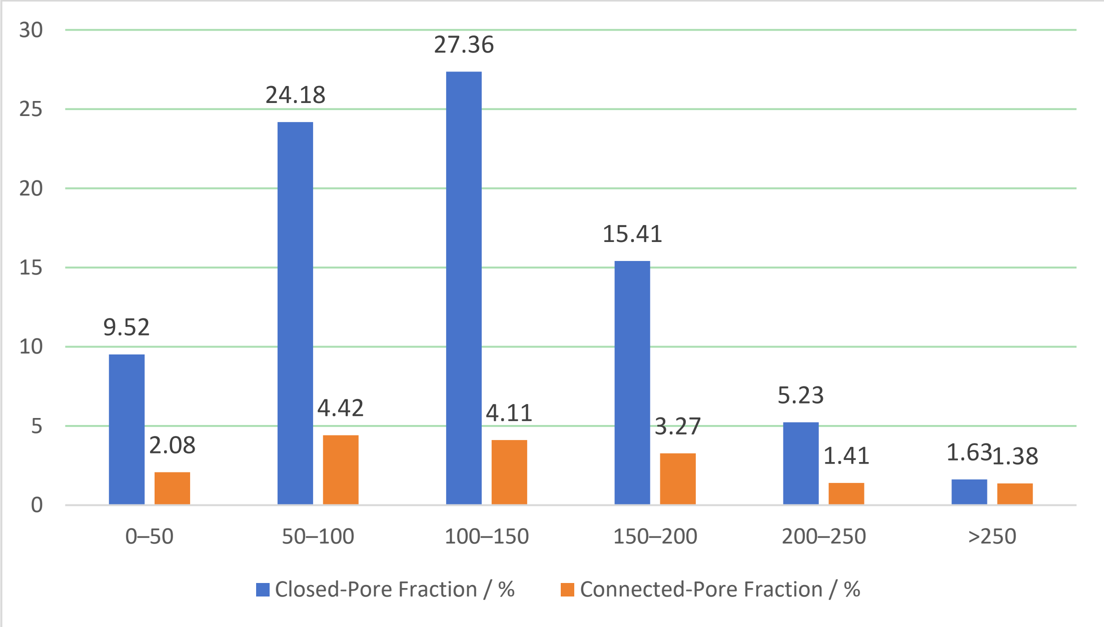


*Figure 3: Corresponding relationship between the proportion of the sample pore number and the obturator ratio in different pore size intervals.*

The figure shows that the obturator foramen is mainly concentrated in the range of 50-150 μm, and the proportion in the range of 50-100 μm and 100-150 μm is 24.18% and 27.36%, respectively, with a total of 51.54%. The proportion of connected holes in each interval is low, and the highest value appears in the 50-100 μm interval, which is only 4.42%. The ratio of obturator and connected pore decreases significantly in the interval above 200 μm, indicating that the pore structure formed under the optimized process is dominated by medium pore size obturator, and the pore fusion phenomenon is well controlled, which is consistent with the results in Table 5 of obturator rate of 83.33%, volume density of 0.3532 g·cm^-3 and thermal conductivity of 0.096 W/(m·K).

## 4.4 Discussion

It can be seen from Table 3 to Table 5 that SiC content has the strongest influence on the total porosity, indicating that the gas generation ability of the foiling agent directly determines the pore expansion degree. The effect of sintering temperature is in the middle, which indicates that the temperature mainly acts on the structure maintenance by adjusting the viscosity of the molten phase and the bubble curing rhythm. The effect of sodium phosphate content is relatively weak, but it still has a continuous correction effect on the melt flow state and bubble stability. This difference indicates that the lightweight closed cell structure is not determined by a single parameter, but is the result of the joint formation of foaming strength, liquid phase encapsulation and pore wall closure.

When the temperature is too low, the gas release is insufficient and the pore expansion is limited. When the temperature is too high, the pore wall is easy to thin and induce pore coalescence, so a moderate temperature window is more conducive to maintaining the stability of the obturator structure. The optimal sample can simultaneously obtain higher obturator ratio, lower volume density and lower thermal conductivity, indicating that the A2B2C2 process combination forms a good matching relationship between gas release rate, pore wall continuity and thermal resistance construction. The data modeling results are consistent with the performance test results, which show that the established parameter optimization path can not only identify the effective process window, but also provide a more stable calculation basis for subsequent sample expansion, surrogate prediction and process iteration. The results interpretation has good stability and consistency.

# 5 Conclusion

In this paper, an intelligent optimization analysis path integrating parameter coding, proxy prediction, multi-index evaluation and combination optimization is constructed for the parameter optimization of the preparation process of light closed cell structure of coal ganguse-based ceramic foam. Through orthogonal organization and calculation screening of sic content, sodium phosphate content and sintering temperature, a unified evaluation framework for total porosity, obturator porosity, bulk density, compressive strength and thermal conductivity was established. The results show that the A2B2C2 process combination can obtain 86.65% of the total porosity, 83.33% of the obturator porosity, 0.3532 g·cm-3 volume density, 3.19 MPa compressive strength and 0.096 W/(m·K) thermal conductivity. It shows that the model can accurately identify the coordination interval among lightweight, closed hole and heat insulation performance, and the empirical process comparison is transformed into a computable parameter determination process. At the same time, the consistency of the result output and the engineering reuse value are enhanced.

The limitations of this paper are mainly reflected in that the sample size is still constrained by the experimental cost, the current data mainly comes from the three-factor three-level combination and its parallel detection results, and the coverage of the parameter space can still be extended. The follow-up research can further introduce more raw material fluctuation conditions, firing rhythm variables and image representation features, improve the sample matrix and surrogate model training mechanism, and combine real-time detection data to build a more stable performance prediction and iterative update chain, so as to enhance the generalization ability, convergence efficiency and engineering adaptability of the model. It provides more adequate support for the high value utilization and computational process design of coal gangue based ceramic foam.

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