Application and Modeling of Reinforcement Learning in Ceramic Process Optimization

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Abstract. In this article, a parametric model of the ceramic process based on CAD (Computer Aided Design) is constructed, and the digital expression of key factors in the production process is realized. Furthermore, an RL (Reinforcement Learning) strategy suitable for ceramic process optimization has been designed. Through autonomous learning and decision-making of agents, efficient exploration is carried out in the parameter space to find the best combination of process parameters. In the research method, this article uses CAD modelling technology to parameterize the geometric shape and production parameters of ceramic products and simulate the production process under different parameter combinations through the simulation experimental platform. RL algorithm adjusts its parameters independently according to the simulation results to maximize the preset reward function, thus realizing process optimization. The experimental results show that the strength, hardness, and appearance quality of ceramic products are significantly improved by the optimized combination of process parameters. Furthermore, compared with the traditional trial and error method, the time and cost required by the proposed method in the optimization process are greatly reduced. In addition, this method has strong universality and expansibility and is expected to be applied to more types of material preparation and process optimization problems in the future.

Keywords: CAD Modeling; Reinforcement Learning; Ceramic Process Optimization
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1 INTRODUCTION

With the continuous development of science and technology, CAD technology has been widely used in various industries, which has brought revolutionary changes to product design and manufacturing. With the widespread application of computer-aided design and manufacturing (CAD/CAM) technology, the application of ceramic materials in dentistry, orthopedics, and industrial fields is increasing day by day. AlMawash et al. [1] evaluated the effect of polishing on the colouring properties of different CAD/CAM ceramic materials through in vitro experiments, providing valuable references for clinical and industrial production. Ceramic materials are widely used in fields such as dental restoration, orthopaedic implantation, and industrial manufacturing due to their excellent biocompatibility, mechanical properties, and aesthetics. CAD/CAM technology provides strong support for the customization and precision manufacturing of ceramic materials. However, in practical applications, the colouring properties of ceramic materials are often affected by polishing treatments. Therefore, studying the influence of polishing on the colouring properties of different CAD/CAM ceramic materials is of great significance. After polishing treatment, the L value of the ceramic material decreases, and the a and b * values change, indicating that polishing has a certain impact on the colouring properties of the ceramic material. In the field of ceramic technology, CAD modelling technology can provide accurate product design and analysis tools, which helps improve production efficiency, reduce production costs and improving product quality. Almeida et al. [2] investigated the influence of CAD/CAM systems on the edge fitting of different ceramic types. Compare the edge fitting accuracy of different ceramic materials in CAD/CAM systems. It analyzed the key factors affecting edge fitting, providing theoretical support for optimizing the design and manufacturing of ceramic restorations. Its application in the manufacturing of ceramic restorations is becoming increasingly widespread. Different ceramic materials may have different edge-fitting effects in CAD/CAM systems due to their unique physical and chemical properties. Therefore, studying the influence of CAD/CAM systems on edge fitting of different ceramic types is of great significance. The edge-fitting effect of CAD/CAM systems on different ceramic types is influenced by various factors, such as material properties, processing parameters, and manufacturing processes. Aluminum oxide ceramics and zirconia ceramics have good edge-fitting accuracy in CAD/CAM systems due to their high hardness and strength. Due to its special crystal structure and thermal expansion coefficient, glass ceramics are prone to deformation and small gaps during processing. However, the optimization of ceramic technology still faces many challenges, such as the nonlinearity of material properties, the complexity of process parameters and the uncertainty in the production process. In the field of ceramic manufacturing, 3D printing technology combining computer-aided design (CAD) and reinforcement learning algorithms provides the possibility for preparing ceramic products with complex shapes and high density. Chen et al. [3] reviewed the latest progress in 3D printing technology based on CAD modelling and reinforcement learning in the preparation of complex-shaped dense ceramics and looked forward to its future development trends. Ceramic materials are widely used in aerospace, medicine, electronics and other fields due to their unique physical and chemical properties, such as high hardness, high wear resistance, and good chemical stability. However, traditional ceramic processing methods often find it difficult to prepare ceramic products with complex shapes and high density. In recent years, with the rapid development of 3D printing technology, especially the application of CAD modelling and reinforcement learning algorithms, new solutions have been provided for the preparation of complex-shaped ceramic products. Therefore, exploring new optimization methods and technologies has become the focus of current ceramic technology research.

As a new machine learning algorithm, RL has shown great potential in solving complex decision-making problems. With the rapid development of 3D printing technology, hybrid biomimetic ceramic lattice structures have received widespread attention due to their unique mechanical properties and lightweight design. However, accurately predicting and optimizing the performance of these structures remains a challenge. Doodi and Gunji [4] proposed a novel method combining artificial neural networks (ANN) for predicting and experimentally verifying the performance of hybrid biomimetic 3D printed ceramic lattice structures. The hybrid biomimetic ceramic lattice structure combines the high strength, high hardness, and lightweight design of ceramics with biological structures, exhibiting excellent mechanical properties. However, traditional design methods often rely on experimental trial and error, which is time-consuming and costly. Therefore, developing an efficient and accurate prediction and optimization method has become particularly important. Artificial neural networks, as a powerful machine learning tool, can handle complex nonlinear problems and provide a new approach for predicting the performance of hybrid biomimetic ceramic lattice structures. Accurate identification of the polymer materials used in 3D ceramic printing is crucial to ensuring printing quality and performance. Fang et al. [5] investigated the impact of reconstruction algorithms based on a combination of artificial neural networks on polymer recognition in 3D ceramic printing. Including improving recognition accuracy, optimizing printing parameters, and enhancing printing efficiency. 3D ceramic printing technology combines the high performance of ceramic materials with the flexibility of 3D printing technology, providing a new approach for the manufacturing of complex ceramic products. In the process of 3D ceramic printing, polymers are often used as supporting structures or adhesives, so accurate identification of polymers is crucial. Traditional polymer identification methods mainly rely on manual experience and physical testing, but this method is inefficient and susceptible to human factors. An artificial neural network is a computational model that simulates the structure of human brain neurons and has strong learning and reasoning abilities. By training a large amount of data, neural networks can learn to recognize different material properties. The reconstruction algorithm can reconstruct the three-dimensional structure of objects based on known information, providing more contextual information for polymer recognition. By combining artificial neural networks with reconstruction algorithms, efficient and accurate identification of polymer materials can be achieved.

The application of CAD technology in the field of dental restoration is becoming increasingly widespread, especially in the synthesis and verification process of some ceramic crowns. Farook et al. [6] explored how to use CAD technology to optimize the design, manufacturing, and validation processes of some ceramic crowns, thereby improving the quality and adaptability of crowns. Ceramic crowns are favoured in dental restoration due to their beauty and durability. However, traditional dental crown design and manufacturing processes often rely on manual skills and experience, making it difficult to ensure the accuracy and adaptability of dental crowns. With the development of CAD technology, we can use digital tools to accurately design, simulate, and manufacture partial ceramic crowns, thereby improving the restoration effect. After manufacturing, the adaptability and comfort of the dental crown can be verified through actual trial wear. CAD technology makes this process more efficient and precise, reducing the number of trials and adjustments. With the development of additive manufacturing technology, extrusion-based 3D printing technology has become an effective means of ceramic product manufacturing. However, the flow behaviour and moulding quality of ceramic slurry during the printing process are influenced by various factors. Hu et al. [7] explored the use of reinforcement learning modelling to optimize the 3D printing process of ceramic slurries and proposed an in-situ forming preservation method to improve the forming accuracy and performance of ceramic products. The extrusion-based 3D printing technology constructs ceramic products layer by layer by squeezing ceramic slurry onto the printing platform through a nozzle. However, the flow behaviour and moulding quality of ceramic slurry during the printing process are influenced by various factors such as slurry properties, printing parameters, and environmental temperature, making it difficult to control the printing process. Reinforcement learning, as an adaptive machine learning technique, can adjust strategies and optimize the printing process based on real-time feedback. Meanwhile, the in-situ forming retention method improves the forming accuracy and performance of ceramic products by fixing the ceramic slurry during the printing process to prevent deformation and shrinkage. Through interactive learning with the environment, RL can adaptively adjust decision-making strategies to maximize long-term returns. RL algorithm is introduced into ceramic process optimization, which can realize automatic adjustment and optimization of process parameters, and is expected to solve the problems that traditional optimization methods are difficult to deal with. The purpose of this study is to combine CAD modelling technology with the RL algorithm and apply it to the optimization of ceramic technology. By constructing a digital model of ceramic technology based on CAD modelling and optimizing the process parameters by RL algorithm, the performance and quality of ceramic products can be improved, the production cost can be reduced and the sustainable development of the ceramic industry can be promoted.

Based on the comprehensive research status, it can be seen that it is an innovative and challenging research direction to combine CAD modelling technology with RL algorithm in ceramic process optimization. In the future, with the continuous development of artificial intelligence technology and the increasing demand for ceramic technology, research in this field will present a broader application prospect and development space. In this study, firstly, the application of CAD modelling technology in ceramic technology will be combed and analyzed in detail, and its advantages and limitations will be summarized. Then, the research will discuss the basic principle and common methods of RL algorithm, and analyze its applicability and potential in ceramic process optimization. On this basis, the research will build a digital model of ceramic process based on CAD modeling, and optimize the process parameters by RL algorithm. Finally, the effectiveness and superiority of the proposed method are verified by simulation experiments.

Specific research methods include literature review, theoretical analysis, algorithm design, simulation experiments and so on. Literature review systematically sorts out relevant research results and development trends; Theoretical analysis deeply studies the principles and methods of CAD modeling technology and RL algorithm; Algorithm design combines the characteristics and requirements of ceramic process to construct RL algorithm suitable for process optimization; In the simulation experiment, the algorithm and digital model are used to verify the simulation, and the experimental results are analyzed and discussed.

The main innovations of this study include:

A ceramic process optimization method based on CAD modelling and RL is proposed, which realizes the automatic adjustment and optimization of process parameters and improves the quality and production efficiency of ceramic products.

RL strategy suitable for ceramic process optimization is designed. Through reasonable reward function and state space definition, agents are guided to explore and learn effectively in parameter space.

A simulation experiment platform was built to simulate the production process of ceramic products, and the effectiveness and superiority of the proposed method were verified. The results of simulation experiments provide powerful guidance and support for actual production.

This article is divided into five sections. The first section mainly introduces the research background and significance, development trend, research content and methods, and structural arrangement. The second section introduces CAD modeling technology and its application in ceramic technology in detail; The theoretical basis and common methods of RL algorithm are expounded. In the third section, the ceramic process optimization method based on CAD modelling and RL is proposed. In the fourth section, the simulation experiment is designed, and the simulation experiment results are analyzed and discussed. The fifth section summarizes the main results of this study and looks forward to it.

2 RELATED WORK

With the rapid development of big data technology and the increasing maturity of machine learning algorithms, their application in ceramic material design is becoming increasingly widespread and in-depth. Mahmoud et al. [8] reviewed the methods and applications of big data and machine learning in the field of ceramic material design. Intended to explore how to utilize these advanced technologies to improve the performance and design efficiency of ceramic materials. Ceramic materials are widely used in aerospace, medical, energy and other fields due to their excellent physical, chemical, and mechanical properties. The traditional ceramic material design method mainly relies on experiments and experience, which is inefficient and costly. By establishing a massive material performance database and collecting data on the composition, structure, process parameters, and performance of various ceramic materials, training data is provided for subsequent machine learning models. Using machine learning algorithms such as regression and classification, establish a material performance prediction model, and predict its performance based on the composition and process parameters of the material. This can greatly reduce the number of experiments and costs, and improve design efficiency. With the rapid development of communication technology, the demand for antenna performance is increasing day by day. The non-uniform ceramic reflection array antenna, a new type of antenna structure, has attracted much attention due to its excellent performance and flexibility. Mahouti et al. [9] explored the application of artificial neural networks in the design of novel 3D-printed non-uniform ceramic reflection array antennas, aiming to improve antenna performance, optimize manufacturing processes, and reduce costs. The non-uniform ceramic reflection array antenna combines the high performance of ceramic materials with the flexibility of reflection array antennas, suitable for applications such as high frequency, high gain, and narrow beam. The traditional antenna design method mainly relies on experience and trial and error, with a long design cycle and high cost. The emergence of 3D printing technology has provided a new approach for the manufacturing of ceramic reflective array antennas. By combining artificial neural networks, precise prediction and optimization of antenna performance can be achieved, improving design efficiency.

Computer-aided design (CAD) has become an important tool in the field of ceramic product design. Saleh et al. [10] explored the importance of CAD-based high-quality ceramic product design and analyzed how CAD technology affects the design quality, production efficiency, and market competitiveness of ceramic products. Ceramic products, as a material with a long history and unique charm, are widely used in daily life, artistic decoration, and industrial production. With the continuous changes in consumer aesthetics and needs, the design requirements for ceramic products are also increasing. The emergence of computer-aided design technology has brought revolutionary changes to the design of ceramic products, enabling designers to achieve creativity more quickly and accurately. CAD technology provides designers with abundant design resources and flexible design tools, which helps to stimulate innovative inspiration. Designers can try different design schemes, materials, and processes through software to achieve more creative and personalized ceramic product design. With the continuous development of computer-aided design (CAD) technology and reinforcement learning algorithms, they are playing an increasingly important role in the design and manufacturing of all ceramic fixed partial dentures (ACFPDs). Saravi et al. [11] explored the application of CAD-based modelling and reinforcement learning in the performance analysis of all ceramic fixed dentures and evaluated their clinical performance. All ceramic fixed dentures have received widespread attention in the field of dental restoration due to their excellent biocompatibility, aesthetics, and durability. However, its design and manufacturing process involves numerous complex factors, such as material properties, structural design, manufacturing processes, etc., all of which can affect its clinical performance. Therefore, it is of great significance to analyze the performance of all ceramic fixed dentures using CAD technology and reinforcement learning algorithms.

Silva et al. [12] investigated the stain resistance and surface roughness of hybrid ceramics processed by CAD/CAM technology. Through comparative experiments and data analysis, the influence of different processing parameters on the fouling resistance and surface roughness of mixed ceramics was evaluated. This provides a theoretical basis for optimizing the process parameters of CAD/CAM processing of hybrid ceramics. Mixed ceramics, as a new type of ceramic material, are widely used in dentistry, orthopaedics, and industrial fields due to their high strength, high hardness, and good chemical stability. CAD/CAM technology provides efficient and accurate solutions for the processing of hybrid ceramics. However, in practical applications, the stain resistance and surface roughness of hybrid ceramics become key factors affecting their performance. Therefore, studying the stain resistance and surface roughness of hybrid ceramics processed by CAD/CAM is of great significance. The experimental results indicate that processing parameters have a significant impact on the stain resistance of mixed ceramics. Vasiliu et al. [13] aimed to compare the changes in edge and internal fit of CAD-CAM single-piece glass ceramic restorations after thermal ageing through in vitro experiments. It evaluates the thermal stability of the restoration and its impact on the edge and internal fit by simulating temperature changes in the oral environment, providing theoretical support for clinical applications. Single-piece glass-ceramic restorations are widely used in dental restoration due to their excellent aesthetic effects and biocompatibility. CAD-CAM technology provides an efficient and accurate solution for the design and manufacturing of single-piece glass ceramic restorations. However, temperature changes in the oral environment may have an impact on the stability of the restoration, thereby affecting its edge and internal fit. Therefore, studying the performance changes of CAD-CAM single-piece glass ceramic restorations after thermal ageing is of great significance. Artificial intelligence (AI) and 3D printing technology are changing various industries. Among them, ceramic composite materials have received widespread attention due to their excellent physical and chemical properties. Verma et al. [14] explored how artificial intelligence can be used for the advanced processing of 3D-printed ceramic composites to improve their performance, optimize production processes, and drive innovation in related industries. Ceramic composite materials combine the high hardness, wear resistance, and good chemical stability of ceramics, as well as the diversity and designability of composite materials, making them widely used in many fields, such as aerospace, medical, and automotive manufacturing. 3D printing technology provides an efficient and flexible method for the manufacturing of ceramic composite materials. AI can be used to monitor and adjust various parameters during the 3D printing process, such as temperature, pressure, speed, etc., to ensure that the microstructure and macroscopic properties of ceramic composite materials meet expectations. Through deep learning and image processing techniques, AI can quickly and accurately detect defects in ceramic composite materials, such as pores and cracks, and provide feedback to improve the printing process.

With the development of ceramic manufacturing technology, complex and finely characterized ceramic structures are increasingly being applied in multiple fields. Zhang et al. [15] explored how to configure controllable ceramic bodies to accurately achieve fine features in CAD modelling. With the increasing maturity of CAD modelling technology, it has become possible to design ceramic structures with complex and fine features. However, factors such as high temperature and shrinkage during the ceramic manufacturing process may lead to differences between the CAD model and the final product. CAD modelling technology allows designers to accurately create and modify three-dimensional models of ceramic structures. These models contain rich geometric and physical information, providing detailed guidance for ceramic manufacturing. However, various factors in the ceramic manufacturing process, such as material properties, forming processes, sintering conditions, etc., may affect the shape and performance of the final product. Therefore, when converting CAD models into ceramic bodies, it is necessary to fully consider these factors to ensure the controllability of the body. With the rapid development of big data technology and the increasing maturity of machine learning algorithms, their application in ceramic material design is becoming increasingly widespread and in-depth. Zhou et al. [16] reviewed the methods and applications of big data and machine learning in the field of ceramic material design, aiming to explore how to use these advanced technologies to improve the performance and design efficiency of ceramic materials. Ceramic materials are widely used in aerospace, medical, energy and other fields due to their excellent physical, chemical, and mechanical properties. The traditional ceramic material design method mainly relies on experiments and experience, which is inefficient and costly. With the emergence of big data and machine learning technologies, they can utilize massive amounts of data and powerful algorithms to accelerate the design and optimization process of ceramic materials. By establishing a massive material performance database and collecting data on the composition, structure, process parameters, and performance of various ceramic materials, training data is provided for subsequent machine learning models.

3 OPTIMIZATION METHOD OF CERAMIC PROCESS BASED ON CAD MODELING AND RL

CAD modelling technology is a modern method for product design, analysis, and optimization using computer systems. Through professional CAD software, designers can create two-dimensional drawings and three-dimensional models to accurately represent the geometric shape, size, material, and manufacturing requirements of products. CAD modelling technology not only improves design efficiency but also allows designers to simulate and test products in a virtual environment, so as to find and correct potential problems in the design stage. As a traditional handicraft, ceramic technology involves many complicated links in its production process, such as raw material preparation, moulding, sintering, and decoration. Traditional design methods often rely on manual drawing and empirical judgment, and it is difficult to ensure the accuracy and consistency of products. Therefore, it is of great significance to introduce CAD modelling technology into ceramic technology.

CAD modelling technology can provide accurate geometric representation and help designers quickly create and modify the design scheme of ceramic products. Furthermore, CAD models can be easily integrated with computer-aided manufacturing systems to realize automatic production and processing. In addition, CAD modelling technology can also support product performance analysis and optimization, such as strength, wear resistance and thermal stability. Through virtual testing and optimization in the design stage, the production cost can be reduced and the product quality can be improved. RL is a branch of machine learning, which studies how agents learn the best behavior strategies in the interaction with the environment to maximize cumulative rewards. In the process of RL, the agent chooses an action to execute by observing the current environmental state and obtains a reward signal according to the execution result. This reward signal reflects whether the action has a good or bad impact on the environment. The goal of the agent is to find a behaviour strategy through trial and error and learning so that the actions selected in any state can maximize the cumulative reward in the future.

RL algorithm can be classified according to different learning styles and application scenarios. Common classification methods include value-based method, strategy-based method and actor-critic method. The value-based method selects actions by estimating the value of each state or state-action pair. Typical algorithms include Q-learning and SARSA. These methods are suitable for discrete action space and the state space is not particularly large. The strategy-based method directly learns the probability distribution of actions, that is, strategy. Typical algorithms include the strategy gradient method, such as the REINFORCE algorithm. These methods are suitable for continuous action space or high-dimensional state space and have good convergence. The actor-critic method combines value-based and strategy-based methods, in which "the actor" is responsible for selecting actions and "the critic" is responsible for evaluating the value of actions. Typical algorithms include actor-critical and Advantage Actor-Critic. These methods have good performance and stability in complex tasks.

When choosing an RL algorithm suitable for ceramic process optimization, the following factors need to be considered: ceramic process usually involves continuous or high-dimensional action space, such as temperature control, time adjustment and other parameters; The quality and performance of ceramic products are often affected by many factors, so it is necessary to consider multiple reward signals comprehensively. There may be noise and uncertainty in the actual production process to interfere with the learning process. Therefore, for ceramic process optimization, we can choose the strategy-based method or actor-critic method as the RL algorithm. These methods can deal with continuous action space and high-dimensional state space, and have good robustness and convergence.

3.1 Parametric Representation of Ceramic Process Based on CAD Modeling

Ceramic process optimization can be regarded as a multi-objective and multi-parameter optimization problem. Goals usually include improving product quality, reducing production costs, and reducing production time. The parameters cover the control variables from raw material selection and molding process to sintering conditions. In the actual production process, these parameters are interrelated and jointly affect the performance of the final product. Create a background grid in a large enough rectangular area, as shown in Figure 1. The significance of establishing a background grid is that the size of most triangles in the grid can be easily controlled and dynamically adjusted according to actual needs.

In order to simplify the problem and make it suitable for the RL algorithm, some assumptions need to be set. Firstly, this article assumes that a series of quantifiable indicators, such as strength, hardness, density, and appearance quality, can evaluate the performance of ceramic products. Secondly, it is assumed that the CAD model can parameterize the main parameters in the production process and can be adjusted and simulated in the simulation environment. Finally, suppose there is a feasible reward function which can evaluate the advantages and disadvantages of different parameter combinations according to the performance index of the product.

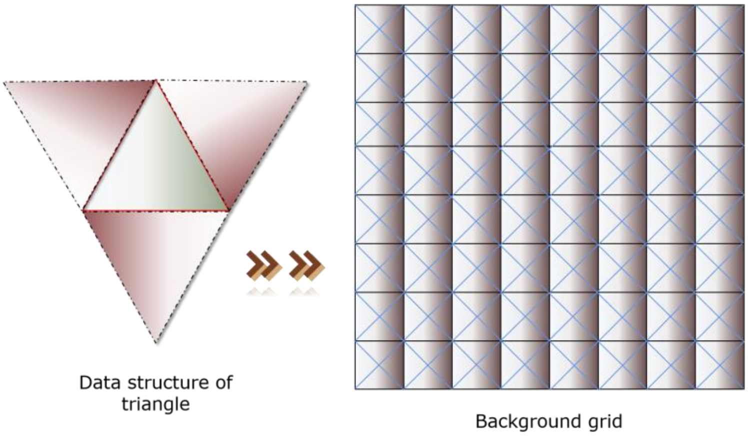


Figure 1: Grid structure and background grid.

Assuming that the two endpoints of the line segment are P_0 and P_1, and the endpoints of the triangle are V_0, V_1 and V_2 in counterclockwise order, any point on the line segment can be expressed as:

$$P = P_0 + t \cdot \vec{d}, \vec{d} = P_1 - P_0, 0 \le t \le 1 \tag{1}$$

Any point on a triangle can be expressed as:

$$Q = wV_0 + uV_1 + vV_2, w + u + v = 1, 0 \le w, u, v \le 1 \tag{2}$$

If the line segment intersects the triangle, the intersection P satisfies the above formula. Simultaneous two formulas can be solved as follows:

$$\begin{bmatrix} t \\ u \\ v \end{bmatrix} = \frac{1}{(\vec{d} \times (V_2 - V_0)) \cdot (V_1 - V_0)} \begin{bmatrix} ((P_0 - V_0) \times (V_1 - V_0)) \cdot (V_2 - V_0) \\ (\vec{d} \times (V_2 - V_0)) \cdot (P_0 - V_0) \\ ((P_0 - V_0) \times (V_1 - V_0)) \cdot \vec{d} \end{bmatrix} \tag{3}$$

If:

$$t, u, v \in [0,1] \tag{4}$$

Then, the line segment intersects the triangle, otherwise, it does not intersect.

In ceramic technology, CAD modelling technology is not only used for the geometric design of products but also can be used to represent various parameters in the production process. By constructing a parametric CAD model, various factors in the production process, such as raw material ratio, moulding pressure, sintering temperature and time, can be easily adjusted and controlled. Let $n+1$ vertices of a given space feature polygon P_i $(i = 0,1,2,3,\ldots,n)$, and then define the vector function of the Bezier curve of n degree as follows:

$$P(t) = \sum_{i=0}^{n} B_{n,j}(t) P_i \tag{5}$$

Among them:

$$B_{n,j}(t) = C_n^i (1-t)^{n-i} t^i \quad (o \le t \le 1) \qquad C_n^i = \frac{n!}{i!(n-i)!} \tag{6}$$

Where $B_{n,j}(t)$ is called the Bernstein basis function. Usually, only the cubic Bezier curve is used in the graphics package, which brings convenience to design and avoids the large increase of calculation due to high-order polynomials. The cubic Bezier curve is generated by four control points, which can be obtained by substituting $n=3$ into the above formula:

$$P(t) = (1-t)^3 \cdot P_0 + 3t(1-t)^2 \cdot P_1 + 3t^2(1-t) \cdot P_2 + t^3 P_3 \quad 0 \le t \le 1 \tag{7}$$

Written as a matrix:

$$P(t) = \begin{bmatrix} t^3 & t^2 & t & 1 \end{bmatrix} \cdot M_{Bez} \cdot \begin{bmatrix} P_0 \\ P_1 \\ P_2 \\ P_3 \end{bmatrix} 0 \le t \le 1 \tag{8}$$

Where the Bezier matrix is:

$$M_{Bez} \cdot \begin{bmatrix} -1 & 3 & -3 & 1 \\ 3 & -6 & 3 & 0 \\ -3 & 3 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix} \tag{9}$$

In this article, the optical triangle method is used to calculate the coordinates of surface points of objects, as shown in Figure 2. It is obtained by an optical triangle composed of the left and right cameras and a point on the surface of the object.

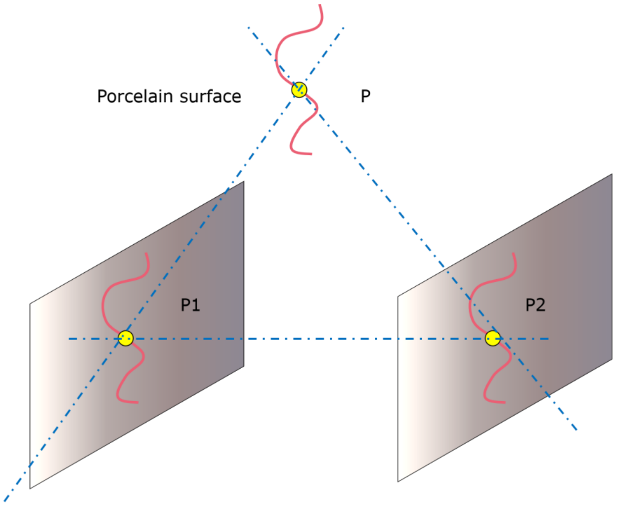


Figure 2: Geometric relationship of the spatial optical triangle.

Among them, P_1 and P_2 are the corresponding points of the same point on the surface of the object that are captured by different cameras, and they are regarded as a point pair. To realize three-dimensional reconstruction, it is necessary to determine the point pairs corresponding to all points on the surface of the object. In this article, the geometric shape and production parameters of ceramic products are defined as variables by using the parametric modelling function in CAD software. Then, by adjusting the values of these variables, product models with different parameter combinations can be generated. These models can be further used for simulation experiments and performance analysis.

3.2 Strategic Design of RL in Ceramic Process Optimization

In the RL framework, it is necessary to design appropriate strategies to guide the optimization algorithm to explore and learn in the ceramic process parameter space. The design of strategy should take into account the characteristics of the problem, the performance requirements of the algorithm and the constraints of actual production.

When solving the problem of ceramic process optimization, a feasible strategy is to adopt an RL algorithm based on strategic gradient. In the process optimization of ceramics, the strategy function can be defined as the probability distribution of the combination of product performance index and current process parameters to adjust the process parameters. The action here can be the adjustment of process parameters such as temperature, pressure and time, while the state can be the performance indexes such as strength, hardness and appearance quality of ceramic products and the current process parameter values. RL algorithm based on strategy gradient updates the parameters of strategy function by calculating strategy gradient. The strategy gradient indicates the expected impact of a small change in the parameters of the strategy function in a certain direction on the cumulative reward. By updating the parameters along the direction of the strategy gradient, the actions selected by the agent in the expected state can get higher rewards. The expected value of the cumulative award is defined as:

$$J\ \theta\ = E_{\pi\theta}\left[\sum_{t=0}^{\infty}\gamma^{t} rt\right] \tag{10}$$

The algorithm will select an action according to the action probability distribution generated by the current strategy function, and execute the action to observe the reward signal fed back by the environment. Then, the algorithm uses the observed reward signal to calculate the strategy gradient and uses the gradient rising method to update the parameters of the strategy function. The purpose of the gradient rising method is to find the parameter value that can maximize the cumulative reward. The updating rules of the policy gradient are as follows:

$$\theta \leftarrow \theta + \alpha\nabla\theta \log \pi\theta\ \ a\middle|s\ \ A^{\pi\theta}\ \ s,a \tag{11}$$

In this way, the RL algorithm based on strategy gradient can gradually learn an effective strategy in ceramic process optimization, and this strategy can choose the action that can get a higher reward (that is, adjust process parameters) according to the current product performance index and process parameters combination. With the progress of learning, the algorithm will gradually converge to an optimized combination of process parameters, thus improving the performance of ceramic products.

4 CONSTRUCTION OF SIMULATION EXPERIMENTAL PLATFORM AND ANALYSIS OF EXPERIMENTAL RESULTS

In order to verify the effectiveness of the proposed method, this section builds a simulation experimental platform and designs the corresponding experimental scheme. The simulation platform can simulate the production process of ceramic products and calculate the product performance indexes under different parameter combinations. Furthermore, the platform also supports the training and testing of the RL algorithm. In the design of the experimental scheme, several key production parameters are selected as optimization variables, such as raw material ratio, moulding pressure and sintering temperature. Then, different experimental schemes are generated by adjusting the values of these variables. Each scheme should be simulated on the simulation platform, and the corresponding performance indicators and reward values should be recorded. Finally, the RL algorithm can be used to study and analyze these data to find the optimal parameter combination. After completing the simulation experiment, this section collects a lot of experimental data, including product performance indicators, reward values and the learning process of the RL algorithm under different parameter combinations. These data are displayed in the form of tables, charts or curves in order to understand the experimental results and algorithm performance more intuitively. The visual diagram of the optimization process shown in Figure 3 clearly shows how the optimization algorithm can gradually find a better combination of process parameters with the increase of iteration times.

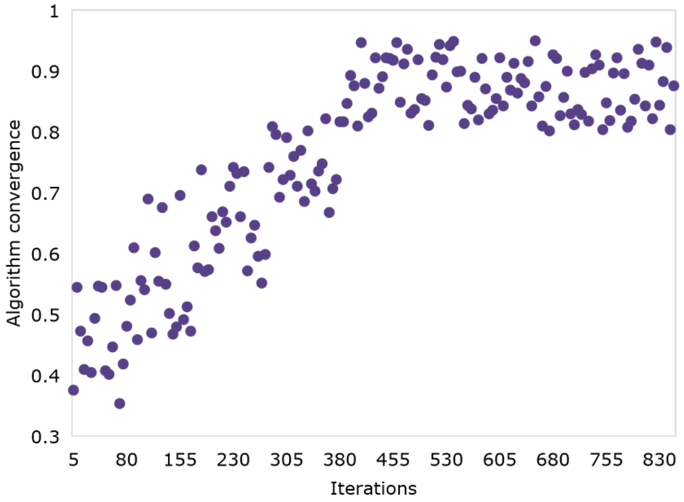


Figure 3: Visualization diagram of the optimization process.

As can be seen from the figure, in the initial stage, the algorithm makes extensive exploration in the parameter space to find the potential optimization direction; With the increase of iteration times, the algorithm gradually converges to the optimal solution and makes fine adjustments. This process fully embodies the advantages of the RL algorithm in autonomous learning and decision-making.

Through the product performance index diagram (as shown in Figure 4), we can directly see the performance of ceramic products under different combinations of process parameters. It is obvious from the figure that the optimized combination of process parameters by the proposed method is located in the region with better performance, which further verifies the effectiveness of the proposed method.

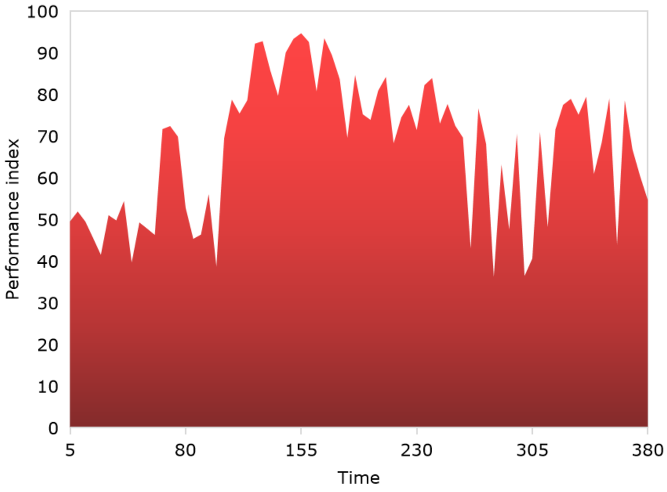


Figure 4: Product performance indicators.

The trend of reward value and iteration times (as shown in Figure 5) shows how the reward value changes with the increase of iteration times of the RL algorithm.

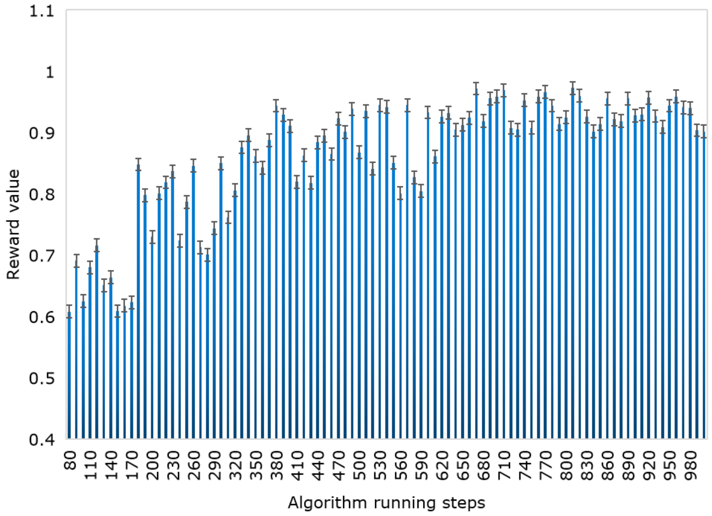


Figure 5: Reward value and iteration number curve.

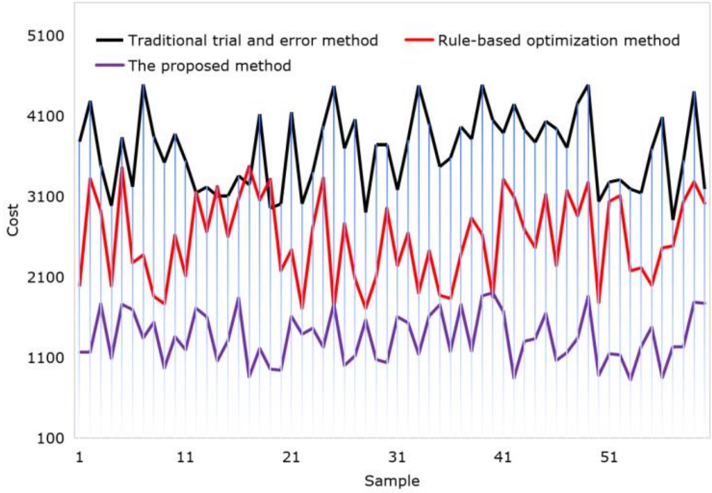
As can be seen from the figure, with the increase of iterations, the reward value gradually rises and tends to be stable, which shows that the algorithm can effectively learn the optimization goal and find a better combination of process parameters. Furthermore, the smoothness of the curve also reflects the stability and convergence speed of the algorithm.

In order to evaluate the optimization effect of the proposed method, the experimental results can also be compared and analyzed. This section compares the proposed method with the traditional trial-and-error method and rule-based optimization method to verify the superiority and effectiveness of the proposed method. The implementation of the optimization method is as follows: (1) The proposed method combines CAD modelling technology and RL algorithm. RL agent makes efficient exploration in parameter space through autonomous learning and decision-making to find the best combination of process parameters. (2) Traditional trial-and-error method: the process parameters are adjusted by experience and repeated experiments until satisfactory product performance is achieved. (3) Rule-based optimization method: adjust the process parameters according to the preset rules and knowledge base in order to achieve the optimization goal. In the comparative analysis, this article pays attention to the following aspects: first, whether the improvement of product performance after optimization is significant; Second, whether the time and cost required in the optimization process have been reduced; Third, the applicability and robustness of the proposed method in different scenarios and problems. Figure 6 shows the comparison of optimization time and cost of several methods. Table 1 shows the performance comparison of ceramic products before and after optimization.

Performance index	*Before optimization*	*After optimization*
Strength (MPa)	120	150
Hardness (HR)	700	800
Appearance quality (rating)	3/5	4.5/5

Table 1: Performance comparison of ceramic products before and after optimization.

(A) Time



(B) Cost

Figure 6: Comparison of optimization time and cost of several methods.

Note: The units of strength and hardness are MPa and Rockwell hardness (HR) respectively. The lifting ratio is calculated by subtracting the value before optimization from the value after optimization and then dividing it by the value before optimization.

Appearance quality adopts a rating system, ranging from 1/5 to 5/5, with 5/5 representing the best appearance quality. As the rating is a discrete value, the promotion proportion cannot be directly calculated, so "-" is used in the column of promotion proportion to indicate that it cannot be calculated.

The comparison of the applicability and robustness of the method is shown in Figure 7. Among them, Scenario A: The production of ceramic products under standard technological conditions. Scenario B: Production of ceramic products in a high-temperature environment. Scenario C:

Production of ceramic products in a low-temperature environment. Scenario D: Production of ceramic products using different raw materials.

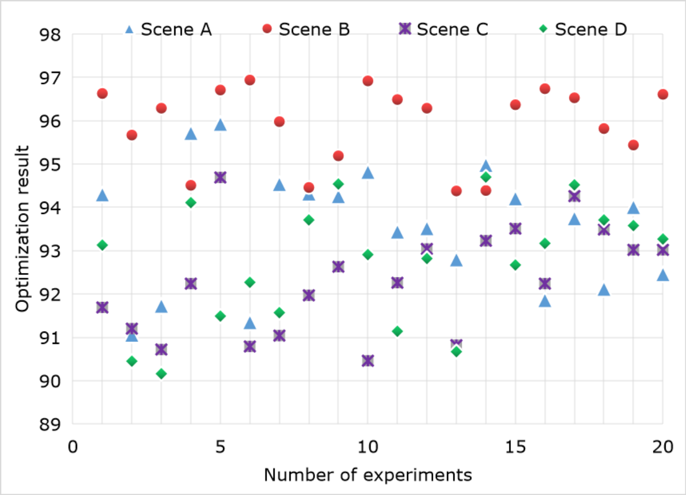


Figure 7: Comparison chart of method applicability and robustness.

Through comparative experiments, the following results are obtained:

Product performance improvement: The experimental results show that the strength, hardness and appearance quality of ceramic products are significantly improved by the optimized combination of process parameters. For example, there are many defects and cracks on the ceramic surface before optimization, and the surface smoothness is improved after optimization, and the defects and cracks are obviously reduced. This shows that the proposed method can effectively find a better combination of process parameters, thus improving product quality.

Time and cost reduction: Compared with the traditional trial-and-error method and rule-based optimization method, the time and cost required by the proposed method in the optimization process are greatly reduced. This is mainly due to the efficient exploration and autonomous learning ability of the RL algorithm, which can find the near-optimal combination of process parameters in fewer attempts.

Method universality and expansibility: The proposed method has strong universality and expansibility. It can be applied to the optimization of different types and specifications of ceramic products and only needs to adjust and modify the CAD model accordingly. In addition, this method can be combined with other optimization algorithms or techniques to further improve the optimization effect.

To sum up, the effectiveness and superiority of the proposed method in the process optimization of ceramic products are verified by experiments. This method not only significantly improves the product performance, but also greatly reduces the time and cost required for the optimization process. This provides strong support for the intelligent transformation of the ceramic industry.

5 CONCLUSIONS

This article mainly focuses on the ceramic process optimization method based on CAD modelling and RL. Through an in-depth analysis of the characteristics and challenges of ceramic technology, this article puts forward a novel optimization method to improve the quality and production efficiency of ceramic products. In the research work, firstly, a parametric CAD model is established, and the visualization and digital expression of the ceramic process are realized. This step provides a solid foundation for subsequent simulation experiments and optimization algorithm design. Then, the RL algorithm is introduced to explore and optimize the ceramic process parameter space efficiently through the autonomous learning and decision-making ability of agents. The application of the RL algorithm not only improves the automation of the optimization process but also effectively reduces the trial and error cost and production time. The experimental results show that the strength, hardness and appearance quality of ceramic products are significantly improved by the optimized combination of process parameters. Compared with the traditional trial and error method, the time and cost required by the proposed method in the optimization process are greatly reduced. Furthermore, this method has strong universality and expansibility.

The ceramic process optimization method based on CAD modelling and RL proposed in this article has significant practical application value and popularization prospects. First of all, this method can significantly improve the quality and production efficiency of ceramic products, reduce production costs and energy consumption, and help enhance the competitiveness and market position of enterprises. Secondly, this method has strong universality and expansibility and can be applied to different types of ceramic products and production scenarios. Finally, with the continuous development and popularization of artificial intelligence and intelligent manufacturing technology, this method is expected to be deeply integrated and upgraded with existing production lines and promote the intelligent transformation and sustainable development of the ceramic industry.

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