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Methods of Optimizing Ceramic Process Design Using Big Data and Machine Learning

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Abstract: The process design of ceramic products has a great impact on the quality and performance of the final product. Traditional methods are not only inefficient, but also consume a lot of resources. In recent years, new technologies such as big data and machine learning have provided new ways to optimize the process of ceramic materials. The machine learning method used in this article is the GA-BP (Genetic Algorithm - Back Propagation) model, which uses big data technology to obtain processing parameters. This parameter includes ceramic material characteristics, process parameter settings, production process monitoring, finished product performance evaluation, etc., while ensuring the accuracy and completeness of the data. This article uses the GA-BP model to optimize the processing parameters. There is a good linear relationship between cutting speed and cutting temperature, but there is a certain gradient change in the local range. Therefore, this article establishes a one-dimensional model based on a one-dimensional linear function, and uses an exponential function to correct it, plus a constant to increase the degree of fit. Compared with the model output result of 134.98MPa, the actual measured surface residual stress is 135.98 MPa. By comparing the model output results with actual measurements, it is proved that the prediction error of this method is far less than 5%. This article helps optimize the processing parameters of engineering ceramic materials.

1. Introduction

When performing micro-wire cutting processing of engineering ceramics, in order to obtain minimum surface residual stress and maximum wear resistance, it is necessary to optimize the design, such as pulse current, operating voltage, pulse interval, number of power tubes, etc. BP network is used for learning and training of neural networks. Its advantage is that it has high search accuracy, but it is easy to fall into local extreme values. This method can effectively overcome some shortcomings of the traditional BP algorithm in the solution process because it has powerful macroscopic optimization capabilities and great probabilistic optimization capabilities. This article combines big data and machine learning methods to form a hybrid learning method to optimize model parameters.

Currently, with the advancement of manufacturing processes, there are more and more manufacturing processes. According to different energy supply methods, they can be divided into mechanical processing methods, electrical processing methods, chemical processing methods, optical processing methods and composite processing methods. At present, the development direction of ceramic manufacturing has tended to be composite, that is, the combination of various technological means. Shi Yunjing took bismuth ferrite-based ceramics as the research object. By adjusting three factors, including pre-firing temperature, pre-firing times, and sintering temperature, he realized the optimization of parameters such as dielectric loss and residual polarization strength of ceramic materials, and improved the piezoelectric properties of the material [1]. Xie Tianshu believes that the manufacturing quality of ceramic bearing rings is directly related to its rotation accuracy and service life. He used a multi-variable composite model, and the relative error between the calculated results and the actual manufacturing results was between 5.83% and 8.99%. The method he adopted can improve cutting efficiency [2]. Li Songhua used orthogonal test correlation characteristics to optimize its design and explore its engineering application prospects. The results showed that the surface roughness of zirconia ceramic materials was closely related to process parameters [3]. Chen Lu took zirconia ceramic materials as the research object and used a single factor experimental method to determine the optimal grinding process parameters [4]. Liu Xiaodong was based on the self-developed ceramic surface forming rapid prototyping system and used ceramic slurry containing oxygen barrier effect. On this basis, he optimized the optimal oxygen content, exposure, stack thickness and other process parameters through orthogonal experiments [5]. In order to solve the problem of poor wettability between zirconia-toughened alumina and Fe in zirconia-toughened alumina ceramic particles reinforced Fe-based composite materials, used electroless nickel plating to coat zirconia-toughened alumina particles [6]. However, their research lacked further process optimization of ceramic materials, and the results of the research were not perfect.

This article uses big data and machine learning to optimize the ceramic process. On this basis, this article uses BP neural network based on genetic algorithm to conduct turning experiments, and constructs the relationship between one-variable and multi-variable cutting temperature, surface roughness and processing parameters [7-8]. On this basis, by solving the built model, an optimal set of ceramic process parameters and material properties were obtained, and their reliability was verified through additional tests [9]. The main contents of this article are as follows:

The first part introduces the background and significance of methods for optimizing ceramic process design using big data and machine learning.

The second part introduces ceramic process optimization methods.

The third part models a single factor based on GA-BP neural network.

The fourth part carries out the optimization of electrical machining parameters and analysis of experimental data.

The fifth part summarizes the full text and draws conclusions.

2. Ceramic Process Optimization Method

2.1 Ceramic Materials

Ceramic materials play a pivotal role in many fields due to their high hardness, high wear resistance, and high heat resistance. However, its weak toughness and high sensitivity to surface defects are bottlenecks restricting its application. Therefore, predicting and regulating the surface quality during the process to achieve the optimal performance of the material is of great significance to engineering practice. At present, the processing methods of engineering ceramics include electric discharge machining, grinding machining and ultrasonic machining. The characteristic of these methods is that they require high experience of operators during the machining process [10]. Therefore, only by selecting appropriate processing methods and optimized process parameters can engineering ceramics obtain the best service performance after processing [11-12]. Ceramics are also called "inorganic non-metals" and can be divided into two types according to their materials and firing methods: one is traditional ceramics and the other is engineering ceramics [13]. The so-called traditional pottery is made of natural silicate minerals calcined at high temperatures, also called silicate ceramics.

Engineering ceramics is a general term for various types of ceramics that have appeared in recent years, also known as new ceramics, high-tech ceramics or fine ceramics. Engineering ceramics are refined from high-purity chemical products and have many advantages such as high strength, high hardness, high wear resistance, and corrosion resistance. It is very different from traditional ceramic concave in terms of chemical composition, internal structure, usability and performance. It is widely used in aerospace, petrochemical industry, instrumentation, machinery manufacturing and nuclear industry. Engineering ceramics are listed as the third largest engineering material after metal materials and engineering plastics, and are gradually used in various high-tech fields. Engineering ceramic materials have high hardness and high brittleness, and conventional cutting processes are difficult to meet their use needs, or even impossible to process. Therefore, it is very important to explore a reasonable process solution in actual production.

But the most commonly used ceramic manufacturing method is still mechanical grinding. The usual choice is a diamond grinding wheel. In this case, the chips will be difficult to discharge, and the grinding wheel will be severely worn, resulting in low processing efficiency and a high probability of edge chipping. Moreover, it will be difficult to meet the demand for dimensional accuracy during secondary processing, resulting in high-cost production. In addition, mechanical grinding is limited to flat and rotating surfaces, which seriously restricts its application scope. Facing more and more complex curved surfaces, high precision, short time and other problems, how to use new processes to process them while ensuring high quality and high efficiency requires a new process. Through the research and exploration of these non-metallic hard and brittle materials, it is found that using CNC grinding process for these non-metallic hard and brittle materials can obtain good surface quality and processing efficiency. First, due to its complex manufacturing process and high precision requirements, it has not been widely used. Second, the requirements for raw materials are relatively high, and it is difficult to ensure consistent performance of each batch of products. There are high requirements for product quality during the production process. Third, the production cost is high, much higher than the cost of hardware accessories. Fourth, it has poor processability and high brittleness.

2.2 Application of BP Neural Network and Genetic Algorithm in the Field of Grinding

BP neural network is a complex network system composed of a large number of simple, highly correlated neurons. It is adopted based on the research results of modern nervous systems. It embodies some basic functional characteristics of the brain and is an important method for simulating artificial intelligence. Its similarity to the human brain has two characteristics: first, the knowledge acquired by the neural network also comes from the external environment; second, the acquired information is stored by correlating the strength of neuron connections. Four main parameters (spindle speed, feed speed, grinding head pressure, grinding head size) will affect the removal rate of engineering ceramics, but there is a complex nonlinear relationship between the two. On this basis, a multi-variable optimization design method based on finite element model is adopted. In addition, a CNC grinding process model based on BP neural network is also used. This article intends to predict and identify the cutting process of engineering ceramic materials by constructing a three-layer BP network, and compare it with the field test results, , thereby more accurately reflecting the intrinsic relationship between the cutting process of engineering ceramic materials and cutting efficiency, tool wear and edge chipping [14].

Usually, in the early stage of iteration, the global optimization ability of the algorithm is improved by increasing the size of the inertia weight; in the later stage of the iteration, the global optimization ability of the algorithm is improved by reducing the inertia weight. To address this problem, this article intends to use methods such as crossover and mutation in genetic algorithms to intersect the extreme points of the particles with the population and mutate themselves to obtain the optimal solution.

2.3 Ceramics in the Context of Big Data

People can understand pottery, learn pottery art, research pottery, find innovative ways of thinking, and discover innovative trends through big data analysis. Through the analysis and establishment of big data, its connotation and perspective are direct contributions to big data analysis, allowing latecomers to innovate on the shoulders of their predecessors and promote the development of ceramic art. All in all, the era of big data has arrived. All kinds of big data are closely related to people's daily lives and people's ceramic aesthetic life. Therefore, the development of modern ceramic aesthetics has greater room for development. Innovative research on ceramic materials based on big data will provide new impetus for the vigorous development of modern ceramic art in China [15].

When designing ceramic materials, try to ensure that the load on the component is compressed to the maximum extent instead of being pulled, minimizing stress concentration and preventing mechanical impact. The product should be small in size and simple in appearance, avoid matching metals with large thermal expansion coefficients, and ensure the accuracy of processing and assembly. Therefore, how to formulate a reasonable CNC grinding process plan is of great significance to solving the above problems. Whether the appropriate process parameters are selected is directly related to the assemble ability of the parts. At the same time, it will have a certain impact on the working performance and surface quality of the product, ensuring the dimensional accuracy and surface roughness after processing, thereby reducing steps, shortening processing time, and reducing manufacturing costs. Therefore, the use of big data to research CNC grinding processing technology of engineering ceramics will introduce more engineering ceramics and smart ceramics in the future and promote the rapid development of the ceramic industry. Therefore, the optimization research of process parameters combined with machine learning is of great significance in industrial production, national defense industry and high-tech fields [16].

3. Single Factor Modeling Based on GA-BP Neural Network

3.1 Effect of Process Parameters on Cutting Temperature

This article takes engineering ceramics as the object and carries out a series of experimental studies. There are interactions between various process parameters, and there is a non-linear relationship between the two, which is difficult to describe using mathematical means. However, in order to obtain better processing results, it must be mathematically analyzed. This article attempts to model and predict the neural network in the CNC grinding process based on a large number of process experiments and analysis. On this basis, the BP neural network was used to optimize the key technical parameters in the processing process (spindle speed, feed speed, feed amount, grinding head particle size, etc.), and used this as the output variable. This article uses three machining effects such as cutting time, grinding head wear and chipping amount as output variables, trains them through BP neural network, and finally constructs a GA-BP model.

On this basis, this article adopts a new method based on GA-BP neural network [17], that is, establishing a GA-BP neural network model and optimizing its initial weights and thresholds through genetic algorithms [18]; by transmitting the cutting speed and cutting temperature signals obtained from the experiment to the input and output neurons of the neural network respectively, the difference between the simulation results and the actual values is maximized by training the neural network. By predicting the trained neural network, sufficient samples are obtained for fitting. Judging from the dispersion of experimental data and theoretical models, generally speaking, there is a good linear relationship between cutting speed and cutting temperature, but there is a certain gradient change in the local range. Therefore, a univariate model based on a univariate linear function was established, and an exponential function was used for correction, and a constant was added to increase the degree of fitting. To summarize, in terms of cutting speed and cutting temperature, the univariate model is assumed to be:

$$W(v) = (am + n)e^{v_d} + d \tag{1}$$

$W(v)$represents cutting temperature, v_d represents cutting speed.

3.2 Effect of Process Parameters on Surface Roughness

During the CNC grinding process, there are complex relationships between various parameters, which are difficult to describe with specific mathematical expressions. This is a highly nonlinear problem [19-20]. On this basis, a CNC grinding process model based on neural network is adopted. In addition, using nonlinear functions in neural networks can solve nonlinear problems in the mathematical model of CNC milling.

On this basis, referring to the mathematical model of cutting temperature, a linear relationship between processing parameters and machined surface roughness is constructed:

$$C_D = 1.776e + Rvs \tag{2}$$

R is the correlation coefficient. Engineering ceramic materials have excellent properties such as high hardness, high temperature resistance, and high wear resistance due to their unique molecular structure. Grinding is the main processing method of engineering ceramics. The selection of process parameters still relies on manual adjustment. Not only does it have problems such as low parameter solving efficiency and difficulty in obtaining the best solution, it also requires the operator to have an in-depth understanding of material processing. Therefore, optimizing and formulating the best process parameters has very important theoretical and practical significance for achieving high quality, high efficiency and better utilization of the processing performance of the grinding processing system of engineering ceramics.

In methods that use big data and machine learning to optimize ceramic process design, a common mathematical formula is the multiple regression equation. The general form of the multiple regression equation is as follows:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn \tag{3}$$

Among them, Y represents the output variable (ceramic performance), $X1, X2, \ldots Xn$ represents the input variable (process parameter), and $\beta 0, \beta 1, \ldots, \beta n$ represents the regression coefficient.

4. Optimization of Electrical Machining Parameters and Analysis of Experimental Data

4.1 Electrical Parameter Optimization Based on GA-BP Neural Network

In order for the GA-BP neural network to have good prediction performance, the GA-BP neural network needs to be used to learn and train different types of processing parameters. Through optimal analysis, the optimal parameters were obtained. Here, two sets of data (optimized parameter groups A and B and non-optimized parameter groups C and D) will be listed separately for processing experiments to verify the reliability of the neural network. The parameter settings of different groups are shown in Table 1.

Table 1: Parameter settings for different groups

Parameter	A	B	C	D
Pulse width(μs)	20	20	20	20
Pulse interval (gear)	6	4	4.9	3.8
Working voltage (V)	130	130	1130	130
Working current (A)	3	2	1.7	0.8
Number of power tubes	6	2	6	2

4.2 Sample Performance and Experiments

This article plans to use a wire electric discharge machine to conduct comparative tests on zirconia engineering ceramic materials using parameters of groups A, B, C, and D. All materials are processed into samples of 6 mm × 7 mm × 8 mm.

4.3 Surface Residual Stress

It was measured using a cathode rotating target X-ray diffractometer from a machinery manufacturing company. The basic principle of determining stress by X-ray diffraction method is to use the displacement of X-diffraction lines within the material to deduce the strain value between each crystal plane, and then deduce the corresponding relationship between stress and strain based on the principle of elastic mechanics, thereby obtaining the stress-strain relationship.

Group A: Compared with the model output result of 134.98MPa, the actual measured surface residual stress is 135.98 MPa. By comparing the model output results with actual measurements, it is proved that the prediction error of this method is far less than 5%. The model output results and the actual measured surface residual stress are shown in Figure 1.

Figure 1: Model output results and actual measured surface residual stress

4.4 Effect of Cutting Speed on Cutting Temperature

The effect of cutting speed on cutting temperature is shown in Figure 2. As the cutting speed increases, the cutting temperature also increases.

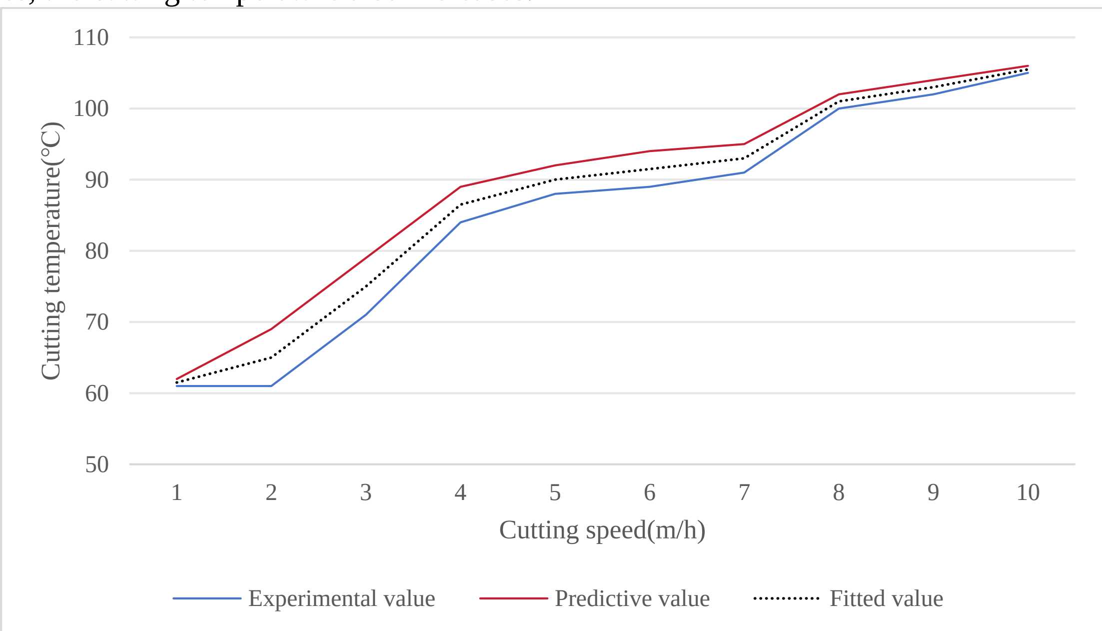

Figure 2: Effect of cutting speed on cutting temperature

4.5 Wear Resistance

The comparison of wear resistance strength between group C and group D is shown in Figure 3. Group C has the highest wear resistance strength of 682.3Pa, and group D has the lowest wear resistance strength of 685.6Pa. The wear resistance of group D has been significantly improved.

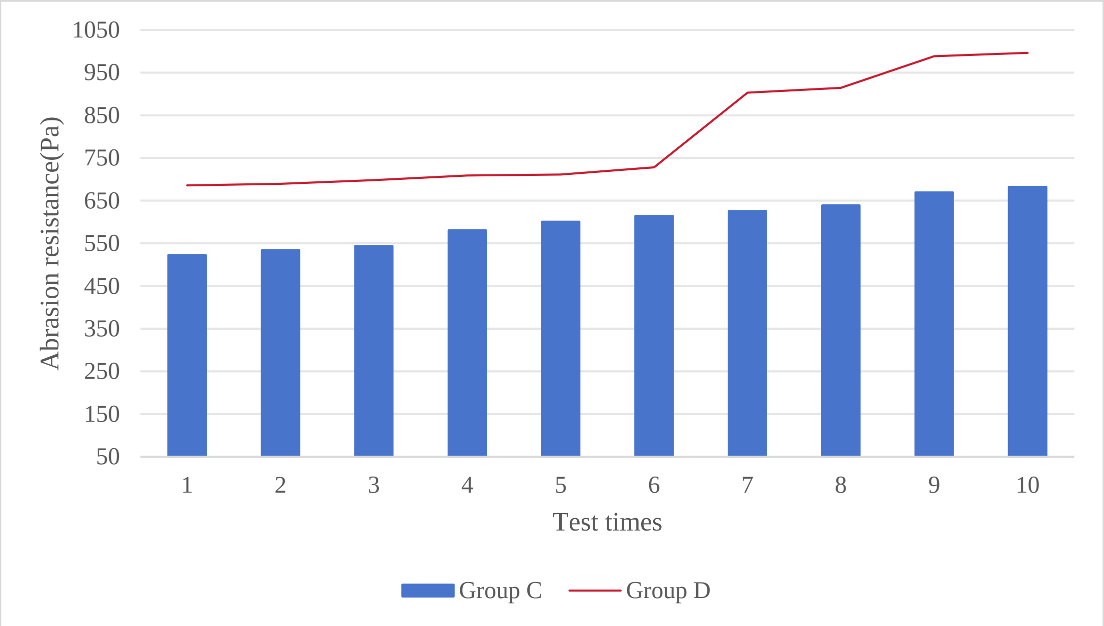

Figure 3: Comparison of wear resistance between group C and group D

5. Conclusion

During ceramic processing, surface roughness and temperature are two key indicators that characterize processing quality. Engineering ceramics have been widely used in mid-to-high-end manufacturing fields due to their special properties. Most of the existing optimization design methods for engineering ceramic materials are based on the process parameters of a specific ceramic material. A large number of studies have shown that mathematical models established for a single test subject are not applicable. To this end, this article intends to introduce the material characteristics during processing into the processing process, and construct the optimization goals of processing surface roughness and wear resistance to achieve optimal processing conditions for different types of ceramic materials, thereby improving the surface quality of ceramic components and extending their service life. The calculation effect of the hybrid particle swarm algorithm is also relatively good, and it can be applied to the optimization of ceramic grinding process parameters in the future.

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