Research article

Multi-response optimization of process parameters in nitrogen-containing gray cast iron milling process based on application of non-dominated ranking genetic algorithm

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ABSTRACT

As a new, high-strength and clean cast iron material, nitrogen-containing gray cast iron has excellent properties and a wide range of application prospects. However, the excellent material properties of the material not only make the machinability challenging, but also the high efficiency and quality of the machining process is a pressing issue. Therefore, it is necessary to study the machining characteristics of nitrogen-containing gray cast iron to obtain the optimal machining parameters to enrich the research work on nitrogen-containing gray cast iron. In this paper, the machining characteristics of nitrogen-containing gray cast iron are systematically studied, and the effects of cutting parameters on milling force, milling temperature, and surface roughness are analyzed. And, based on the machinability assessment, the objective function weights under different production requirements are determined by using hierarchical analysis trade-offs, and an integrated optimization model based on non-dominated ranking genetic algorithm and hierarchical analysis (AHP) is proposed. The model outputs the optimal combination of milling parameters by inputting the cutting speed (vc), feed rate per tooth (fz) and cutting depth (ap), surface roughness and cutting efficiency as the objective functions. The experimental results show that cutting depth has the greatest effect on the cutting force and cutting speed has the greatest effect on the cutting temperature and the surface roughness. The passivation effect of nitrogen on the graphite tip resulted in an increase in both cutting force and cutting temperature. The parameter optimization results indicated that the optimized roughing parameters significantly improve the surface quality while machining efficiently; the optimized finishing parameters improve Ra by 23.53% while ensuring higher MRR, which can achieve efficient and high-quality machining under different production requirements and provide an experimental basis for practical engineering applications of nitrogen-containing gray cast iron.

1. Introduction

Gray cast iron has good strength, wear resistance, vibration damping, excellent casting performance, and low manufacturing costs [1]; as a result, it is currently the most commonly used material for cast iron parts. The world output of gray cast iron parts reached 49.53 million tons in 2019, accounting for approximately 46.9% of the world output of castings. These parts are used in a large number of fields [2], such as the beds of industrial instruments, bearing housings, end caps, and the automotive industry. With the continuous innovation of industrial technology, to meet the engineering requirements for high-quality, lightweight, and energy-efficient construction machinery and the needs of sustainable development, thin-walled and high-reinforcement gray iron castings are becoming a trend in the engineering community [3]. As a result, the mechanical qualities of gray cast iron metals are being demanded more regularly. This promoted the rapid development of high-performance gray cast iron [4]. At present, the mechanical properties of gray cast iron materials are improved mainly by adding metal alloying elements such as Cr, Mo, Sn, Ni, and Nb [5] or using various types of efficient inoculants such as rare earth and calcium-silica-barium materials [6],

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which can alter the matrix organization and gray cast iron carbon morphological characteristics to improve its performance. However, the method of adding alloying elements to improve the strength of gray cast iron has the disadvantage of a high scrap rate. Nowadays, due to the increase in production costs, the use of traditional production processes inevitably leads to a decrease in the economic efficiency of enterprises. In addition, a large number of metal alloying elements and metal additives are not conducive to resource conservation and environmental protection.

Therefore, some scholars have proposed the use of nitrogen as a substitute for metal alloying elements to improve the strength of gray cast iron [7]. Nitrogen is abundant and inexpensive, and it can be added to gray cast iron to enhance its strength, which in turn improves the performance index of the product; thus, this process not only reduces the cost to a great extent but is also environmentally friendly and provides significant advantages and development potential [8]. In recent years, scholars have conducted numerous studies on nitrogen-containing gray cast iron and gray cast iron's machinability. Chisato Okada [9] studied the effect of nitrogen addition on the mechanical properties and microstructure of gray cast iron. The strength of gray cast iron could be enhanced by 5–7 MPa with each 0.001% increase in nitrogen content, while the hardness could be increased by 3–4 HB when Fe–Mn–N alloy was added under a specific addition process, according to the findings. Mountford [10] and Wilberforce F [11] found that with increased nitrogen addition, the graphite length decreased, the pearlite refinement and content increased, and the tensile strength and elongation of gray cast iron increased. Similar conclusions were reached by Tei-Nishiku [12], M. C. McGrath [13], Chunhuh He [14], and other scholars. These previous studies showed that the addition of nitrogen resulted in the refinement of the graphite and pearlite morphology, increased the pearlite content, and significantly improved the properties of gray cast iron.

It should be noted that research on nitrogenous gray cast iron has mainly focused on the effects of the nitrogen content on the mechanical properties and microstructure of the material, whereas few studies have focused on the machining properties of nitrogenous gray cast iron. However, with the increase in the pearlite content of gray cast iron, the improvement in its material properties will also cause problems such as milling temperature and force variations, that will affect machining surface quality. Luiz Roberto Muñoz Dias [15] et al. noted that gray cast iron with higher pearlite content produced a higher milling force and faster tool wear during cutting at different cutting speeds. Martin et al. [16] investigated the machining properties of gray cast iron treated with various inoculants and discovered that a good carbon microstructure and a higher pearlite content were detrimental to the material's machining; longer tool lives at low cutting speeds were also reported. In addition, Scholars have also conducted extensive research on the gray and vermicular cast irons. Rosemar Batista Da Silva [17] et al. conducts research on the outer surface polishing of three cast-iron grades (nodular, compacted and gray graphite). He discovers that the three cast-iron grades are grindable in the following order: gray cast iron, compacted graphite iron, and nodular cast iron. Aline Elias da Silva [18] et al. look into the relationships between the mechanical and metallurgical properties of high-strength cast irons and machinability during the drilling process. The study shows that nitrogen-containing cast gray iron has superior mechanical qualities to regular gray cast iron, but it also has issues with machinability. While vermicular cast iron offers superior mechanical qualities to nitrogen-containing gray cast iron, the latter's machining qualities have significant benefit. Therefore, considering the role of nitrogen addition on the mechanical properties and microstructure morphology of gray cast iron. It is necessary to analyze the cutting characteristics of nitrogen-containing gray cast iron under various cutting parameters to provide a theoretical basis for solving the various problems encountered in its actual production.

Cutting and machining costs for castings are frequently more than the cost of the casting. Therefore, a major challenge in the cutting and machining of cast iron materials is to minimize manufacturing costs and increase production efficiency without affecting engineered parts' quality or the high-strength properties. Because the effect of cutting parameters on the machining efficiency and surface quality of nitrogen-containing gray cast iron during actual machining is not clear, it is difficult to ensure an effective selection of cutting parameters to achieve a balance between machining efficiency and surface quality. Therefore, optimization techniques are needed to select appropriate machining parameters to guide the selection of efficient cutting parameters for nitrogen-containing gray cast iron.

Currently, many optimization techniques are supported by modern artificial intelligence (AI) and machine learning (ML) methods and are widely used in the field of material processing. For example, Seyed Hasan Musavi et al. [19] explored the impact of various cold lubrication conditions on the surface condition and tool abrasion during the turning of AA2024 alloy and developed a mathematical model for predicting the surface roughness using the response surface methodology with optimized parameters. The study found that changing the dry process and Free Machining (FM) process to a minimal quantity lubrication (MQL) process could significantly reduce the tool wear. P. Suresh et al. [20] optimized the processing parameters of Al–SiC–Gr hybrid metal matrix composites using a grayscale fuzzy algorithm, and the results showed that when the mass fraction of SiC–Gr in the hybrid metal matrix composites was 5%, 7.5%, and 10%, the corresponding tensile strengths were 170, 210, and 204 MPa, respectively. Using the Taguchi optimization method, G. Selvakumar et al. [21] adjusted the process parameters for the electrical discharge machining (EDM) wire cutting of 5083 Al alloy and achieved the optimum machining settings. Sarkar et al [22] explored the ideal cutting conditions for machining -titanium aluminum alloy using a neural network model founded on Pareto optimality. R. Arkia-dass et al. [23] studied the milling characteristics of LM25Al/SiCp composites. The experimental data were used to develop a mathematical model using the response surface methodology to describe the effects of various machining parameters on the wear rate of the rear tool face. The results showed that the mathematical model could successfully describe the effect of each milling machining parameter, and the minimum rear tool face wear rate was obtained using the optimized parameter combination. Wang T. et al [24] found that the strain hardening index of Ti60 alloy decreased with the increase of deformation temperature and obtained an optimized range of machining process parameters for Ti60 alloy. In order to achieve low-carbon-oriented integrated optimization of cutting parameters and tool path for cavity milling, Guanghui Zhou [25] et al. offer a novel multi-objective optimization model that has as its goals processing time, carbon emissions, and processing cost. Xuewei Zhang [26] et al. introduced a new consider energy usage model and cutting parameter optimization. Grey correlation analysis was used by Kanchana J [27] et al. to improve the process parameters of hardened custom 465 steel during end machining processes. In order to manage the suggested dual-objective optimization model, Wienie Wang [28] et al. developed an improved artificial bee colony (ABC) intelligent algorithm, which in turn advanced the milling factors.

Although these studies have made contributions to optimization, the large data requirements and lack of flexibility of the usual optimization models largely limit the application of parametric optimization. Our approach has advantages due to the small amount of data required. In addition, most multi-objective optimization methods only end up with Pareto fronts, and many combinations of parameters bring confusion to engineering practice under different operating conditions. Therefore, in this paper, an integrated optimization model based on multi-objective optimization algorithm combined with hierarchical analysis is proposed for this material based on the cutting and machining characteristics of nitrogen-containing gray cast iron to determine the optimal combination of its milling parameters under different production conditions. Our study not only enriches the previous work on the machining characteristics of this nitrogen-containing gray cast iron, but also determines the optimal combination of parameters that are important for improving its machining efficiency while improving its machining quality. In this
study, Response surface method (RSM) is applied to establish the association between the input and output parameters. Then, the cutting parameters are optimized using a multi-objective optimization technique, and the hierarchical analysis method is introduced to determine the weights. Finally, the optimized data set is screened to determine the optimal parameters under different working conditions.

In summary, this study’s goal is to examine the machining characteristics of high-strength gray cast iron containing nitrogen and to establish an efficient and accurate model for optimizing cutting parameters. Therefore, this research analyzes the implications of milling parameters and their interactions on the surface roughness of nitrogen-containing gray cast iron based on orthogonal tests and single-factor experimental data. The input-output link is built using RSM and GA-BP neural network based on the trial data, and the prediction accuracies are compared under different sample conditions. In addition, to maximize the machining efficiency and surface quality, the multi-objective optimization issue is solved using the controlled NSGA-II. Finally, the Pareto solution set is filtered using hierarchical analysis to find the best set of milling parameters for nitrogen-containing gray cast iron under different production requirements.

2. Experimental methods and materials

2.1. Experimental materials and equipment

The tested material was nitrogen-containing gray cast iron. The graphite was flake graphite, the pearlite content was approximately 95%, and its elemental components and mechanical characteristics are summarized in Table 1. The details of the hardness measurement test are as follows. We use AVH-5L Vickers hardness tester to test the hardness of gray cast iron containing nitrogen. First take the number of the single-cast test bar with the nearest average tensile strength, intercept the hardness specimen at the location of the single-cast test bar, and then roughly grind it with 600-grit sandpaper. After the surface of the specimen is shiny and smooth, the hardness can be measured by hardness tester. During the measurement process, five different directions are randomly selected on the specimen for material hardness testing. Finally, take the average value as the reference value of hardness of gray cast iron material. After the test, the obtained Vickers hardness value is converted to Brinell hardness value according to the comparison table.

The test platform in this paper is shown in Figure 1, and the machine axis direction is shown in Figure 1(b). The experimental tool is a PVD coated carbide tool. The insert and the supporting tool holder are shown in Figure 2, and the specific geometric parameters of the insert and the tool holder are shown in Tables 2 and 3. The test workpiece is a rectangular block with dimensions of 80 mm × 140 mm × 50 mm.

The experimental test platform is shown in Figure 3. Kistler9257B piezoelectric three-way force gauge is used to detect cutting forces and it is mounted underneath the machine clamping equipment. When performing milling experiments, we calculate the combined milling force based on the measured milling component forces in the x,y,z directions. Figure 3 illustrates the output curve of the cutting data during the test. The green line represents the milling force in the Y-axis direction, red represents the force in the X-axis direction, and blue represents the force in the Z-axis direction. The milling force is the combined force in the three directions.

The instrument used in this test for online inspection of the milling temperature of gray cast iron containing nitrogen is the FLUKE-Ti400 infrared thermal imaging camera. It has a resolution of 320 × 240 pixels, a temperature measurement range of -20 °C–1400 °C, measurement accuracy of ±0.2 °C, an infrared spectral band of 7.5–14 μm, and thermal sensitivity of no more than 0.05 °C (50 mK). The brief operation steps of temperature detection are as follows: first, install a tripod to fix the camera shooting position and then zero calibration according to the field temperature; then, set the transmittance of gray cast iron and the file saving position; finally, shoot and save the file online in real time according to the milling test process.

The SJ-310 portable surface roughness measuring instrument was used for this milling test. Its resolution is 0.001um, and the uncertainty is below 0.02. We select three equally spaced areas on the machined surface

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### Table 1. Elemental composition and mechanical properties of the nitrogen-containing gray cast iron.

|   | C       | Si      | Mn      | Ti      | S       | P       | Cu      | Hardness | Tensile strength |
|---|---------|---------|---------|---------|---------|---------|---------|----------|-----------------|
| Value| 3.218   | 2.055   | 0.735   | 0.013   | 0.0797  | 0.028   | 0.548   | 219 (HBW) | 313 (MPa)       |

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![Figure 1. Setup of the milling test platform.](image)
for measurement in order to ensure the accuracy of the test data in the process of determining the surface roughness results. Then, we calculate the average of the three sets of data and the dispersion using the STDEV function based on the measured data. Finally, an error bar graph is made based on the mean and STDEV.

The test platform and measurement procedures are described in detail below. Before the milling test starts, the surface casting hard skin is first removed from the nitrogen type gray cast iron using a non-test tool. Then, the test machining and testing system was built, as shown in Figure 3. At the beginning of the test, the tool setting operation was performed first, and then programmed in the CNC machine operator interface according to the parameters of the orthogonal test table, and the specific milling parameters used for programming are shown in Table 4. The milling time was set to 60s and the milling width ae 5 mm for each group of tests, and the milling force and milling temperature were collected in real time using the three-way force measurement system software and the thermal imaging camera at 10s, 30s and 50s for each group of tests, respectively, and the measurements were repeated three times and saved in time. After each set of tests, the table and workpiece were cleaned, and then the surface roughness of the workpiece was measured with a surface roughness meter. After one set of test, replace a new carbide insert, and then change the milling parameters in the CNC machine operator interface for the milling program.

After the completion of the experiment, we used ANOVA to process the experimental data. Furthermore, we used RSM to design the experiment because this test planning method codes the factors and levels of the test parameters, which not only gives accurate and valid test results but also minimizes the number of trials.

2.2. Response surface methodology experimental design

RSM, also known as regression design, is an experimental design method in which data are actively collected to obtain an improved regression equation [29]. A three-factor, three-level orthogonal test design was used for the initial experiments. The initial machining parameter ranges were a milling speed, vc, of 50–150 m/min; feed per edge, fz, of 0.1–0.18 mm; and cutting depth, ap, of 0.4–1.2 mm. Because the radial cutting depth, ae, has a minor impact upon that machined surface roughness but has a significant impact on the material removal rate, it had a constant value of 8 mm in these experiments. After that, we designed a single-factor supplemental test in order to further explore the relationship between Ra and the law of parameters. and based on the results of factor analysis. We refined the parameter intervals of cutting speed and feed rate per tooth in the single-factor experimental design.

With -1, 0, and +1 representing low, zero, and high levels, respectively, the remaining three process parameters were coded [29].

\[
x_i = \frac{X_i - X_0}{\Delta X}
\]

where \(x_i\) is the coding of the variable, \(X_i\) is the cutting parameter variable, \(X_0\) is the zero level of the cutting parameter variable, and \(\Delta X\) is the variation interval. The experiments were designed using RSM, and the specific processing parameters for each group of tests are shown in Table 4.
2.3. Controlled NSGA-II-based multi-objective optimization

Traditional optimization algorithms that iterate from a single initial value to find the optimal solution are prone to collapsing local optimum solutions. In contrast, genetic algorithms start searching from a string set, which covers a wider range and is more conducive to a global optimization search. The controlled NSGA-II method has considerable advantages in terms of solution speed and solution set convergence [30]. Therefore, the controlled NSGA-II algorithm was used in this study to optimize the parameters of the multi-objective model based on the objective functions of the material removal rate, Q, and surface roughness, Ra; the constraints are the parameter ranges of actual machining process parameters vc, fz, ap, and ae as well as the cutting force, F, cutting temperature, T, and machine spindle speed, n.

Non-DominatedSorting, CalcCrowdingDistance, and EliteSorting are denoted as NonDominatedSorting, CalcCrowdingDistance, and SortPopulation, respectively. A flowchart of the algorithm is shown in Figure 4.

2.4. Hierarchical analysis approach

A set of Pareto - optimal solutions is the output of the multi-objective optimization; however, in actual engineering applications, it is more crucial to select the best parameter combination according to the actual processing conditions. Therefore, it is necessary to filter the optimal solution from the Pareto solutions according to the actual processing conditions. The hierarchical analysis is a convenient and practical multi-criteria decision-making method for problems that are difficult to analyze quantitatively [31]. Because many factors affect the optimal parameter selection in the multi-objective optimization problem, hierarchical analysis is used to determine the multi-objective weight coefficients under different working conditions more accurately and efficiently in this study. The procedure for the hierarchical analysis is as follows.

- A hierarchy is constructed based on the objectives and evaluation criteria to determine the objective weights (objective layer A), the four most important cutting parameters that influence the decision (criterion layer B), and the two objectives that require weight determination (program layer C).

- A two-by-two comparison is performed between the criteria, and the judgment matrix is constructed by calculating the weights of each criterion for each target using the eigenvector method. The comparison process is based on the matrix judgment scale (1–9 scale method), as summarized in Table 5.

- The maximum eigenvalue, $\lambda_{\text{max}}$, of each judgment matrix and its eigenvector, $W$, are calculated. The eigenvectors are normalized, and then the weight values indicating the importance of each element at the same level for the target at the previous level are obtained. To ensure the consistency of the assigned scores, a consistency test is required, and the consistency is satisfied only when the consistency ratio (CR) is less than 10%. CI is the consistency index, and RI is the random consistency index, defined as follows [31]:

$$CI = (\lambda_{\text{max}} - n) / (n - 1)$$

(2)

$$CR = CI / RI$$

(3)

where $\lambda_{\text{max}}$ is the maximum characteristic root of judgment matrix A, n is the matrix order. The consistency index is RI, while the consistency ratio is CR. The RI value of the corresponding order can be obtained from Table 6.
The appeal step is repeated, and the relative weights are synthesized to obtain the total evaluation weights.

3. Results and discussion

3.1. Surface roughness exploration

The surface roughness values were measured in orthogonal cutting tests for nitrogen-containing gray cast iron with different cutting parameters, and the test results are shown in Figure 5. Three data measurements were performed for each set of tests. The mean and dispersion of the three sets of data were calculated based on the measured data, and then the error bar graph was plotted. It can be seen that the use of different machining parameters has a significant influence on the machined surface quality. The extreme difference analysis of the experimental machined surface roughness shows that the degree of impact of each parameter is as follows: \(v_c > f_z > a_p\). Plots illustrating the contribution of every milling factor on Ra were generated and investigated in depth to better depict the impact of each factor on Ra.

3.1.1. Impact of milling parameter levels on the surface roughness

According to the test results, the surface roughnesses corresponding to the same levels of cutting parameters \(v_c\), \(f_z\), and \(a_p\) are added and averaged to obtain the reference value under each level. The resulting curves showing the relationships between the cutting parameter levels and surface roughness are illustrated in Figure 6. Figure 6(a) is drawn based on the results of the orthogonal test. It represents the average value of the test results when the cutting speed is 50, 100 and 150 m/min, and the feed rate per tooth and cutting depth are taken at three levels, respectively. Similarly, the feed rate per tooth and cutting depth were evaluated in the same way, and the test results are shown in Figure 6(b), (c) respectively.

As shown in Figure 6(a), the Ra reduces with the improvement in \(v_c\), and this trend becomes more gradual after \(v_c > 100\) m/min. The main

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Table 5. Matrix judgment scales [31].

| Scale | Meaning |
|-------|---------|
| 1     | Two compared elements have the same importance |
| 3     | The first element is slightly more important than the second |
| 5     | The first element is significantly more important than the second |
| 7     | The first element is extremely more important than the second |
| 9     | The first element is strongly more important than the second |
| 2, 4, 6, 8 | Intermediate values of the above adjacent judgments |
reasons for this are as follows: first, as the milling speed increases, irregular cracks and fractures at the edges of the graphite cavities in the gray cast iron material do not have time to develop fully, and the impact of fractures is reduced during chip formation; as a result, vibration is reduced, and the machined surface roughness decreases. Moreover, owing to the flake graphite in the nitrogen-containing gray cast iron, the material is curved and fine, and the tip is blunted; thus, the cutting effect of graphite on the matrix is lower, resulting in fewer cracks around the graphite cavities, which can further reduce the shock and vibration phenomena during machining. Second, when the milling speed is low, vibration patterns are easily generated during the milling process. However, these vibration patterns are gradually eliminated with an increase in the milling speed, resulting in a reduction in the machined surface roughness. In addition, the workpiece’s plasticity is improved as the milling speed increases and the milling temperature rises, which makes the milling process relatively smooth and reduces Ra.

Figure 6(b) shows that Ra increases with the increase in fz, especially at feed rates greater than 0.14 mm/tooth. The theoretical roughness equation indicates that the surface roughness of the workpiece during machining is proportional to the square of the feed rate (considering the radius of the tooltip arc), and thus the surface roughness will increase significantly as the feed rate increases. This occurs because on one hand, as fz improves, the residual area of the milled workpiece surface increases in height, and the Ra increases. In addition, as fz rises, the thickness of the milling increases, the volume of plastic deformation of
the metal increases, and the milling force also enlarge, which leads to poor surface quality after machining.

Figure 6(c) depicts the gradual rise in Ra as cutting depth is increased, and the effects of cutting depth on Ra are more moderate compared with that of the milling speed and feed rate per tooth. As the milling depth gradually increases, the milling width will increase, and the milling temperature and milling force will also gradually increase, increasing the surface roughness. Under a large cutting depth, the tool is prone to microchips, which intensifies the tool wear, causing milling vibration and increasing the surface roughness. In addition, during the machining of cast iron, the graphite in the cast iron has low strength; thus, when the tool is cut, the cutting edge will cause the nearby ferrite and pearlite to deform. However, owing to the presence of graphite boundary cracks, when the material is not fully deformed under the action of the cutting force, it will extend and fracture along the graphite boundary cracks, forming chips, which can easily cause vibration. At the same time, the machining characteristics of the milling will further aggravate the vibration phenomenon; therefore, when ap increases, the milling force, and impact vibration rise dramatically. This caused the surface quality to deteriorate.

To learn more about the impact of cutting settings on machined surface roughness, single-factor tests were conducted by refining the parameter intervals to obtain experimental data based on the level of impact of each parameter on Ra obtained from the extreme difference analysis.

Table 7 shows the milling force, milling temperature, and surface roughness at a depth of cut of 0.8 mm at different milling parametrization settings. Figure 7 shows the cutting data output, and the surface plot demonstrates the effect of the coupling between the parameters on the output. The curves are more intuitive to demonstrate the effect of parameter changes on the output.

The cutting force rises as the milling speed and feed rate improves, as shown in Figure 7(a), and the three-dimensional surface shape of the cutting force shows obvious fluctuations. In particular, these fluctuations become increasingly significant with the gradual improvement in the fz. This occurs because on one hand, nitrogen-containing gray cast iron is a brittle metal, and thus the deformation and friction during machining are small; therefore, the cutting speed has less of an impact on the milling force, while the feed volume has far more consequence upon this milling force increase. When the feed rate went up, the volume of material removed per unit time improves. However, the changes in the cutting deformation and friction generated by machining are non-linear with the improvement in the fz. Furthermore, increasing vc causes the milling force to gradually diminish, which weakens the increase in the cutting force caused by the increased feed rate, resulting in a fluctuation in the cutting force. On the other hand, because milling is an intermittent cutting process, the periodic contact between the cutting edge of the tool and the material to be machined causes the cutting force to show obvious fluctuations. Therefore, these two factors cause the cutting force to exhibit significant fluctuations, which is not conducive to improving the surface quality. In addition, owing to the higher strength of nitrogen-containing gray cast iron compared to normal gray cast iron, the machining shear strength increases, as a result, the milling force has risen dramatically. Moreover, owing to the passivation effect of nitrogen on the graphite tip, the rounded, short, thick, and slightly curved graphite form increases the toughness of nitrogen-containing gray cast iron to a certain extent. This results in increased cutting deformation during the cutting process and severe friction between the cutting piece and tool, which aggravates the fluctuation range of the cutting force.

Figure 7(b) depicts the change in cutting temperature. The cutting speed has a remarkable impact on the variance in cutting temperature, followed by the feed rate. With increases in the vc and fz, the temperature increases. When fz is less than 0.15 mm/tooth, the temperature remains low, but when the feed rate exceeds 0.15 mm/tooth, the milling temperature rises significantly, and the milling temperature exhibits a certain gradient characteristic. This occurs because as feed rate per tooth and milling speed improve together, the volume of material sliced per unit time grows, the friction and deformation increase, and the work done by the cutting process increases, leading to a significant increase in cutting heat. On the other hand, in nitrogen-containing cast iron, owing to the rounded, blunt, short, thick graphite, the cutting effect on the matrix is weakened, and the graphite tips in cracks are reduced, which increases the cutting difficulty to a certain extent, further causing the cutting temperature to rise. Under the effect of a high cutting heat, the metal substrate in the tool-workpiece contact area softens, resulting in a lower friction coefficient and a smoother machining process, which is conducive to reducing the surface roughness.

For a fixed cutting depth, Figure 7(c) displays the impact of milling speed and feed rate of each tooth on surface roughness. The machined surface quality is poor at milling speeds of approximately 60 m/min and 150 m/min and is significantly influenced by the feed per tooth, as can be seen; the surface quality will deteriorate as the feed rate rises. However, at 180 m/min or higher cutting speeds, the cutting process becomes stable, the surface quality is significantly improved, and the influence of the feed rate is significantly reduced. To further examine the variation in the surface roughness with the cutting speed at different feed rates per tooth, the line graph shown in Figure 7(c) was plotted. It is clear that when the vc improves from 170 m/min to approximately 200 m/min, the Ra declines more significantly; this trend is particularly clear when the feed rate of each tooth is 0.17 mm/tooth or 0.2 mm/tooth.

### Table 7. Input and output parameters of the optimization model.

| Test number | vc/(m/min) | fz/(mm/tooth) | ap/(mm) | Force/(N) | Temperature/°C | Ra/(μm) |
|-------------|------------|---------------|---------|-----------|----------------|---------|
| 1           | 50         | 0.11          | 0.8     | 255       | 105.1          | 1.172   |
| 2           | 50         | 0.14          | 0.8     | 300.5     | 141.2          | 1.27    |
| 3           | 50         | 0.17          | 0.8     | 310       | 185.8          | 1.603   |
| 4           | 50         | 0.2           | 0.8     | 363       | 192.1          | 2.135   |
| 5           | 80         | 0.11          | 0.8     | 190       | 156.3          | 1.25    |
| 6           | 80         | 0.14          | 0.8     | 290       | 131.3          | 1.377   |
| 7           | 80         | 0.17          | 0.8     | 341       | 152.7          | 1.665   |
| 8           | 80         | 0.2           | 0.8     | 350       | 249.7          | 2.005   |
| 9           | 110        | 0.11          | 0.8     | 235.5     | 139.5          | 1.358   |
| 10          | 110        | 0.14          | 0.8     | 283       | 165.3          | 1.476   |
| 11          | 110        | 0.17          | 0.8     | 299       | 191.1          | 1.564   |
| 12          | 110        | 0.2           | 0.8     | 309       | 251.2          | 1.610   |
| 13          | 140        | 0.11          | 0.8     | 273.5     | 123.5          | 1.183   |
| 14          | 140        | 0.14          | 0.8     | 382.5     | 215.3          | 1.792   |
| 15          | 140        | 0.17          | 0.8     | 425.5     | 237.2          | 1.906   |
| 16          | 140        | 0.2           | 0.8     | 499       | 258.9          | 2.024   |
| 17          | 170        | 0.11          | 0.8     | 320.5     | 117.9          | 1.359   |
| 18          | 170        | 0.14          | 0.8     | 383.5     | 150.3          | 1.671   |
| 19          | 170        | 0.17          | 0.8     | 407       | 214.6          | 1.837   |
| 20          | 170        | 0.2           | 0.8     | 424       | 178.9          | 2.113   |
| 21          | 200        | 0.11          | 0.8     | 364       | 146.1          | 1.126   |
| 22          | 200        | 0.14          | 0.8     | 499.5     | 136.9          | 1.182   |
| 23          | 200        | 0.17          | 0.8     | 470       | 142.5          | 1.201   |
| 24          | 200        | 0.2           | 0.8     | 540       | 143.7          | 1.334   |
| 25          | 230        | 0.11          | 0.8     | 250       | 96.7           | 0.827   |
| 26          | 230        | 0.14          | 0.8     | 290       | 150.3          | 1.067   |
| 27          | 230        | 0.17          | 0.8     | 391       | 138.7          | 1.084   |
| 28          | 230        | 0.2           | 0.8     | 335       | 147.5          | 1.110   |

### 3.1.2. Response surface results analysis

The response surface plots and contour plots of the impact of milling parameters on the Ra were obtained by fitting the test data using a quadratic multiple regression, as shown in Figures 8, 9, and 10, to analyze the effects of the interactions of cutting parameters on the surface roughness.
The response surfaces and regression equations show that the surface roughness is strongly influenced by the cutting parameters; the equations include linear terms, second-order terms, and their interactions. Figure 8 shows that at a cutting depth of 0.8 mm, the machined Ra gradually decreases with an improvement in vc and decrease in fz; the minimum Ra can be obtained at the maximum vc and minimum fz. The contour plot in Figure 8(b) shows that the distribution of contours has a particular pattern and is evenly spaced. This indicates that as one factor is changed, the rate of change of the other factor remains almost constant, i.e., the interaction between vc and fz is not significant.

As shown in Figure 9, better surface quality is obtained at a higher cutting speed and a lower cutting depth at a feed rate of 0.14 mm/tooth. Moreover, there is no significant interaction between the cutting speed and cutting depth. Increasing the cutting speed has a positive effect on
the surface quality improvement; however, an increased cutting depth removes a greater volume of material, making the machining process more challenging. In particular, the trend of increasing surface roughness values with increasing cutting depth stabilizes at a constant cutting speed. However, at a constant cutting depth, the trend of decreasing surface roughness values with improving milling speed is significant owing to the impact of the linear term of vc as well as the second-order term, which creates a curvature on the response surface. This also demonstrates that the milling speed has the most effect on the surface roughness. Figure 10 illustrates that the interaction between the milling depth and the feed rate of each tooth is more significant, and the surface roughness increases significantly with an increase in feed rate per tooth and cutting depth at a vc of 100 m/min. The fz has a more remarkable impact on surface roughness.

3.2. Multi-objective process parameter optimization

3.2.1. Model construction and analysis

In the actual production process, it is desirable to select a set of process parameters to maximize MRR while minimizing Ra; however, the relationship between the two objectives and the constraints of the cutting conditions limit the selection of cutting parameters. Consequently, based on the actual machining conditions, the two objective functions of the multi-objective optimization problem and the constraints can be formulated as follows [30]:

$$\min \ f(x) = \{ f_1(x), f_2(x) \}$$  \hspace{1cm} (4)

s.t. \( x_{\min } \leq x_i \leq x_{\max }, (i = 1, 2, 3, 4, 5) \)

where \( x_i \) represents the cutting parameters (vc, fz, ap), spindle speed, n, and cutting force, F. The cutting force, F, is a function of the milling settings based on the empirical equation for the cutting force approximation and is constrained to the extreme value of the cutting force for non-extreme machining of cast iron-like materials [32]. Objective function \( f_1(x) \) is the material removal rate used to characterize the cutting machining efficiency, as shown in Eq. (5); \( f_2(x) \) denotes the surface roughness, Ra, which is a function of the cutting parameters based on the RSM polynomial approximation under the previous response surface analysis [29], as shown in Eq. (6).

$$Q = \frac{1000v_c \cdot f_{c} \cdot a_p \cdot a_e}{nD}$$  \hspace{1cm} (5)

$$R_a = 3.644 - 0.021v_c - 27f_z + 0.738a_p + 0.00008v_c^2 + 90.6f_z^2 - 1.031a_p^2 + 10f_z a_p$$  \hspace{1cm} (6)

An accurate and reasonable objective function is the key to establishing the optimization algorithm. Therefore, to evaluate the model accuracy, we conducted an analysis of variance (ANOVA) on the model of objective function \( f_2(x) \), and Table 8 summarizes the findings.

As indicated in Table 8, the p-value of the response equation for the surface roughness is 0.04, which is less than 0.05 (95% confidence level), and the equation-adjusted coefficient of determination R2 (adj) is 99.7%, which is very similar, indicating that the established response surface model is reliable. In addition, the cutting speed has the greatest effect (with a contribution of 44.93%), followed by feed rate per tooth (30.96%) and milling depth (23.94%).

To further prove the effectiveness, the forecast outcomes of RSM were compared with those of GA-BP [33]; the parameters of the GA-BP are illustrated in Table 9. In addition, we divided the results of the orthogonal and single-factor tests into two data sample spaces of different sizes (orthogonal test data set, orthogonal + single-factor data set) to analyze the prediction performance of the two models with different sample sizes; the results are shown in Figure 11(a) and (b), respectively.

The prediction values of both the response surface model as well as the GA-BP neural network model for higher sample sizes are similar to the true values, as shown in Figure 11(a). The mean square errors (MSEs) of the two models are calculated as 0.0153 and 0.0079, and the R2 values are 99.7% and 99.93%, respectively, with only a 3.73% difference in prediction accuracy. However, as shown in Figure 11(b), the prediction accuracy of the response surface technique is 18.91% greater than that of the GA-BP model for a small sample size. Moreover, owing to the small sample space, the amount of data used for training is small, causing the GA-BP neural network to often fail to converge.

The prediction results show that the prediction accuracy is similar for the larger sample space; however, when the sample data are limited, the prediction accuracy of the neural network is significantly reduced, and its prediction performance is inferior to that of the RSM. However, increasing the sample space will inevitably increase the number of experiments and the corresponding cost. Therefore, the RSM can effectively predict the surface roughness, establish the association between input and output, and construct the objective function for issues of multi-objective optimization.

The NSGA-II was run using MATLAB with a population size of the optimization model of 50 and a maximum number of iterations of 200; the generated Pareto frontier is shown in Figure 12(d). Each solution in the figure is non-dominated, which means that each solution is better than the other points for at least one combination of objectives, while the individual constraints considered in the optimization ensure that the processing parameters correspond to the resulting Pareto frontier meet the actual processability criteria. The optimal ranges of parameters for the multi-objective optimization are shown in Figure 12(a), (b), and (c), where the points of different colors correspond to the optimal solution sets with different objective function priorities: the solution with the largest material removal rate as the goal is represented by black points, pink points represent the solution set with the minimum surface roughness, and green points represent the solution set with the largest surface roughness. The prediction accuracy is similar for the larger sample space; however, when the sample data are limited, the prediction accuracy of the neural network is significantly reduced, and its prediction performance is inferior to that of the RSM. However, increasing the sample space will inevitably increase the number of experiments and the corresponding cost. Therefore, the RSM can effectively predict the surface roughness, establish the association between input and output, and construct the objective function for issues of multi-objective optimization.
roughness as the objective, and red points represent the balance between the two objective functions.

3.2.2. Pareto optimal solution evaluation based on analytic hierarchy process (AHP)

Based on objective functions $f_1$ and $f_2$, the optimal solution screening function is established as follows [30]:

$$
R = w_1 \frac{f_1 - f_{\min}}{f_{\max} - f_{\min}} + w_2 \frac{f_2 - f_{\min}}{f_{\max} - f_{\min}}
$$

where $w_1$ and $w_2$ are the weight coefficients of the material removal rate (MRR) and surface roughness (Ra), respectively, satisfying $w_1 + w_2 = 1$.

In the actual machining process, different machining conditions affect the selection of cutting parameter combinations; for example, in rough machining, the focus is on a larger MRR, while semi-finishing and finishing have more stringent demands for the surface roughness. By determining the appropriate weight coefficients through the AHP-based weight analysis method and calculating the function values using Eq. (7), the Pareto optimal solutions corresponding to different production requirements can be obtained.

The specific steps for determining the weights using AHP based on the production requirements of the finishing process are described in Section 2.4.

3.2.2.1. Build the hierarchy.

The three cutting parameters affecting the decision are compared and used as evaluation criteria, and the final established hierarchy is shown in Figure 13.

3.2.2.2. Construct the judgment matrix.

Based on a previous study, the criterion layer comprises three criteria: the cutting speed (B1), feed rate per tooth (B2), and cutting depth (B3). Relative to the target layer, the target weights are determined and combined with the ANOVA results of the previous experiment. The cutting speed has the greatest influence, with a contribution of 44.93%, followed by feed rate per tooth (30.96%) and cutting depth (23.94%). The scoring is performed for each criterion based on a two-by-two comparison, and the criterion layer (B) for the target layer (A) judgment matrix is obtained as follows, where the scale value $a_{ij}$ indicates the importance of element i compared with element j and satisfies $a_{ji} = 1/a_{ij}$ [31]:

Table 8. Analysis of variance of the surface roughness, Ra, of nitrogen-containing gray cast iron.

| Source  | Degrees of freedom | Adj SS | Adj MS | F-Value | P-Value |
|---------|--------------------|--------|--------|---------|---------|
| Returning | 7                  | 1.57620| 0.225171| 375.29  | 0.040   |
| $v_c$   | 1                  | 0.09764| 0.097638| 162.73  | 0.050   |
| $f_z$   | 1                  | 0.04374| 0.043740| 72.90   | 0.074   |
| $a_p$   | 1                  | 0.00609| 0.006089| 10.15   | 0.194   |
| $v_c^2$ | 1                  | 0.06400| 0.064000| 106.67  | 0.061   |
| $f_z^2$ | 1                  | 0.04205| 0.042050| 70.08   | 0.076   |
| $a_p^2$ | 1                  | 0.05445| 0.054450| 90.75   | 0.067   |
| $f_z a_p$ | 1                | 0.05120| 0.051200| 85.33   | 0.069   |
| Error   | 1                  | 0.00060| 0.000600|         |         |
| Total   | 8                  | 1.93597|         |         |         |

$R^2 = 99.96\%$, $R^2 (adj) = 99.7\%$.

Table 9. GA-BP model training parameters.

| Input Parameters | Output parameter | Normalization function | Target Error | Learning Rate | Max. training steps |
|------------------|------------------|-----------------------|--------------|---------------|---------------------|
| $v_c$, $f_z$, $a_p$ | $R_a$             | maplinmax             | 0.0001       | 0.01          | 100                 |

Figure 9. Effect of the cutting speed and cutting depth on the surface roughness of N-containing gray cast iron.

Figure 10. Effect of the feed rate per tooth and cutting depth on the surface roughness of N-containing gray cast iron.
A = \begin{bmatrix}
 a_{11} & a_{12} & a_{13} \\
 a_{21} & a_{22} & a_{23} \\
 a_{31} & a_{32} & a_{33}
\end{bmatrix} = \begin{bmatrix}
 1 & 3 & 4 \\
 1/3 & 1 & 2 \\
 1/4 & 1/2 & 1
\end{bmatrix} \quad (8)

It is calculated that CR = 0.0176 \leq 0.1, and thus the results are in satisfactory agreement.

As the requirements for surface roughness are much greater than the MRR during finishing, in the case that the four factors of the guideline layer have the same degree of influence on the MRR, focus should be on their impact on the Ra. In the previous analysis, the parameters with the greatest effects on the Ra were the vc and fz, while the ap and radial feed rate had little influence. Therefore, the judgment scale can be taken as 4, 3, and 1/4 in order. Thus, the judgment matrixes of each element of the program layer (C) on the three elements of the criterion layer (B) are as follows:

Cutting speed : B^{(2)}_1 = \begin{bmatrix}
 1 & 4 \\
 1/4 & 1
\end{bmatrix}

Feed rate per tooth : B^{(2)}_2 = \begin{bmatrix}
 1 & 3 \\
 1/3 & 1
\end{bmatrix}

Cutting depth : B^{(2)}_3 = \begin{bmatrix}
 1 & 4 \\
 1/4 & 1
\end{bmatrix}

3.2.2.3. Hierarchical single sort. The maximum eigenvalue of A is \( \lambda_{\text{max}} = 3.0183 \), and thus the corresponding eigenvectors are

W_A = (0.6250, 0.2385, 0.1365)^T

Similarly, the eigenvalues and eigenvectors of matrix B are calculated. It is determined that the maximum eigenvalues of matrices B^{(2)}_1, B^{(2)}_2, and B^{(2)}_3 are all \( \lambda_{\text{max}} = 2 \).

The eigenvectors are...
The consistency ratios, CR, are all zero, and thus judgment matrix B has a perfect consistency, indicating that the weights of the evaluation factors are reasonably assigned.

3.2.2.4. Total hierarchical ranking. To calculate the total weights, the two relative weights of \( W_B \) and \( W_A \) are synthesized to obtain the optimal weight assignment.

\[
W = W_B W_A = \begin{bmatrix} 0.6617 \\ 0.3383 \end{bmatrix}
\]

Therefore, the surface roughness weight is 0.6617 and the MRR weight is 0.3383 in the case of finishing. The judgment matrix can be similarly adjusted according to the actual production requirements in the case of roughing and semi-finishing, resulting in surface roughness and MRR weights of 0.2816, 0.7184, and 0.5123, 0.4877, respectively. The optimal cutting parameters and corresponding predicted values of the surface roughness and MRR under the three working conditions are summarized in Table 10.

It can be seen that the optimized parameter combination provides the maximum MRR under the rough machining condition, and although the surface quality is relatively poor at this time, the surface quality is already excellent at the same large level of the MRR. In the finishing machining condition, the surface quality is highest because more attention is paid to the surface quality, and the MRR is smaller than under the other two conditions; however, it is also in the middle and upper levels among the same level of parameter combinations. Under the semi-finishing machining condition, the surface roughness and MRR are both better with the optimized combination of parameters, taking into account the surface quality and machining efficiency.

In addition, to verify the effectiveness of the optimized machining parameters under the three working conditions, experiments were conducted on the experimental platform described in Section 2 to verify the errors between the true and predicted values measured under the three working conditions, as illustrated in Figure 14. The mean error of \( Ra \) is approximately 7.51%, whereas the average deviation of the MRR is approximately 2.37%. The results agree well with the predicted values, and thus the proposed method is effective.

### 4. Conclusions

In this study, the cutting performance of a new cast iron material, nitrogen-containing gray cast iron, was investigated by orthogonal and single-factor cutting tests. The cutting forces, cutting temperatures, and surface roughness during milling of nitrogen-containing gray cast iron are investigated under different cutting parameters. In addition, an integrated model of multi-objective optimization algorithm combined with

| Working condition       | Cutting parameters | \( R_a \) (\( \mu \)m) | MRR (mm\(^3\)/min) |
|-------------------------|--------------------|------------------------|---------------------|
| Rough machining         | 205.02             | 0.18                   | 2                   |
| Semi-finishing          | 220.76             | 0.16                   | 1.79                |
| Precision machining     | 264.93             | 0.13                   | 1.37                |

The mean error of \( Ra \) is approximately 7.51%, whereas the average deviation of the MRR is approximately 2.37%. The results agree well with the predicted values, and thus the proposed method is effective.
AHP is used to determine the optimal combination of parameters under different production requirements according to the machining characteristics of nitrogen-containing gray cast iron, where RSM is used to develop input-output interrelationships under small sample data conditions. Through the above machining characteristics evaluation and optimal cutting parameters acquisition of nitrogen-containing gray cast iron, the machining process of nitrogen-containing gray cast iron can be better optimized to improve the machining efficiency and machining quality. The main conclusions are as follows:

1. The milling speed, feed rate, and milling depth were all conducive to the increase in milling force, and the impact of the cutting depth on the cutting force was most significant. Due to the cutting characteristics of intermittent milling, the rise in cutting force is accompanied by significant fluctuations in the superposition of cutting volume and cyclical impact. In addition, the passivating effect of nitrogen on the graphite tip - the round, short, thick, slightly curved graphite morphology increases the toughness of nitrogen-containing gray cast iron to some extent, which exacerbates this fluctuation phenomenon.

2. The cutting speed has a remarkable impact on the variance in cutting temperature, followed by the feed rate. As the vc and fz grew, the milling temperature slowly rose. When fz was less than 0.15 mm/tooth, the milling temperature increased gradually. However, when the feed rate of each tooth was greater than 0.15 mm/tooth, the milling temperature raised significantly, and under the combined effect of plastic deformation of the metal and tool-chip friction, the cutting temperature showed a certain gradient characteristic.

3. The magnitude of the impact of the milling parameters on the surface roughness of nitrogen-containing gray cast iron was as follows: milling speed > feed rate per tooth > milling depth. The impact and vibration during milling decreased as vc improved, the generated vibration pattern was gradually eliminated, and the surface roughness was gradually reduced. At vc > 100 m/min, this trend was slowed by the cutting force and tool wear. The surface quality will deteriorate as the feed rate rises, particularly for feed rates greater than 0.14 mm/tooth.

4. The quadratic multiple regression model using RSM was used to establish the relationship between the surface roughness and milling parameters, and the ANOVA gave a p-value of 0.04 and an R2 of 99.7%. The prediction accuracies of the response surface model for milling force, and tool wear were 22.47% and 23.53%, respectively. Therefore, our model can reduce costs in practical engineering applications.

5. A controlled NSGA-II optimization algorithm is used to optimize the objectives of maximum MRR and minimum surface roughness. AHP was used to determine the target weights based on the production requirements; thus, the Pareto solution set was filtered, and finally, the optimal combinations of cutting parameters under various working requirements were obtained. The experimental validation results indicated the optimized parameters improved the surface roughness by 23.53% while the MRR remained unchanged. The average error of the surface roughness was approximately 7.51% and the average deviation of the MRR was approximately 2.37%. Therefore, the experimental results match well with the predicted values, which proves that the method is effective.

This study investigated the cutting performance of nitrogen-containing gray cast iron and provided a parameter optimization scheme. Theoretical support and reference directions are provided to solve the milling processing problems encountered in the large-scale production of high-strength nitrogen-containing gray cast iron. Future work will further consider the role of the unique microstructure of nitrogen-containing gray cast iron in the machining process and the objectives of the parameter optimization to decrease the machining energy consumption.

Consent to publish

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Code availability

The authors can obtain the code upon request.

Declarations

Author contribution statement

Yongchuan Lin: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.
Jiyang Ma, Debin Lai: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.
Jingru Zhang, Weizhu Li, Shengzhu Li: Contributed reagents, materials, analysis tools or data; Wrote the paper.
Shengjian He: Performed the experiments; Wrote the paper.

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Data included in article/supp. material/referenced in article.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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