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Data-Driven Low-Carbon Control Method of Machining Process—Taking Axle as an Example

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Abstract: It is an inevitable trend of enterprise development to optimize the low-carbon machining process and reduce the carbon emissions generated by this system. The traditional quality-based manufacturing method is no longer suitable for today's concept of sustainable development. Therefore, a data-driven method based on uncertainty evaluation for low-carbon control in machining processes is proposed. Firstly, the framework for the data-driven method was established, then the data collection for the input and output in the machining process was carried out. Secondly, by establishing the carbon emission data model and analyzing data with carbon emission uncertainty evaluation indicators during processing, the carbon emission optimization strategy was proposed. Finally, axle processing technology was applied to the experimental verification, exploring the uncertainty of emissions finishing machining steps and other work sequences, while carrying out targeted strategy optimization, which verifies the feasibility and effectiveness of the method. The results show that the uncertainty of each process is reduced after optimization. This study provides theoretical and methodological support for promoting low-carbon emissions for manufacturing enterprises.

Keywords: data-driven; carbon emission; uncertainty; manufacturing

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1. Introduction

With the continuous advancement of the industrialization process and rapid economic development, coupled with the extensive use of fossil fuels such as coal and oil, the concentration of carbon dioxide emitted by combustion has increased by 35% compared with the past few million years. This increase heats up our planet through the greenhouse effect [1,2], which causes much disruption to human life. As a rapidly developing country, China has a higher proportion of carbon dioxide emissions from manufacturing [3], and low-carbon transformation has become an effective way of achieving regional development [4]. Ensuring low carbon levels is a challenge of globalization [5], and how to realize low-carbon, high-efficiency manufacturing, as well as a sustainable and green manufacturing system have become the core aims for the future development of the industry, and we need to keep researching and exploring [6,7]. Since 2003, the concept of a low-carbon economy has been proposed, and it is proposed that economic development should adopt a strategy of low energy consumption, low pollution and low emissions [8]. Reducing carbon emissions is the key to achieving low-carbon manufacturing in the context of various manufacturing systems [9].

In recent years, many experts and scholars have studied carbon emissions in manufacturing enterprises and found a series of important results in theory and practice: Gao et al. [10] developed a new mathematical model to predict carbon emissions in the stamping process and achieve carbon reduction through process decomposition. Xiao et al. [11] established a low-carbon and low-cost multi-objective optimization model according to the processing characteristics of complex box-like blank parts and used a particle swarm algorithm to solve the optimization model to meet the low-carbon demand. Jeswiet et al. [12] proposed a quantitative model of carbon emissions for the manufacturing process. Hirohisa et al. [13] considered the environmental burden, manufacturing time and total number of work piece setups and proposed the evaluation index of the process "eco-efficiency" and operation plan. Zhang et al. [14] established the carbon flow model of the iron making system based on the carbon balance theory, which can calculate the carbon emission data in actual production and analyze the influencing factors of carbon emission. Cai et al. [15,16] used energy benchmarking to improve the energy efficiency and performance of the machining system.

Liu et al. [17] established a low-carbon optimization model of the machining process route, and then applied it to the machining process of a machine tool motor, the correctness and validity of the optimization model are verified. Li et al. [18] proposed a low-carbon optimization model for the quantification of multi-source carbon emissions, manufacturing process parameters, and process routes in the machining system, and carried out a practical analysis to verify its feasibility. Zheng et al. [19] studied the sand casting process, modeled carbon emissions in the process, and calculated the carbon emissions with the process carbon source, and its feasibility is verified by an example. Deng et al. [20] established a multi-objective machining process route optimization model based on a genetic algorithm (GA), which takes the minimum machining time (high efficiency) and optimal carbon efficiency (low carbon) as the optimization goals, and conducted an experimental case study on the grinding box. Zhang et al. [21] studied the optimal control method of carbon footprint based on dynamic programming in machining process by considering the constraints of machining accuracy and time, achieving minimum carbon emissions.

Digital drive technology is gradually applied to advanced manufacturing, di Capaci et al. [22] presented data-driven models for the description of the acid gas treatment process by imposing generalized binary noise (GBN) sequences to the flow rate of $Ca(OH)_2$, which appears reliable and promising for control purposes. Leng et al. [23] proposed a novel digital twin-driven approach for the rapid reconfiguration of automated manufacturing systems. Meanwhile, Leng et al. [24] applied digital-twin technology to production line debugging, making the commissioning of a new flow-type smart manufacturing system more sustainable. Zhang et al. [25] proposed a digital-twin-driven smart manufacturing workshop carbon emission prediction and low-carbon control in order to achieve carbon emission reduction in intelligent manufacturing workshops. Vaccari et al. [26] established a geothermal power generation simulation model to predict and control pollutant emissions, and the predicted value is essentially consistent with the actual measured value.

Many researchers have conducted successful studies on low-carbon processing, which provide us with methods and references. However, in the specific process of manufacturing, the quantification of the specific generated carbon emissions and the uncertainty evaluation of these emissions are still missing. Therefore, how to quickly find the influencing process in the manufacturing and propose a strategy optimization for the process is the target of this paper. To achieve this goal, the research framework is as follows. Section 2 details the method, which mainly introduces the framework of the processing system, the carbon emission quantification model and the carbon emission uncertainty evaluation index. Section 3 takes the axle machining system as an example to verify the effectiveness and feasibility of the method, and Section 4 is the conclusion.

2. Method

2.1. Framework

In this paper, a data-driven method was devised to measure and assess the carbon emission efficiency of processes. The framework consists of four parts, including data collection, data modeling, data analysis, and innovation practice. Data collection primarily consists of inputs and outputs emissions from processing systems, and then conversion with carbon emissions. Data modeling is used to establish the carbon emission calculation model of the processing process. Data analysis refers to the carbon emission uncertainty evaluation index during the processing system. Innovation practice proposes effective strategy optimization based on reducing uncertainty.

This method can calculate the carbon emissions of each process involved in manufacturing and quickly find the processes that affect carbon emissions according to the level of uncertainty. Enterprises can also benefit from a reduction in carbon emissions, such as improving economic and ecological benefits and providing better conditions for the development of enterprises. The framework of the method is shown in Figure 1.

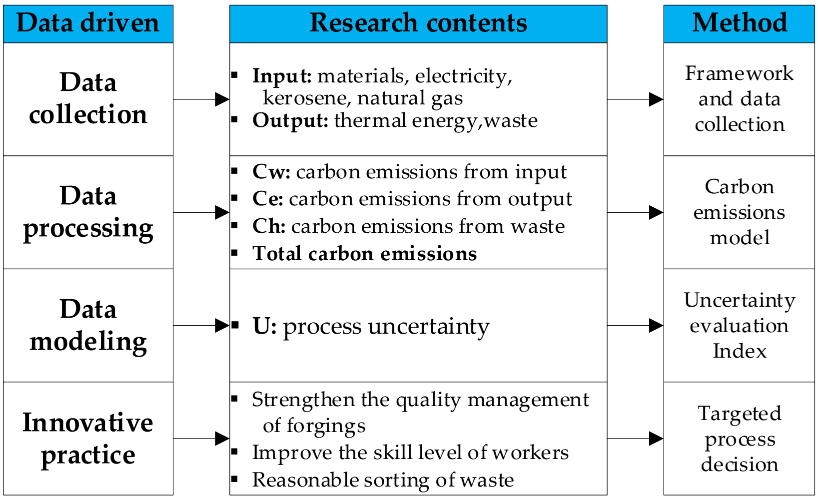

Figure 1. Method framework.

2.2. Data Collection

In the process of axle manufacturing, the carbon emission analysis should not only consider the characteristics of the system, but also the flow of external energy. By analyzing capital investment, human management, and the final axle products, the carbon emissions of the manufacturing process were divided into two aspects: inputs and outputs.

The inputs mainly include materials used in the process, as well as electricity, coal, oil, and natural gas. The main inputs in axle production are 45 steel (kg), electricity (kW·h), cutter (kg), cutting fluid (L), and grinding fluid (L). The outputs mainly include finished products, waste scrap, waste liquid, waste gas, etc. [27,28]. The outputs in axle production are mainly waste fluid (L) and waste scrap (kg).

The collection measures mainly include literature reviews, production data collection, production log, invoice, sample collection and analysis, technical worker consultation, data benchmarking in the same industry, etc. In axle production, a power meter and stopwatch are used to calculate electric energy under no-load and load conditions, the balance is used to test the material mass before and after the parts of each working step, and the measuring cylinder is used to measure cutting fluid and abrasive fluid.

2.3. Carbon Emission Model

Based on the investigation and analysis of the production process of manufacturing enterprises, by collecting the data of energy, production materials, and waste of the manufacturing system, the carbon emission measurement model of the manufacturing system was built.

Model assumptions of a manufacturing system: the equipment required in the manufacturing process is independent of each other, and one station includes one type of production equipment. One station at the same time can only handle one processing process; each process of the production station is carried out according to the standards of the operation instructions, and once the production starts, it is not allowed to cancel or interrupt; faults and abnormalities in the manufacturing process are not considered.

(1) Calculation of carbon emissions from material

In the manufacturing system, input materials mainly include steel, alloy, cutting fluid, cleaning oil, water, etc.

Consider the consumption of each step i (i = 1, 2 ... i_0), the type of material is j (j = 1, 2 ... j_0), and the input material loss is recorded as $W_{i,j}$, the carbon emission factor of the consumed material is $f_{wi,j}$ [29], and the generated CO_2 formula is as follows:

$$C_W = \sum_{\mathrm{i}=1}^{\mathrm{i}_0} \sum_{j=1}^{j_0} W_{i,j} \times fw_{i,j} \tag{1}$$

(2) Calculation of carbon emissions from energy

The energy of the manufacturing system is mainly comprises sources of electricity, some of which are coal (for heating), natural gas, hydrogen (cutting), etc.

Considering the energy consumed by each step i (i = 1, 2 ... i_0), the type of energy is k (k = 1, 2 ... j_0), the energy is recorded as $E_{i,k}$, the carbon emission factor of the energy is $fe_{i,k}$ [29], and the generated CO_2 formula is as follows:

$$C_e = \sum_{\mathrm{i}=1}^{\mathrm{i}_0} \sum_{k=1}^{k_0} E_{i,k} \times fe_{i,k} \tag{2}$$

(3) Calculation of carbon emission calculation from waste

Wastes mainly include waste water, waste gas, and waste residue. Considering the number of emissions produced in each step i (i = 1, 2 ... i_0), the type of emissions is l (l = 1, 2 ... l_0), and the consumption of emissions is recorded as $H_{i,l}$, the carbon emission factor is $fh_{i,l}$ [29], the generated CO_2 formula is as follows:

$$C_h = \sum_{\mathrm{i}=1}^{\mathrm{i}_0} \sum_{l=1}^{l_0} H_{i,l} \times fh_{i,l} \tag{3}$$

Therefore, the carbon emissions of the production process can be expressed as:

$$C = \sum_{\mathrm{i}=1}^{\mathrm{i}_0} \sum_{j=1}^{j_0} W_{i,j} \times fw_{i,j} + \sum_{\mathrm{i}=1}^{\mathrm{i}_0} \sum_{k=1}^{k_0} E_{i,k} \times fe_{i,k} + \sum_{\mathrm{i}=1}^{\mathrm{i}_0} \sum_{l=1}^{l_0} H_{i,l} \times fh_{i,l} \tag{4}$$

By calculating the specific values of carbon emissions generated by input materials, output energy, and emissions in mechanical production, the total carbon emissions generated by this process can be obtained.

2.4. Evaluation Index of Carbon Emission Uncertainty

For axle manufacturing systems, the goal is to minimize total carbon emissions. The total carbon emission needs to take into account the carbon emission generated by each step of the whole process. In each manufacturing process, there are uncertainties in the production schemes, tasks, consumption characteristics of resources and environment, etc. There are disadvantages of simply comparing processes based on carbon emission values. Therefore, the uncertainty relation of carbon emissions is introduced to consider the optimization scheme of the overall process.

On the basis of carbon emission processes, uncertainty is proposed as the evaluation index and an optimization strategy to reduce the uncertainty. The carbon emission uncertainty model is established as follows:

(1) Calculation of the sample mean

$$\overline{X} = \frac{1}{n}\sum_{k=1}^{n} X_k \tag{5}$$

Among these values, $\overline{X}$ represents the sample mean; n is the sample size.

(2) Calculation of the sample standard deviation

After the mean of the data is obtained by calculation, the standard deviation of this data set is calculated, and the formula is as follows:

$$\sigma_S = \sqrt{\frac{1}{n}\sum_{k=1}^{n} (X_k - \overline{X})^2} \tag{6}$$

Among these values, σ_S is the standard deviation.

(3) Calculation of the step uncertainty range

On the basis of obtaining the sample size n and the standard deviation σ_S, according to the IPCC guidelines [29], select the mathematical value t corresponding to the 95% confidence level, and calculate the uncertainty range. The formula is as follows:

$$u_s = \left[-\frac{\sigma_s \cdot t}{\sqrt{n}}; +\frac{\sigma_s \cdot t}{\sqrt{n}}\right]\% \tag{7}$$

Among these values, the U_S indicates the uncertainty range of the step.

(4) Calculation of the uncertainty range of the process

The above model obtains the uncertainty range U_S of a certain step, and the uncertainty needs to be combined for the entire manufacturing process. The carbon source relationships of the process exist in juxtaposition to each other, and the addition and subtraction operations are selected. The formula is as follows:

$$U_C = \frac{\sqrt{(U_{S1} \cdot C_{S1})^2 + (U_{S2} \cdot C_{S2})^2 + \cdots + (U_{Sn} \cdot C_{Sn})^2}}{C_{S1} + C_{S2} \cdots C_{Sn}} \tag{8}$$

Among these values, U_C indicates the uncertainty of the process and C_S represents the carbon emissions of each step.

This model can obtain the uncertainty of each process through emission impact factors, find out the processes that have a greater impact on emissions and optimize them, and finally reduce carbon emissions. Considering the influence of sample mean change on uncertainty, in order to reduce the sensitivity of uncertainty, the method of random sampling was used for sensitivity analysis.

2.5. Decision on Low-Carbon Optimization Path for Manufacturing

Based on the carbon emission uncertainty model of the manufacturing system above, the specific application of the low-carbon optimization path decision is as follows: first, the carbon emissions generated by the comprehensive action of various factors are calculated through the production data of enterprises, and the degree of influence of each factor is analyzed from the perspective of uncertainty. Then, the highly linear influencing factors of uncertainty are identified, and corresponding improvement measures and methods from the aspects of material selection, processing and management are formulate in order to reduce the uncertainty of carbon emissions in the manufacturing system. Then, the implementation effect is verified according to the plan requirements, and the experience and problems of the improvement process are determined. Finally, it is necessary to affirm successful experiences and formulate them into standards, procedures, and systems. Lessons from failures can also be incorporated into corresponding standards, procedures, and systems. Therefore, the optimization decision can provide a quantitative basis for reducing the uncertainty of carbon emissions in manufacturing systems.

3. Case Study

3.1. Axle Machining System

This paper takes the axle machining system of an enterprise as the research object, which is mass-produced. The process includes forging, rough turning, heat treatment, fine turning, rough grinding, fine grinding, and milling. The specific steps are shown in Figure 2:

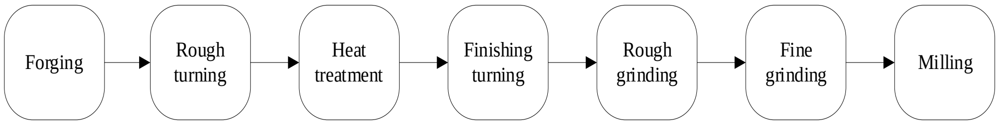

Figure 2. Machining process of axle.

The machining process of the axle is a typical and representative system, which is used for carbon emission calculation and uncertainty analysis, providing new theoretical and sustainable improvement methods for machine manufacturing systems.

3.2. Result

According to the data from the axle factory and the actual investigation and analysis of the axle machining process, it can be found that each process has its own carbon footprint characteristics from forging to fine grinding because of the various tools used and different waste produced in the process.

The carbon emissions in this calculation are calculated by the emission factor method, which is based on the output of manufacturing process. Among them, products and the empirical emission factors of products are included in the carbon emission factor, which refers to the statistical average of CO_2 quantity produced under general conditions, expressed as the greenhouse gas production accompanied by the consumption per unit mass. It is an important parameter to characterize the emission characteristics of greenhouse gas from a certain energy source, as well as the basic data for calculating the carbon footprint. According to the relevant literature, carbon emission factors of some common materials are organized, as shown in Table 1.

Table 1. Carbon emission factors of common materials.

Common Materials	Unit	Carbon Emission Factors	References
Steel	Kg/kg	2.69	[29]
Cutting fluid	Kg/L	2.85	[29]
Grinding fluid	Kg/L	0.978	[29]
Cutter	Kg/kg	29.6	[29]
Electricity	Kg/KW·h	0.7125	[29]
Scrap steel	Kg/kg	0.361	[29]
Waste cutting fluid	Kg/L	0.21	[29]

After data collection, the external circular lathe CA6140 was used as the manufacturing equipment in the finishing turning process. The common parameters of this enterprise in the finishing process are a spindle speed of 250 R/min, a feed rate of 0.3 mm/ R, and a cutting depth of 2 mm.

In the actual manufacturing process, due to the existence of dimensional tolerance of parts, the level of workers' operation, the proficiency of equipment usage, and the defects of raw material supply, there are differences in the material input, energy output, and emissions in the finished turning.

Data were collected according to the actual production process, the sample number is 50, and the t value is 2.01. Thirty samples were randomly selected and the test was repeated 20 times to obtain the uncertainty range of each work step for sensitivity analysis. The carbon emissions and uncertainties of refined vehicles are shown in Table 2:

Table 2. Carbon emissions and uncertainty in the finishing turning.

Finishing Turning		**Remove Material (g)**	**Carbon Emissions (g)**	***Us***	***Uc***
Input	Turning plane	170.82	459.58	1.5% (1.2–1.8%)	3.2% (2.4–4.1%)
	Turning cone	680.5	1830.55	6.8% (5.7–8.6%)	
	Chamfering	988.4	2658.79	7.5% (6.4–9.8%)	
	Threading	61.3	164.89	5.6% (4.3–7.5%)	
	Drill	54.7	147.14	1.6% (0.3–2.4%)	
	Cutter	2.72	80.51	1.4% (0.8–3.1%)	
	Cutting fluid	0	0	0%	
		Electric energy (kW·h)			
	No-load Electric energy	0.0144	10.29	0.5% (0.2–1.6%)	
	Processing Electric energy	1.791	1280.92	2.6% (1.2–3.4%)	
Output	Waste	1955.72	706.01	6.5% (4.8–7.2%)	

From the data results in Table 2, it can be seen that the uncertainty of the finished product is greatly affected in the turning cone, chamfering, threading, and some other work steps that require a high level of technology, because of the gap in the technical level of workers. At the same time, waste residue and waste liquid are mixed, and there is also a phenomenon of greater uncertainty in the separation and collection of emissions. The values in the brackets indicate the uncertainty range recorded in the process of randomly sampling 30 samples for 20 repeated tests. The overall sample uncertainty is within the range, so the result meets the sensitivity requirements.

In the same way, the carbon emissions and uncertainties of other processes are calculated in turn, and the specific results are shown in Figure 3.

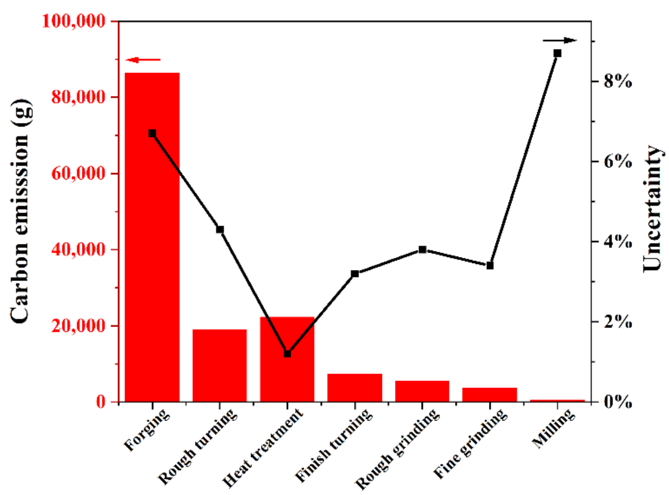

Figure 3. Carbon emissions and uncertainty values in each process of the axle.

Figure 4 shows the uncertainty of carbon emissions in the whole manufacturing process of the axle. It can be found that in the initial stage of manufacturing and the process with a low-accuracy stage, the uncertainty of carbon emissions increases. This is due to more removal materials and a higher technical level workers. Higher precision processes have lower emissions uncertainty because less material is removed, and the tolerance range is small. Furthermore, we can see from Table 2 that a high waste uncertainty may be caused by the gap in the collection and treatment of emissions. Meanwhile, it shows that the enterprise lacks green awareness and an operation mode, and the low-carbon management of production methods is unreasonable.

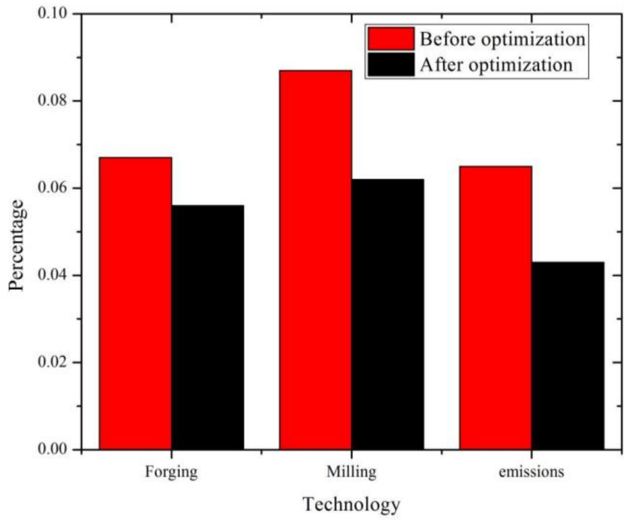

Figure 4. Method implementation effect.

By analyzing the uncertainty of carbon emissions of the enterprise's axle processing data, the current situation and difficulties faced by the enterprise in the current production can be accurately diagnosed. It can provide practical method guidance for the green production of enterprises.

Optimization decision 1: Strengthen the quality management of forgings. During the forging process, strengthen the quality inspection process and exclude products with large differences in size; meanwhile, try to reduce waste, standardize the operation, and stabilize the production process. The uncertainty after implementing the decision was reduced from 6.7% to 5.6%.

Optimization decision 2: Improve the skill level of workers. In the process of keyway processing, clarify the matching relationship of parts, reduce tolerances, and carry out regular technology training to improve the operation level of workers. After the decision was implemented, the uncertainty dropped to 6.2%.

Optimization decision 3: Reasonable sorting of waste. In terms of emission treatment, a special person is responsible for the classification and recovery of slag and liquid, scientific management, and the improvement of the accuracy of data collection. Uncertainty reduced to 4.3% after decision implementation.

Since the implementation of this method in 2021, as shown in Figure 4, forging, milling keyways, and emissions disposal carbon emissions uncertainties have all been reduced. The enterprise has completed the goal of green and low-carbon production.

3.3. Discussion

Following a comparison with other research [11,12,19], this method has the following advantages:

(1) This method analyzes the input and output of the part manufacturing process from the perspective of carbon emissions, and establishes the uncertainty model of carbon emissions based on data-driven methodologies.
(2) It can provide support for the low-carbon transformation and upgrading path of the production system of manufacturing enterprises; meanwhile, it can help policymakers strengthen quality management, improve the skills of workers, properly manage

emissions, and reduce the uncertainty of carbon emissions in manufacturing systems. It is the basis of the low-carbon production management of enterprises.

(3) Compared with energy benchmarking method applicable to high-end enterprises [15,16], this method is easy to understand, implement, and provides decision-making reference for managers in small enterprises; meanwhile, it can improve the comprehensive level of low-carbon, green and clean manufacturing systems, condense and enhance the core competitiveness of enterprises, and provide practical help for manufacturing enterprises.

(4) Furthermore, in this study, we only focus on one part without considering the whole manufacturing system, in view of the advantages of a digital-twin drive, we will introduce the a digital-twin-driven intelligent manufacturing method into the field of carbon emission statistics in the whole manufacturing system [30–32].

4. Conclusions

Under the current development background, energy saving, emission reduction, and low-carbon manufacturing are bound to be the mainstream trends in industrial manufacturing systems. This paper employs a data-driven method to calculate carbon emissions and uncertainties in processing systems. The main innovation is that it established a carbon emission model for axle processing, determines the uncertainty evaluation index and the carbon emission uncertainty of a process, and optimize this process with greater uncertainty. In the uncertainty of forging and milling, emissions reduced to 5.6%, 6.2%, and 4.3% from 6.7%, 8.7%, and 6.5%. Through a data analysis and evaluation of the axle processing system, it was found that strengthening the quality inspection process, training workers to improve their technical level, and rationally dealing with emissions can significantly reduce uncertainty. This research has a good reference for the green transformation and upgrading of manufacturing enterprises; and can provide effective solutions for decision-makers. The application of data-driven methods based on uncertainty evaluation theory in the whole process of mechanical production has great significance for the development of sustainable manufacturing.

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