Proceedings of the ASME 2022
International Design Engineering Technical Conferences and Computers and Information in Engineering Conference
IDETC/CIE2022
August 14-17, 2022, St. Louis, Missouri

DETC2022-XXXX

A DATA-DRIVEN APPROACH DESIGN FOR CARBON EMISSION PREDICTION OF MACHINING

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ABSTRACT

The issue of carbon neutrality for manufacturing industry attracts increasing attention. As a major contributor, the carbon emission prediction of machining processes has been established as one of the most crucial research targets. However, due to the complexity of machining, the carbon emissions of which are influenced by many factors, and show dynamic characteristics. At the moment, these indicators and characteristics are difficult to be fully considered in the existing method, which may cause the inaccurate results of the carbon emission prediction. The purpose of this study is to design a carbon emission prediction model of machining through a data-driven approach. First of all, the multiple sources and impact factors of carbon emissions in machining are studied, and the dynamic characteristics of carbon emissions are described through the relationship between them. Based on the collection of the related data, a carbon emission prediction approach is designed, and data feature extraction and predictive methods are proposed by using the ridge regression and the BP neural network based on Genetic Algorithm (GA-BP) respectively. An experimental study using the carbon emission data of a real turning machining shows the merits of the proposed approach.

Keywords: Carbon emission prediction, Data-driven, Approach design, Machining, Ridge regression, BP neural network based on Genetic Algorithm

1. INTRODUCTION

Climate warming caused by a significant increase in carbon dioxide emissions has become a global environmental crisis. The industrial sector is one of the major contributors to cause carbon emissions, as it consumes large amounts of resources and energy, and discharge waste. Statistics from the International Energy Agency (IEA) show that the industry is still the third-largest source of global carbon emissions, which generate nearly 36% of the global carbon emissions [1, 2]. Therefore, moving to low carbon economy is of critical importance to the sustainable development of the industry.

Manufacturing, as an important part of industry sectors, plays an essential role in the global economy. In the meantime, its energy-intensive operations contribute significantly to the carbon emissions [3]. Especially in China, the manufacturing industry accounts for over 30% of the end-use energy and produces large amounts of carbon emissions [4, 5]. Machining with machine tools in the manufacturing consumes massive energy and resources, which is seen as a major source of the carbon emissions [6]. It is noted that only about 25% of the energy is used to cut the parts in machining, a large portion of energy is consumed when the machines are idle [7]. Therefore, reducing the carbon emissions of machining has a huge potential, and has become an emerging topic nowadays.

Carbon emission prediction is helpful to identify the improvements, which is a priori technology for carbon emission reduction. However, due to the complexity of machining, there are many impact factors related to the carbon emissions. It is difficult to take all the factors into account, which may cause the inaccurate results of the carbon emission prediction. To this end, this paper designed a data-driven method to predict the carbon emissions of machining considering whole impact factors. The rest of the paper is organized as follows. Section 2 introduces research status of carbon emission prediction approach in machining. Section 3 analyzes the characteristics and impact factors for the carbon emissions of machining. Section 4 outlines the designed data-driven approach for carbon emission prediction. Section 5 presents a case study to demonstrate the effectiveness and practicability of the method. Section 6 concludes with our work summary.

2. LITERATURE REVIEW

2.1 Carbon emission characteristics of machining

In machining, the carbon emissions are caused by the materials consumption (both raw materials and auxiliary materials), energy consumption and waste disposal [8]. Based on the analysis of machining system, Li et al. [9, 10] pointed out the indirect characteristics and generalized boundary of carbon emissions of machining, and established a series of models to quantify the carbon emission caused by material removal, cutting fluid consumption, chip recycling, electricity consumption, etc., respectively.

Within this analysis framework, several works are found to analyses the carbon emissions from conventional machining, such as turning, milling etc. Zhao et al. [11] studied the carbon emission characteristics in turning machining, and proposed a carbon emission calculation method. Cao et al. [12] focus on the energy and materials consumption of machine tools, and presented a carbon efficiency method to characterize the carbon emissions throughout the life cycle. Sihag et al. [13] established a mathematical model to calculate the carbon emissions in a milling process. Zhou et al. [14] studied the relationship between carbon emission and cutting parameter in turning machining, and presented a carbon emission optimization method.

Some scholars studied the characteristics and quantification methods of carbon emissions from unconventional machining. Zheng et al. [15] studied the carbon emission characteristics of a WEDM process, and proposed a predictive model for the CO_2 emissions. Zhang et al. [16] presented a quantitative method of the carbon emissions in the FDM process according to its characteristic and the electric power consumption.

2.2 Predictive approach for carbon emissions

When the characteristics and impact factors of carbon emission of machining are understood, several prediction or quantification methods are proposed by different researchers. Gao et al. [17] presented a method for carbon emission forecasting for the industrial sectors based on Gompertz's law and fractional grey model. Ma et al. [18] identified the multi-dimensional factors of carbon emission from different scenarios of machining with association rule algorithm, and established a hybrid carbon emission prediction model through the relationship of them. Zhou et al. [19] established a novel grey rolling prediction model for the Chinese carbon emissions. Liu et al. [20] developed an ensemble system for short term carbon dioxide emission forecasting, which were composed of model selection, phase space reconstruction, ensemble point prediction, and interval prediction. Aiming at previous studies only focused on carbon emissions forecasting accuracy and neglected stability, Qiao et al. [21] proposed an improved lion swarm optimization algorithm for carbon emission prediction. Fang et al. [22] proposed an improved Gaussian processes regression method for carbon emissions forecasting. These methods will contribute positively to help the carbon emissions calculation in this paper.

With the development of information and data technology, more and more data related to the carbon emissions could be collected utilizing the Industrial Internet and Internet of Things (IoT) technologies. Several novel data analyzing approaches are also proposed to predict the carbon emissions. It will provide a strong support for the carbon emission prediction of machining. For instance, Hosseini et al. [23] proposed a predictive method for carbon emission in Iran by using the Multiple Linear Regression (MLR) and Multiple Polynomial Regression (MPR). Ren et al. [24] established a model to predict the carbon emission with Fast Learning Network (FLN) algorithm. Abbas Mardani et al. [25] proposed a carbon emission prediction method by using the clustering and machine learning techniques. Zhang et al. [26] propose a digital twin-driven carbon emission prediction and low-carbon control of intelligent manufacturing job-shop. These works show the great potential for carbon emission prediction. However, there are few of them are used in machining.

Summarizing the findings of the above discussion, it can be claimed that, the work on carbon emission prediction of machining is limited. In fact, we believe that the carbon emission reduction will hardly be achieved without a predictive model of carbon emissions of machining.

3. CARBON EMISSION SOURCES AND IMPACT FACTORS IN MACHINING

According to the functional model of manufacturing process, the carbon emission characteristics could be described in FIGURE 1.

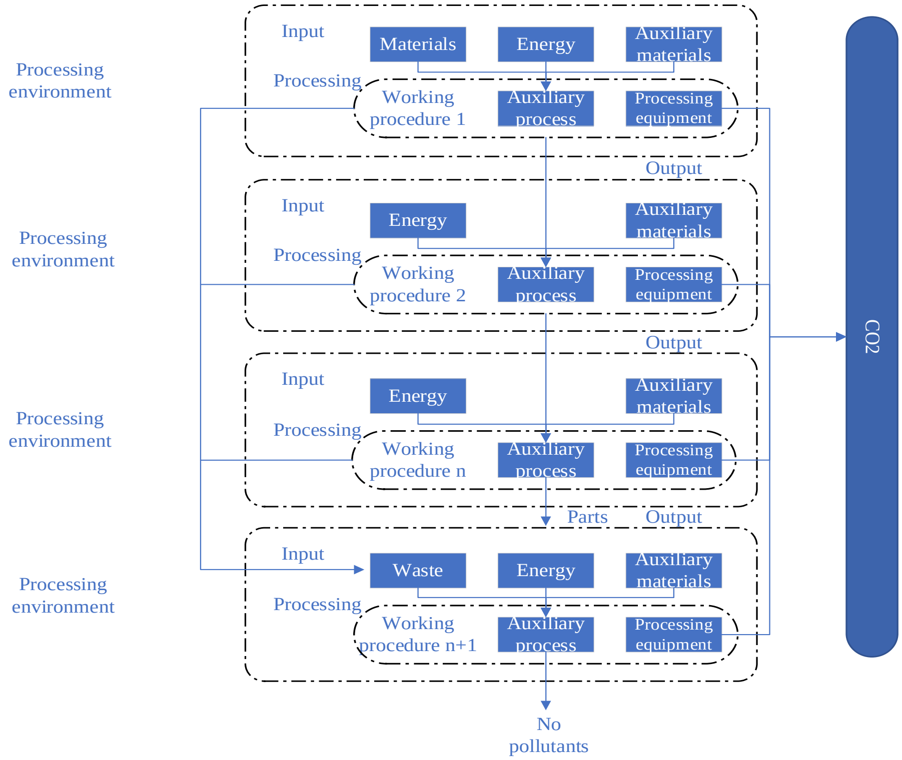

FIGURE 1. CARBON EMISSIONS OF MACHINING

The carbon emissions in machining are mainly caused by raw material consumption, auxiliary material consumption, energy consumption, and waste disposal [27]. It could be expressed with Eq (1).

$$CE_{total} = CE_r + CE_a + CE_e + CE_w \tag{1}$$

Where: CE_{total} is the total carbon emissions of a machining process, CE_r, CE_a, CE_e and CE_w present the carbon emissions caused by raw materials consumption, auxiliary materials consumption, energy consumption and waste recycling respectively.

There are numerous impact factors related to the carbon emissions in machining. For instance, the CE_r is affected by the part size, part material type, and part removal amount, etc. the CE_a is mainly caused by tools consumption, cutting fluid consumption, which is related to tool material, cutting fluid type, cutting fluid flow and machining time, etc. the CE_e is generated from the electricity consumption, which is affected by the performance of machine tools, and machining parameters, etc. the CE_w is the carbon emissions caused by the recycle process of waste chips, and waste fluid, etc., which is related to the treatment amount of the waste.

Specially in machining, the impact factors of CE_r mainly include the blank material (such as hardness, strength, and toughness, etc.), blank size (length and diameter, etc.) and so on. The blank size determines the removed volume of the parts. The larger the volume removed, the more energy will be consumed, and the more carbon emissions are indirectly produced. The removed material is turned into waste, and the disposal of waste also produces carbon emissions.

The impact factors of CE_a consist of tool material (hardness, strength, etc.), tool parameters (rake angle, relief angle, leading angle, etc.), cutting fluid consumption, cutting fluid type, cutting fluid flow rate, number of cutting fluid changes, fixture material (hardness, strength, etc.). Different factors such as tools, fixtures and coolants determine the energy consumption in preparing the material, and influence the amount of carbon emissions. Due to the action of force, the tool will be worn during the using time, and the worn part will turn into waste. The difference of tool determines the difficulty of processing, thus affecting the processing efficiency and energy consumption. The fixture function is fixing the workpiece during the processing of workpiece, so it will be subjected to force, and causing wear and tear, thereby producing waste. The cutting fluid functions are cooling, lubricating and chip removal. A large amount of cutting fluid will be used in the workpiece processing, although part of it is reused, it will also produce a large amount of waste fluid, and dealing with the waste fluid will also produce a large amount of carbon emissions.

The impact factors related to CE_e include machine tool standby power, spindle rated power, material removal power, feed shaft power loss, coolant spray power, etc. Some of the power in the CNC machine tool processing are usually relatively large, the higher the power, the longer the processing time, the more electricity consumed, and the more carbon emissions produced indirectly.

The impact factors of CE_w are composed of tool loss, waste processing, waste liquid processing, fixture loss, etc. The amount of tool wear is usually small, but the it can produce a large amount of carbon emissions. The amount of waste debris and waste liquid are usually relatively large, and a lot of carbon emissions will be produced in post-processing.

Based on the above analysis, the impact factors and their relationships could be described in FIGURE 2.

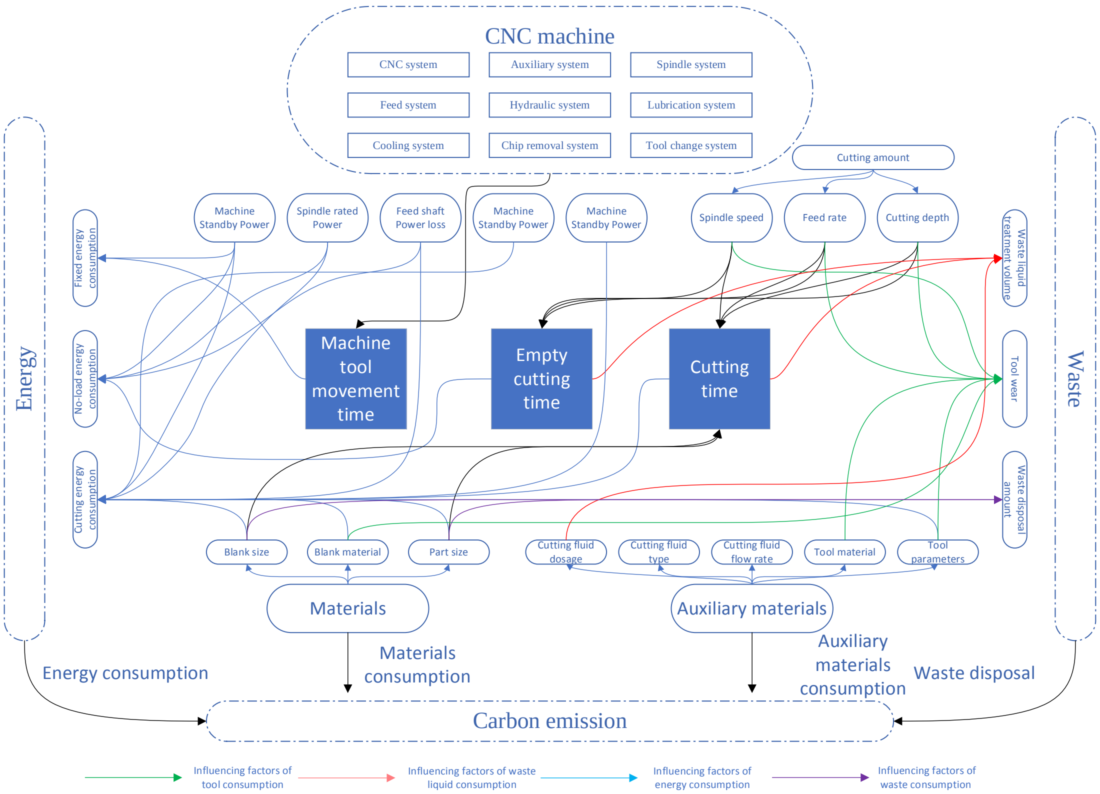

FIGURE 2: THE DESCRIPTION FOR IMPACT FACTORS OF CARBON EMISSIONS IN MACHINING

4. DESIGN OF THE PROPOSED APPROACH

The proposed data-driven approach for carbon emission prediction is designed with four parts, namely data collection and preprocessing, feather selection, prediction model establishment and model validation. The details of the four parts are as follows.

4.1 Data collection and preprocessing

With the help of the Internet of Things (IoT) and industrial internet technologies, more and more data could be obtained through various intelligent sensors, and some advanced approaches, such as data mining, data transport, and data warehousing, etc., are also used to process the data. These technologies and methods are helpful to the carbon emission prediction of machining. Comprehensive considering the above impact factors related to the carbon emission of machining, a framework for data collection and preprocessing are established in this paper, as shown in FIGURE 3.

In FIGURE 3, the data of material hardness, material strength, cutting fluid type, tool material, etc. are obtained by the look-up table. The data of blank length, blank diameter, etc. are collected by their CAD model. The data of energy consumption, such as machine standby power, spindle rated power, material cutting power are obtained by the power analyzer. The data of cutting fluid usage, waste liquid volume could be collected with the intelligent liquid flowmeter. Meanwhile, the carbon emission coefficient could be obtained from the previous work [28-29]. Then, the collected data are transmitted to the server using wired network to the servers, and the relational databases are employed to store these data, such as SQL Server, Oracle, MySQL, etc.

In order to establish the carbon emission predictive model, the collected raw data should be preprocessed, including data cleaning, data normalization and data integration.

Aiming at data missing, format inconsistency and logical errors, using the method of data cleaning can remove or fill missing data, verify data, and correct data, etc. Compared with the traditional Euclidean distance calculation method, k-means can ignore the magnitude limitation in calculation process. Thus, in this paper, the k-means are employed to fill the missing values. the k-means calculation formula is as follows.

$$dist(x_m, x_n) = \sqrt{(x_m - x_n)^T \sum (x_m - x_n)^{-1}} \qquad (2)$$

Where, $\sum$ is the covariance matrix; x_m is the missing data; x_n is the no-missing data.

The normalization method is applied as Eq (3).

$$x_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \qquad (3)$$

where: x_i is the data value corresponding to the i-th group of samples; x_{min} is smallest sample data value; x_{max} is largest sample data value. By establishing data integration rules, designing middleware, and obtaining a global data model to access database of different information systems. Based on it, subsequent the carbon emissions prediction is expanded.

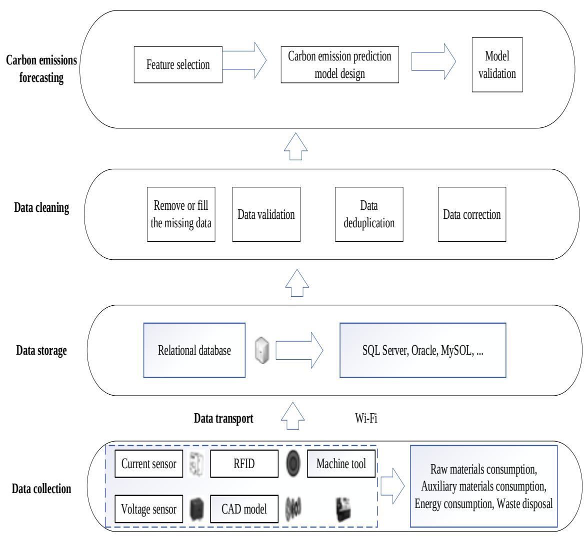

FIGURE 3. THE FRAMEWORK FOR DATA COLLECTION AND PREPROCESSING

4.2 Feature selection

Feature extraction is an effective way to improve the accuracy and efficiency of carbon emission predictive model [30]. Thus, the data should be treated with feather selection. the purposes of feature selection are to eliminate the features which have little impact or irrelevant on carbon emissions, and selecting features with large impact as the input variables of the predictive model.

In this paper, the ridge regression is employed to extract the feature data considering the better stability of its regression coefficients [31]. The regression function of the ridge regression can be expressed the following formula.

$$\varepsilon = \min(XW - Y)^2 \qquad (4)$$

where: X is the independent variable matrix; W is the regression coefficient matrix; Y is the dependent variable matrix, and ε is the error.

We can solve the weights for W with the following formula.

$$W = (X^T X)^{-1} X^T Y \qquad (5)$$

When the $X^T X$'s value approach to "0", the error will become extremely large, which is obviously not allowed. In order to solve this problem, an "L2" regular term can be added to the regression function, and the regression function can be transformed into formula (6).

$$\varepsilon = \min((XW - Y)^2 + (\lambda W)^2) \qquad (6)$$

where: $\lambda = alpha \times I$, I is the identity matrix, and alpha is the coefficient.

Therefore, W can be described as Eq (7), as follows.

$$W(k) = (X^T X + alpha \times I)^{-1} X^T Y \qquad (7)$$

The transformed formula obviously does not have $X^T X$'s value approach to "0", which prevents error have abnormal changed.

4.3 Carbon emission prediction model

Back propagation neural network (BPNN) is a common approach to establish the carbon emission prediction model. It could reach a good predictive accuracy as well as meet the requirement of efficient operation [32]. However, there are still some deficiencies in BPNN, it is easy to fall into the local optimum and the overfit [33].

To overcome these drawbacks, a BP neural network based on Genetic Algorithm (GA-BP) is designed to predict the carbon emissions of machining. Garcia et al. [34] proposed the Genetic Algorithm flexibility against non-differentiable functions and convergence to a viable solution with low computational cost. In this sense, the Genetic algorithm is a commonly used algorithm to improve BP neural network, which is usually used to solve the optimal solution problem, and the algorithm has strong adaptability. In this paper, the genetic algorithm is selected to optimize the BP neural network, because the BP neural network use the way of repeated iterations to obtain the ideal weights and thresholds. But in actual process, learning rate, weights, and thresholds etc. randomness parameters may appear some problems, such as low learning effect and low prediction accuracy of the model. Aiming at this shortcoming, genetic algorithm is used to optimize the parameters of BP neural network, which is a computational model for searching for the global optimal solution and obtain the optimal parameter values, it can greatly improve the learning effect and prediction accuracy of BP neural network.

Based on this, this paper proposes to optimize the carbon emission prediction model with GA-BP. The flowchart of the prediction model is shown in FIGURE 4.

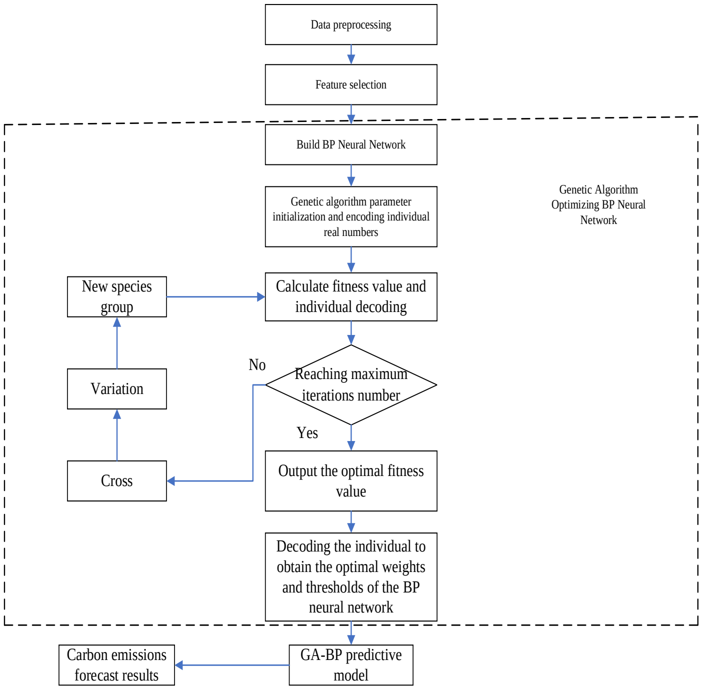

FIGURE 4. FLOWCHART FOR CARBON EMISSION PREDICTION WITH GA-BP

The main steps are as follows.

(1) Establishing and initializing the BP neural network model. Including the number of layers and neurons in the neural network, the learning efficiency, the maximum number of iterations and the minimum performance gradient.
(2) Initializing the genetic algorithm parameters. Including population size, maximum number of iterations, crossover probability and mutation probability, and encodes the real number of population individuals.
(3) Determining the fitness function and calculate the fitness value, and obtaining the initial weight and threshold by decoding the individual.
(4) According to the obtained fitness value, using the genetic algorithm to perform crossover and mutation operations on individuals to form a new population. In order to avoid generating local optimal solutions, recalculating the fitness value for the new population.
(5) By looping operation (3) and operation (4) to find the optimal fitness value. The maximum number of iterations is used as the standard to decide whether to end. When the maximum number of iterations is reached, the operation is stopped and output the optimal fitness value.
(6) By decoding the individuals corresponding to obtain optimal fitness values and decoding it into the weights and thresholds of the BP neural network, obtaining the optimal parameters.
(7) By the genetic algorithm obtain new weights and thresholds are used as the initial weights and thresholds of the BP neural network, constructing the GA -BP predictive model.

4.4 Model validation

The purpose of model validation is to evaluate the efficiency and accuracy of prediction model. In this paper, the root means square error (RMSE) and the mean relative percentage error (MPAE) are selected as the evaluation indicators to describe the model performance. The formulas are as follows.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[f(x_i) - y_i]^2} \tag{8}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{f(x_i)-y_i}{y_i}\right| \times 100\% \tag{9}$$

Where: $f(x_i)$ is Group i measurement; y_i is Group i actual value.

5. CASE STUDY

5.1 Experimental conditions and parameter settings

In order to verify the above approach, a CNC turning experiment is designed. In this experiment, the two types of machine tools, three types of blanks, four types of tools and two types of cutting fluid are used. The detail of the experimental conditions and equipment is listed in FIGURE 5, FIGURE 6 and TABLE 1 respectively.

Figure 1

FIGURE 5. CNC turning experimental equipment

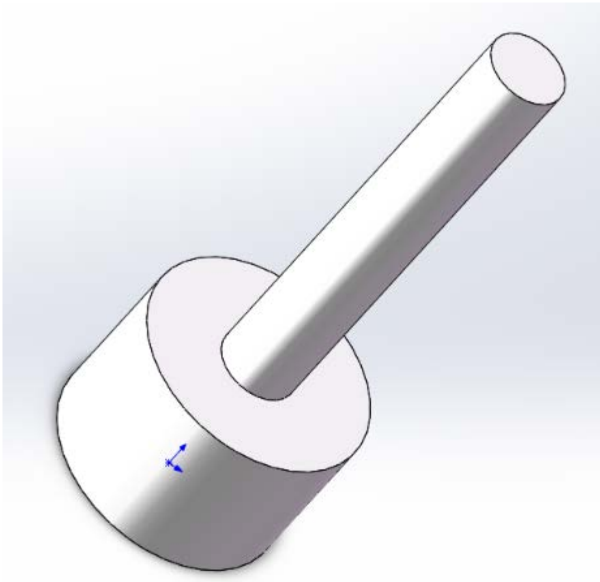

FIGURE 6. 3D drawing of CNC turning parts

Serial number	Name	Type
1	Raw materials	45Steel,6061aluminum alloy, QT500-7 ductile iron
2	CNC machine	CK6136i, CK6153i
3	Tool materials	YG8, YT5, W18Cr4V, W6Mo5Cr4V2
4	Cutting fluid	Clearedge EP 690 water-soluble cutting fluid, MCF-2012 micro-emulsion

TABLE 1. THE TYPE OF PROCESSING MATERIALS AND PROCESSING EQUIPMENT

Then, the related parameters are set and collected the relevant raw data and preprocessing the data-set. Getting the relevant characteristic attribute of carbon emissions and ranges, there are shown in TABLE 2.

property number	property name	Ranges
1	Workpiece hardness/HB	(97, 262, 200)
2	Tool material hardness/HRC	(63~81)
3	Tool rake angle/°	(-7,8~10,25~30)
4	Turning length/mm	(30~90)
5	Spindle speed/ $(r \cdot min^{-1})$	(150~2000)
6	Feed rate/ $(mm \cdot r^{-1})$	(0.05~0.4)
7	Depth of cut/mm	(0.5~2.4)
8	Part diameter/mm	(20~60)
9	Cutting time/s	(80~100)
10	Cutting fluid dosage/L	(30~40)
11	Machine standby power/W	(361,371)
12	Spindle rated power/kW	(5.5,7.5)
13	Coolant power/W	(0,132,270)
14	Carbon emission/g	(600~1400)

TABLE 2.THE VALUE RANGE OF THE FEATURE ATTRIBUTE OF THE MACHINING PROCESS OF THE MACHINE TOOL

Normalizing the filtered feature attribute data set, using the ridge regression feature selection algorithm to calculate the data set, and selecting seven main features, including: turning length, part diameter, cutting time, machine standby power, spindle rating power, spray coolant power and cutting fluid consumption.

Divide the data set into training set and test set, BP neural network by genetic algorithm optimized is used to train the training set data respectively, and then use the trained model to predict the test set. The parameters related to the model are set as follows:

(1) Setting of the initialization parameters of the genetic algorithm: the population size is 10; the maximum number of iterations is 1000; the crossover probability is 0.2; the mutation probability is 0.1.

(2) Setting of initialization parameters of BP neural network: the number of input neurons is 7, the number of output neurons is 1, the number of neurons in the hidden layer is related to many factors The minimum number of layers is 5. The input layer includes turning length, part diameter, cutting time, machine tool standby power, spindle rated power, cooling fluid power and cutting fluid consumption, and the output layer is carbon emissions, the network structure is 7-5-1. The learning rate is 0.09; the maximum number of iterations is 1000; the minimum performance gradient is 1e-5.

5.2 Analysis of results

The ridge regression algorithm is used to extract features from the above data. The generated ridge trace is shown in FIGURE 7, and the resulting data is shown in TABLE 3:

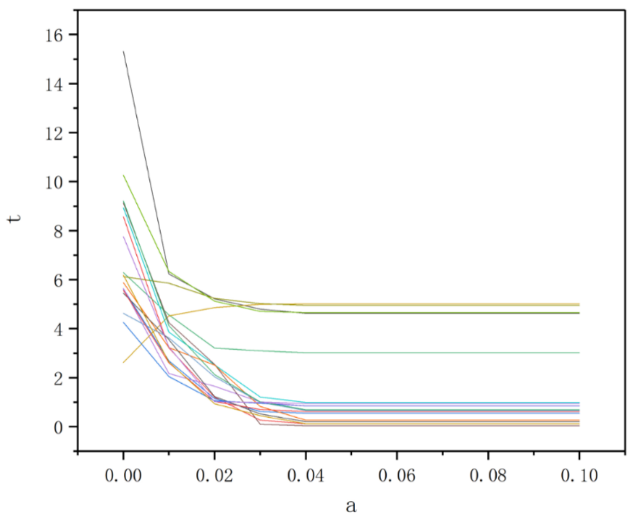

FIGURE 7. RIDGE TRACE

Variable	Parameter estimating	Standard error	t value	Pr>|t|
Intercept	-1.5639			
X1	0.5326	0.1523	4.625	2.36e-6
X2	0.0259	0.3056	0.233	0.2235
X3	0.3006	0.1101	0.556	0.1312
X4	0.1269	0.1056	3.012	2.42e-4
X5	-0.3533	0.2462	0.946	0.6568
X6	0.0265	0.1562	5.011	6.53e-6
X7	0.5548	0.3455	0.988	0.3254
X8	-0.2366	0.2014	0.045	0.2547
X9	0.1355	0.1806	4.956	1.53e-5
X10	0.1562	0.1256	0.265	0.4321
X11	0.4516	0.3625	0.663	0.3225
X12	0.6233	0.2325	4.652	3.36e-6
X13	-0.1289	0.1203	0.205	0.4136
X14	0.1568	0.1452	0.625	0.3354
X15	0.2645	0.3125	0.846	0.2526
X16	0.2255	0.2814	0.698	0.3111
X17	-0.3352	0.1002	0.852	0.1236
X18	0.1212	0.2042	0.125	0.4231
α	0.0326			

TABLE 3. RELATED PARAMETER VALUES

In FIGURE 7, when the α value is 0.03, all the ridge trace curves tend to be stable. The relevant parameter values are shown in TABLE 3. From the view of t value in table, when the α value is 0.0326, the impact of most variables are not large. From the view of p value, the variables below 0.05 are impacted, and corresponding this requirement factors are X1, X4, X6, X9, X12, and other variables are not impacted, so these five variables are extracted as characteristic factors, and others are removed. The selected five characteristic factors are: turning length, part diameter, spindle rated power, spray coolant power and cutting fluid consumption. And then the five characteristic factors will be used as the input variables of the GA-BP neural network prediction model for training and prediction.

The 370 groups data in data-set are used as training-set and 10 groups are used as testing-set, and GA-BP neural network is used to train the training-set.

Then, using the GA-BP neural network to predict the testing-set and compare it with the actual value. And the result of RMSE and MAPE are as follows.

Result: RMSE=12, MAPE=1.31%

In TABLE 4, the predicted and actual value of RMSE and MAPE are both relatively small, the RMSE value is 12 and the MAPE value is 1.31%. In this paper, it means that using the GA-BP neural network can achieve the target of accurate predict the test samples, and the validity and reliability of the data-driven model proposed in this paper are demonstrated.

Sample	Predictive value	Actual value	Absolute error	Relative error
1	928	940	12	1.28%
2	890	860	30	3.49%
3	901	890	11	1.24%
4	965	970	5	0.52%
5	1099	1100	1	0
6	800	792	8	1.01%
7	985	986	1	0.10%
8	1000	978	22	2.25%
9	1040	1050	10	0.95%
10	900	880	20	2.27%

TABLE 4. COMPARISION OF PREDICTION AND ACTUAL VALUES

6. CONCLUSION

Aiming at the problem of carbon emission prediction in the process of CNC lathe processing, this paper proposes a data-driven method, by the steps of raw data acquisition, data preprocessing, feature attribute preprocessing, feature selection, and energy consumption prediction to achieve the purpose of predicting carbon emissions in the machining process. This paper proposed a scheme of optimizing BP neural network by genetic algorithm to predict carbon emissions, the experimental results verify that this paper proposed the scheme that has high accuracy, and contributed new ideas to research in related fields.

The content of this paper is mainly based on the data-driven method to predict the carbon emissions in CNC machining process, which provides technical support and theoretical basis for research in this field. However, due to the CNC system is very complex, the research has limitations in this paper. For example, the processing parts are too simple in this experiment and few types of experimental equipment. Therefore, there still have some problems to be solved.

ACKNOWLEDGEMENTS

The authors would like to thank the support from the National Natural Science Foundation of China (NO.51975432).

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