Resource environment load prediction method for metal material machining based on process condition similarity matching

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Introduction: Resource environment load data are important for analyzing and improving the environmental performance, which are affected by the process condition of metal material machining processes. However, the environmental performance assessment in previous research focused on the results under the specific process conditions. The resource environment load data need to be re-collected when the process conditions are changed for a credible assessment, which is time- consuming and tedious.

Methods: This paper proposed a process condition- oriented prediction method of resource environment load data with limited samples. The significance of process condition elements on the resource environment load data was analyzed, and then the resource environment load was predicted according to the similarity between the process condition to be predicted and the existing process conditions.

Results and Dicussion: The results show that the average prediction accuracy of this method exceeds 90%, and further the accuracy for predicting the environmental performances using the predicted data is more than 93% which would help process designers to choose the better process condition for machining the metal materials.

KEYWORDS

environment performance, process condition, resource environment load, similarity matching, machining

1 Introduction

The manufacturing industry is the important pillar of world's economic development. Simultaneously, metal machining process also results in significant resource and energy depletion, accompanied the generation of a large amount of environmental waste in the form of solids, liquid, gas and airborne particulates (Du et al., 2020; He Y. et al., 2022). International Energy Agency (IEA) had reported that it is responsible for approximately 30% of global final energy consumption and over 20% of global CO_2 emissions (Agency, 2008). Consequently, to address on the environmental issues, environmental performances are evaluated based on the life cycle assessment (LCA) methodology which has been widely applied in the metal machining process to guide enterprises toward Green Manufacturing. The accuracy of the environmental performance results directly depends on the resource

environment load data in life cycle inventory (LCI) which is the second of four phases of the LCA methodology regulated by the ISO 14040 and ISO 14044 series of international technical standards (Ferrari et al., 2021). Therefore, it has become a crucial concern to obtain the reliable resource environment load data.

Resource environment load data in LCI for evaluating the environmental performances of metal machining process can be divided into primary data (when the data are obtained directly at the production sites and associated to the related process units) and secondary data (when the data come from databases, literature, estimates) (Ferrari et al., 2021). Some researchers have evaluated the environmental performances based on the secondary data. Bekker et al. evaluated the environmental performances of computer numerical control (CNC) milling according to the resource environment load data entries in SimaPro software (Bekker and Verlinden, 2018). He et al. investigated the environmental performances of an automotive fuel-line clip produced with recycled polyamide 12 from the selective laser sintering process in comparison to the conventional polyamide 66 counterpart, based on commercial LCA databases (He D. et al., 2022). Soares et al. conducted a comparative environment performance assessment between hobbing 20MnCr5 with minimum quantity lubrication and flood lubrication based on the data obtained from database provided by GaBi (Soares et al., 2022). Vukelic et al. monitored the negative environment impact of cutting processes through midpoint and endpoint assessment based on Ecoinvent database (Vukelic et al., 2020). In the above research, the environmental performances were predicted with the secondary data which mainly depend on material and process types (Narita et al., 2008). Once the material and process types are determined, the resource environment load data would be predicted to be the constant value. However, during the metal machining process, the resource environment load data are associated with the specific process conditions (Liu et al., 2022), which not only relate to the process type and material type, but also depend on process parameters, equipment, etc., (Khettabi et al., 2007; de Souza Zanuto et al., 2019; Wang et al., 2021). The change of process conditions will lead to the change of resource environment load. For example, the disc mechanism consumes 478% more energy than the two-cylinder mechanism on average to grind the single 2-m-long timber beams made of three wood species: ash, pine and spruce. (Warguła et al., 2022). Therefore, the secondary data without considering specific process conditions is unsuitable for accurate environmental impact assessment for the actual metal machining process (Dai et al., 2022).

Employing the reliable primary data obtained directly at production or experiment sites is critical for obtaining credible assessment results (Kalverkamp et al., 2020). Some researchers focused on the environmental performances considering the primary data. Afzal et al. had analyzed the environmental performances of three different welding processes based on the resource environment load data collected on site for welding 1 m long and 2.5 thick AISI 304 stainless steel sheets under given experimental conditions (Afzal et al., 2021). Pittner et al. conducted an environmental impact assessment using the resource environment load data obtained from experiments for different fusion welding processes of the shear test specimens and automotive cap profile under specified parameter settings, and the results showed that laser beam welding brings about up to 60% reduced environmental performances for both cases in comparison to the resistance spot

welding (Pittner and Rethmeier, 2022). Khanna et al. presented the comparison of dry and cryogenic LCO2 machining based on the collected data on the consumption of electricity and LCO2 for milling a slot with 1,000 mm. And the results show that considering all impact categories, more than 95% higher impacts have been generated in the case of LCO2 condition in comparison with dry machining (Khanna et al., 2022). Shah et al. evaluated the environment performance for drilling the Inconel 718 using cryogenic cutting fluids based on the collected primary data in each cutting test, and the representative impact category results at three different cutting speeds between the two cryogenic environments were obtained (Shah et al., 2021). However, these studies performed the environmental performance assessment using the primary data and these data are directly obtained under the given process conditions. Further, the resource environment load data in LCI is changeable in different process conditions. When the process condition change, new resource environment load data are required to assess the environmental impact of the metal machining process. Using the above methods, the resource environment load data needs to be re-collected when the process conditions are changed for a credible assessment, which is time-consuming and tedious. Therefore, the motivation for this research was to investigate the resource environment load data prediction under the new process condition for evaluating the environmental performances and further promoting the efficient improvement of metal machining process conditions.

Therefore, the major aim and novelty of this research is to effectively predict the resource environment load under changeable process condition and accurately evaluate the environmental performance. In this method, the process condition is introduced to comprehensively describe the process type, materials, processing mode, equipment, process parameters and other information during the metal machining process. And then, the resource environment load database is constructed based on the concept of process condition to store the collected data. Moreover, a process condition similarity matching method based on weighted Euclidean distance is proposed for predicting the resource environment load data of new process conditions with limited sample data. Finally, a case study was conducted to validate the proposed method. The predicted data can be used for assessing the environment performance under the new process condition for machining the metal materials.

2 Materials and methods

2.1 Resource environment load database construction

The actual production processes are complex and diverse, the process conditions are not identical in different processes. For example, in the cutting process, the type of material and processing method may be the same, while process parameter and equipment are different. However, different process conditions such as Equipment, Processing Modes, Material Types, Process Parameters, etc., may lead to different energy requirement, processing time, etc., These differences would further result in the changes of resource environment load data. Taking the same product as an example, the energy consumption and emissions generated by a small lathe and a large CNC lathe are different, while other process conditions are the same. Therefore, it is necessary to define and store the process conditions corresponding to the current resource environment

TABLE 1 Process condition elements of machining process and the explanations.

	Process condition elements	Explanation
1	Processing Type	Turning, Milling . . .
2	Material Types	Steel, Aluminum . . .
3	Equipment	Lathes, Milling machines . . .
4	Processing Modes	Dry cut, Wet cut . . .
5	Process Parameters	Feed speed, Cutting force . . .
6	Condition description	Time, Location . . .

load. The concept of process condition is used to comprehensively describe process conditions including information related to material, process parameters, processing mode, processing method, equipment and condition description. Table 1 shows the elements of the machining process condition and its explanation in detail as an example.

As shown in Table 1, the processing methods include milling, turning, etc., The processing materials include steel, aluminum, etc., The processing equipment may use lathes, milling machines, etc., The processing modes include wet cutting, dry cutting, etc., while the processing parameters in the processing process include Feed speed, Cutting force, etc., and the description of the current processing location and time.

Further, the ultimate purpose of the resource environment load in LCI is to evaluate the environmental problems caused by actual production, and reduce the degree which harm to the human body and the environment, and further to provide scientific and accurate evidences for process designers. Based on process condition description, the resource environment load can be analyzed in detail. The resource environment load usually includes the input of resources, energy and environmental output. Resource and energy input include the amount of process objects, the amount of auxiliary materials, and energy consumption; Environmental outputs include air pollution, water pollution, solid waste, and occupational health. The resource environment load is shown in Figure 1.

Specifically, the resource environment load under a process condition is mainly represented by the input and output model (IPO). For example, in the machining process, resource inputs include raw materials, energy inputs (mainly refer to electrical energy), and the output mainly includes finished workpieces, and some environmental pollutants (such as waste liquid, Gaseous waste, occupational hazards and so on). The above information is presented using the IPO diagram, as shown in Figure 2.

The type of resource environment load in the target condition can be clarified through the IPO diagram. When evaluating the environmental performances, the resource environment load data can be selected according to the demand for analyzing and assessing the resource environment load in the target condition. For example, if the purpose of studying resource environment load is to reduce human body damage, the main research resource environmental load indicators are occupational health, air pollution, etc., The selection of resource environment load indicators should follow a few principles.

- Systematic principle: the selection of indicators must be reasonable in hierarchy, which can comprehensively characterize the process environmental problems.
- The principle of quantification: the selection of indicators needs to consider the quantification of resource environment load, and the purpose of assessing environmental problems in actual process conditions can be achieved through monitoring and collecting the basic data of resource environment load.
- The principle of operability: During the selection of resource environment load indicators, it is necessary to take into account the operability to facilitate the evaluation of environmental indicators.
- The principle of independence: the indicators should avoid the intercorrelation. If they are related to each other, it will lead to unreasonable selection of indicators, which will increase the basic data collection workload of resource environment load,
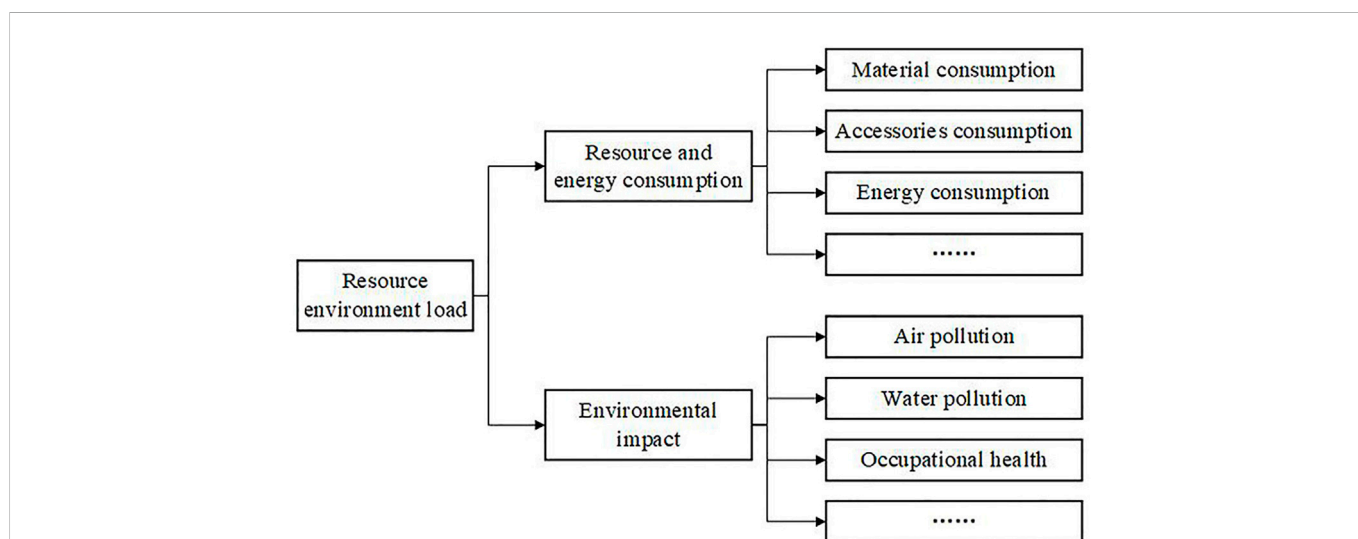
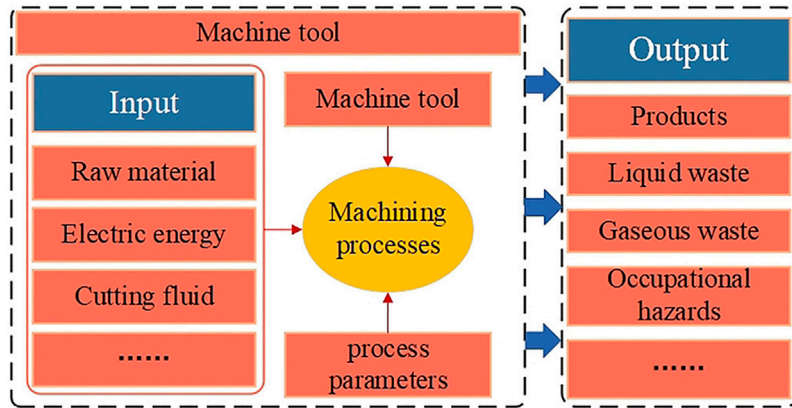

FIGURE 1
Resource environment load.

FIGURE 2
IPO model of the machining processes.
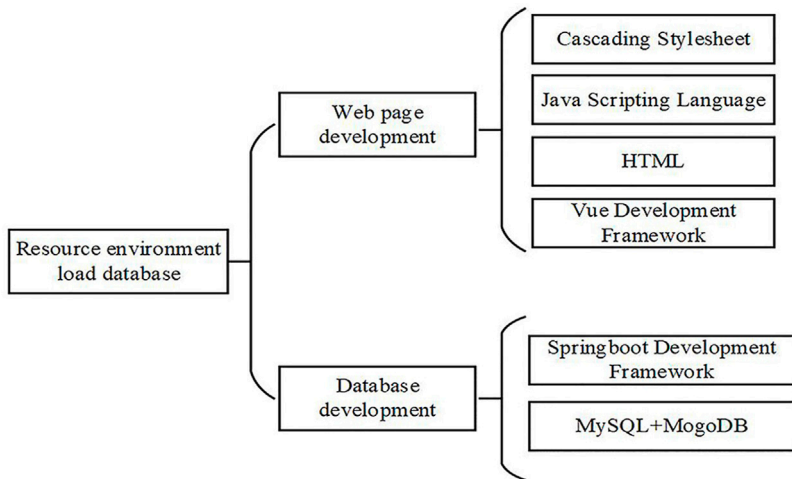
FIGURE 3
Database development technology system.

and ultimately affect the accuracy of resource environment load evaluation results.

Further, in order to ensure the accuracy of the environmental performances results, primary data at the production site are usually the basis of the evaluation. According to the input and output information described in the IPO diagram, the corresponding data are collected by sensors equipment such as power meters (measuring energy consumption), dust sensors (measuring the dust or oil mist, noise sensors, gas testers, etc.,). However, the resource environment load data collected by the sensor are difficult to structure in the actual process. Therefore, there is an urgent need to build a resource environment load database to manage resource environment load data.

In order to solve the above problems, this paper adopts B/S architecture to achieve WEB-based data access, and decouples the development of the front and back ends. The front-end page adopts

Html, Css and JavaScript development, and the progressive development framework Vue is selected to simplify the development process. The Vue framework abstracts the state and behavior of the view based on the MVVM model. The back-end mainly uses the Springboot development framework, and the data storage uses MySQL and MogoDB for data persistence. Implement user-oriented data sharing services and applications, and support dynamic data update and structured management. The database development technology system is shown in Figure 3.

2.2 Resource environment load prediction method

2.2.1 Prediction method framework

Considering the similarity of resource environment load data in homogeneous process conditions, this paper evaluates the resource

FIGURE 4
The framework of resource environment load prediction.
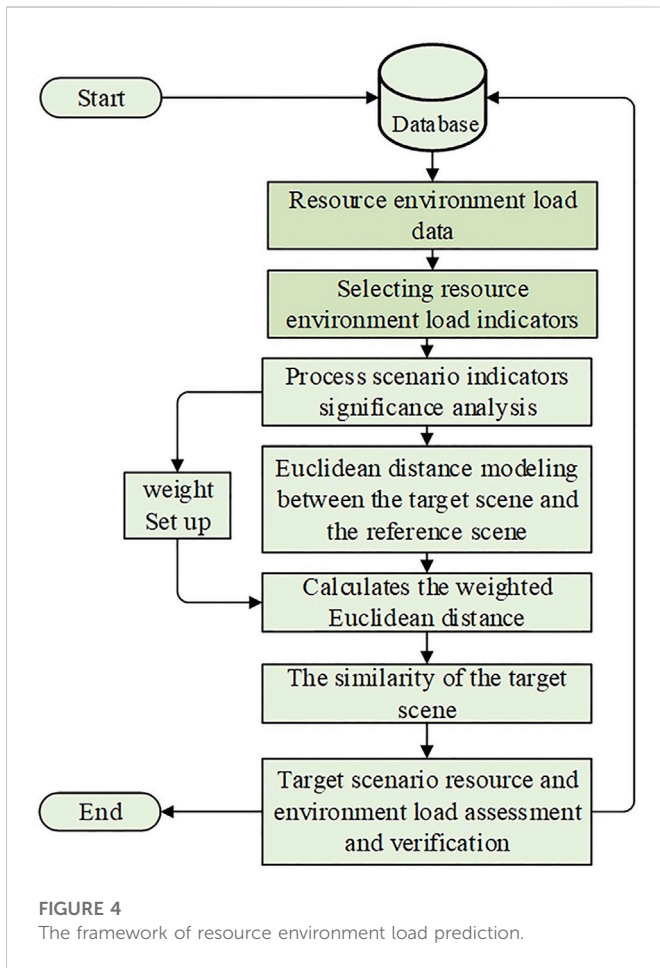
environment load corresponding to the target condition by matching the existing data. Based on this, a framework of evaluating the resource environment load for process conditions is constructed and shown in Figure 4.

The resource environment load prediction method for process condition flow is as follows: Firstly, select the data from the resource environment database and environmental indicators. Secondly, analyze the significance of each resource environment load indicators according to the data. Thirdly, according to the significance of the resource environment load indicator, set the relative weight of each indicator. Fourthly, the weighted Euclidean distance and similarity are calculated between the target condition and the reference condition according to the resource environment load indicators and the corresponding weights. Fifthly, select the resource environment load data corresponding to the process condition with the greatest similarity as the evaluation value of the new process condition. And then, verify the evaluation values and giving an explanation. Finally, store reasonable evaluation results.

2.2.2 Significance analysis of process condition

Different process condition elements have different impacts on resource environment load. Therefore, significance analysis is used to explore the significant impact of process condition elements on resource environment load. Assume that there is correlation between resource environment load y and $m (m \geq 2)$ process condition elements, and satisfies:

$$\begin{cases} y_j = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_m x_m + \varepsilon \\ \varepsilon \sim N(0, \sigma^2) \end{cases} \quad (1)$$

That is $y \sim N(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_m x_m, \sigma^2)$, where $\beta_0, \beta_1 \cdots, \beta_m, \sigma^2$ is an unknown parameter unrelated to $x_1, x_2 \cdots, x_m$, ε is an unobservable random variable.

In general, if there is no linear relationship between y and $x_1, x_2 \cdots, x_m$, then all the $\beta_i (i = 1, 2, \cdots, n)$ in the model are 0. Therefore, to test that there is linear relationship between y and $x_1, x_2 \cdots, x_m$ is to verify whether the hypothesis $H_0: \beta_0 = \beta_1 \cdots = \beta_m = 0$ is true.

It can be seen from $S_T = S_E + S_R$ that the larger S_E is, the smaller S_R is, which means the closer the linear relationship between a and b is, where S_T, S_R, S_E represent sum of square of deviations, Residual Sum of Squares, Explained Sum of Squares respectively. Therefore, it is conceived to test hypothesis H_0 with the ratio of S_E/S_R as a statistic. So it is necessary to determine the distribution of the test statistics.

$$S_T = \vec{Y}^T \vec{Y} = \|\vec{Y}\| = \sum (y_i - \bar{y})^2 \quad (2)$$

$$S_R = \sum (y_i - y_i)^2 \quad (3)$$

$$S_E = \sum (y_i - \bar{y})^2 \quad (4)$$

In this model, if the hypothesis H_0 is true, where the following is true:

$$\frac{S_E}{\sigma^2} \sim \chi^2(m)$$

$$S_R/\sigma^2 \sim \chi^2(n - m - 1)$$

$$F = \frac{\frac{S_E}{m}}{\frac{S_c}{(n-m-1)}} = \frac{S_E}{S_c} \cdot \frac{n - m - 1}{m} \sim F(m, n - m - 1) \quad (5)$$

Where F is the statistic that tests hypothesis H_0, so for a given significance level α, the F-value calculated from the sample detection value. If $F_i \geq F_a(1, n - m - 1)$, the tests hypothesis H_0 will be rejected, that is, the regression effect is considered significant; Otherwise, accept H_0, that is, the regression effect is considered not significant. When the overall regression effect is verified, it is also necessary to test whether each process condition element x_i has a significant linear impact on the resource environment load data.

2.2.3 Process condition similarity matching based on weighted euclidean distance

Euclidean distance method can reflect the absolute difference of different sample characteristics, which mostly used to analyze the difference in the size of dimension values (Terrados-Cristos et al., 2021). In a multidimensional data spatial structure, Euclidean distance is a method for measuring the spatial distance of two vectors. The magnitude of the Euclidean distance reflects the degree of similarity between the two vectors, i.e. the smaller the value, the smaller the difference between the two vectors (Ji and Ni, 2022).

First of all, the coordinates of the p-dimensional vector (i.e., the vector composed of process condition factors) of the reference condition M and the target condition N as follows:

$$M_x = (x_{m1}, x_{m2}, \cdots, x_{mp}) \quad (6)$$

$$N_x = (x_{n1}, x_{n2}, \cdots, x_{np}) \quad (7)$$

According to the concept of Euclidean distance, the distance d_{MN} between the reference condition and the target condition can be

TABLE 2 Resource environment load data with different process conditions.

	V_c (m/min)	f (mm/r)	ap (mm)	ae (mm)	CC	Noise (dB)	PM (g)	Carbon emission (g)
M1	90	0.2	0.8	2.5	1	82	108.00	114.23
M2	165	0.2	1.2	4	1	82	138.33	49.00
M3	115	0.28	0.8	4	1	85	118.00	77.43
M4	140	0.2	2	3.5	1	86	134.67	51.75
M5	140	0.24	1.6	4	1	89	101.33	88.67
M6	90	0.24	1.2	3	1	84	100.00	66.40
M7	140	0.28	1.2	2.5	1	85	95.30	79.78
M8	115	0.32	1.2	3.5	1	86	88.67	62.77
M9	165	0.24	0.8	3.5	1	84	98.33	70.80
M10	165	0.32	1.6	2.5	1	87	92.00	104.95
M11	90	0.28	1.6	3.5	1	85	90.30	154.08
M12	140	0.32	0.8	3	1	96	98.00	55.80
M13	115	0.2	1.6	3	1	84	88.33	62.95
M14	90	0.32	2	4	1	90	78.00	76.01
M15	115	0.24	2	2.5	1	88	86.00	64.96
M16	165	0.28	2	3	1	89	112.33	37.21
M17	90	0.2	0.8	2.5	2	94	90.67	230.08
M18	165	0.2	1.2	4	2	106	101.00	100.49
M19	115	0.28	0.8	4	2	90	90.33	173.11
M20	140	0.2	2	3.5	2	104	88.67	181.81
M21	140	0.24	1.6	4	2	102	84.67	101.20
M22	90	0.24	1.2	3	2	88	79.00	185.53
M23	140	0.28	1.2	2.5	2	101	85.67	240.80
M24	115	0.32	1.2	3.5	2	100	88.00	161.91
M25	165	0.24	0.8	3.5	2	97	98.00	157.98
M26	165	0.32	1.6	2.5	2	106	85.67	185.94
M27	90	0.28	1.6	3.5	2	89	89.33	165.25
M28	140	0.32	0.8	3	2	92	99.00	154.69
M29	115	0.2	1.6	3	2	88	85.67	282.19
M30	90	0.32	2	4	2	101	83.33	157.50
M31	115	0.24	2	2.5	2	94	93.67	138.67
M32	165	0.28	2	3	2	105	106.67	165.51

obtained, as expressed in formula 8. Further, the process condition similarity (PCS) is used to describe the similar between the reference condition and the target condition as expressed in formula 9 (Xu and Zhen-jun, 2005):

$$d_{MN} = \sqrt{\sum_{i=1}^{p} (x_{mi} - x_{ni})^2} \tag{8}$$

$$PCS = 1 - d_{MN} \tag{9}$$

However, in the traditional Euclidean distance method, all variables in the similarity matching model are treated equally and consistently. In fact, the similarity between the corresponding elements should be fully considered. For example, in the machining process, the cutting speed has a greater impact on noise and significantly less on carbon emissions. Therefore, it is more practical to consider the weight based on the significance of each variable.
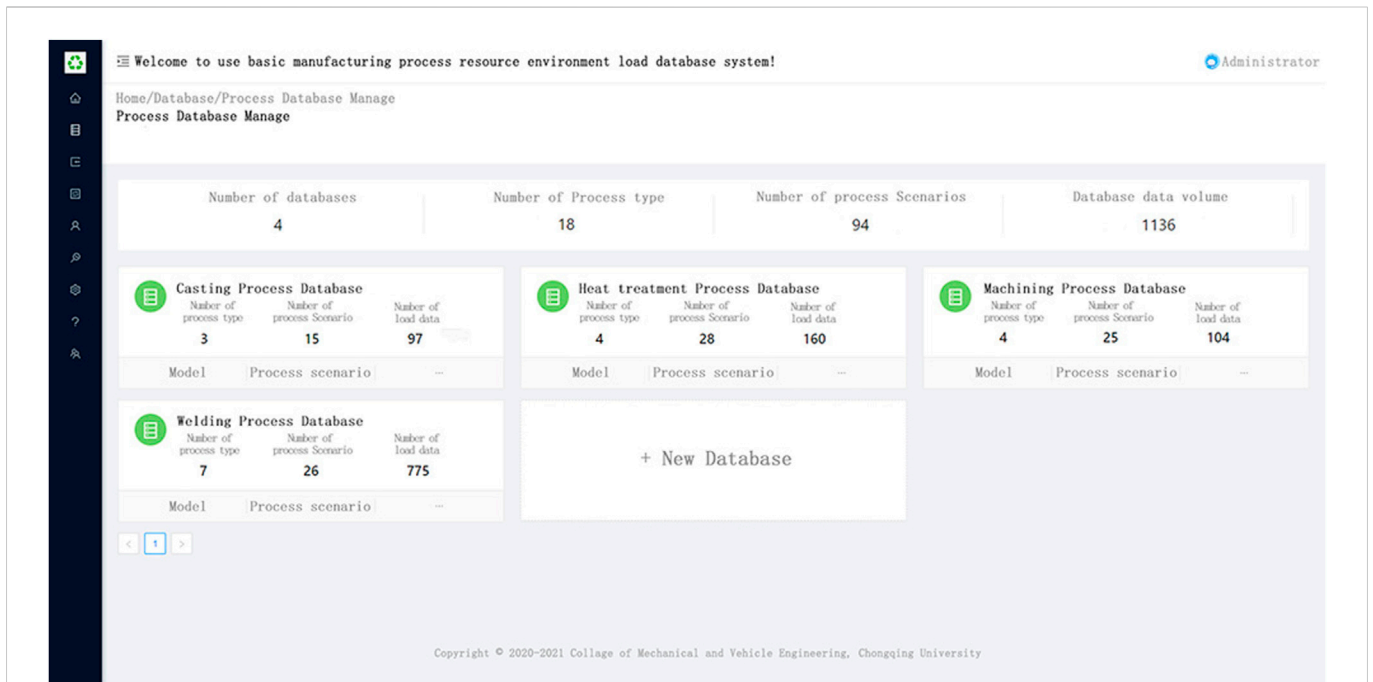
FIGURE 5
Resource environment load database interface.
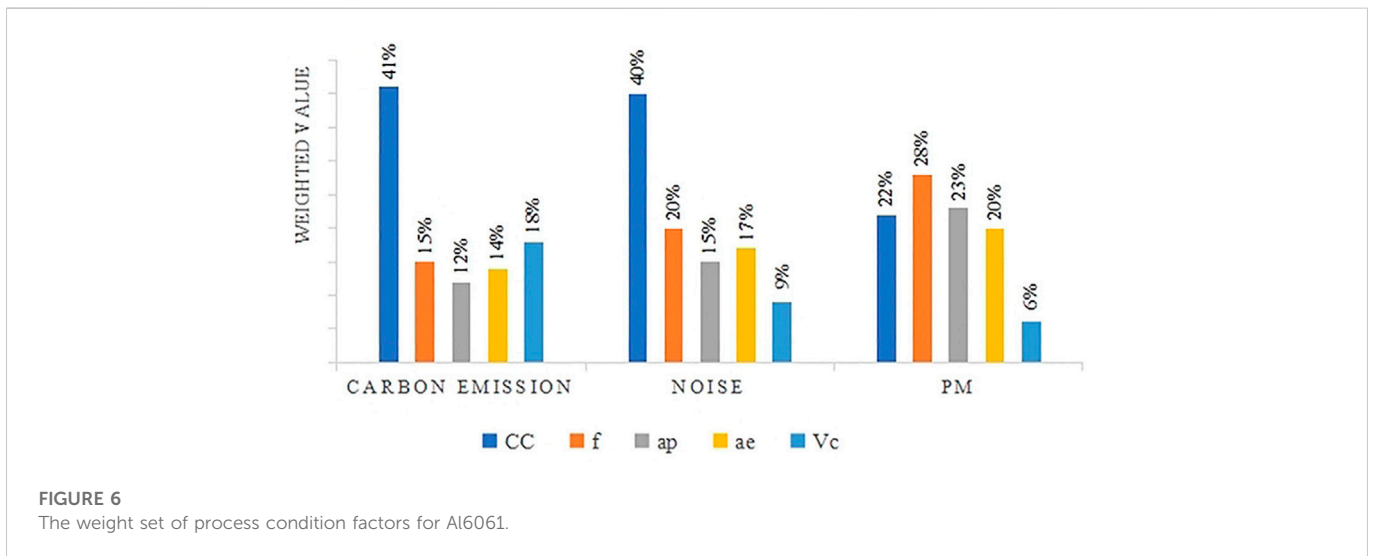
FIGURE 6
The weight set of process condition factors for Al6061.

TABLE 3 The range analysis results of resource environment load corresponding to Al6061 process condition.

Resource environment load	V_c	f	ap	ae	CC
Carbon Emission (g)	34.6	27.4	34	42	97
Noise (dB)	5.4	4	4.6	2.4	10.9
PM (g)	14.2	11.9	10.4	3.2	11.1

Assuming that there are q resource environment load indicators corresponding to process conditions M and N, which are represented by $y_j, j = 1, 2, ..., q$. The weighted Euclidean distance between process conditions M and N can be expressed as follows:

$$d_{M_j N_j} = \sqrt{\sum_{i=1}^{p} w_{ij} \left(\frac{x_{mi} - x_{ni}}{S_i} \right)^2} \qquad (10)$$

where w_{ij} is the weight that x_{mi} corresponds to the resource environment load indicator y_j, and $w_{ij} > 0, i = 1, 2, \cdots p; j = 1, 2, ..., q;$ S_i represents the standard deviation of each dimension; x_{mi} is the normalized indicator value, which can be expressed as follows:

TABLE 4 The matching results corresponding to N1.

Reference condition	Carbon emission		Noise		PM	
	$d_{M_jN_j}$	Similarity	$d_{M_jN_j}$	Similarity	$d_{M_jN_j}$	Similarity
M1- N1	0.381	0.619	0.396	0.604	0.453	0.547
M2- N1	0.323	0.677	0.326	0.674	0.375	0.625
M3- N1	0.303	0.697	0.276	0.724	0.291	0.709
M4- N1	0.274	0.726	0.291	0.709	0.341	0.659
M5- N1	0.237	0.763	0.185	0.815	0.181	0.819
M6- N1	0.208	0.792	0.260	0.740	0.306	0.694
M7- N1	0.237	0.763	0.187	0.813	0.182	0.818
M8- N1	0.210	0.790	0.227	0.773	0.278	0.722
M9- N1	0.264	0.736	0.303	0.697	0.347	0.653
M10- N1	0.323	0.677	0.326	0.674	0.375	0.625
...	...	...	...	...	...	...
M31- N1	0.725	0.275	0.690	0.311	0.551	0.449
M32- N1	0.710	0.290	0.701	0.299	0.582	0.418

TABLE 5 Prediction accuracy for N1.

	Prediction value	Experimental value	Matched condition	Accuracy (%)
Carbon Emission (g)	66.4	71.8	M6	92.5
Noise (dB)	89	82	M5	91.5
PM (g)	101.3	115	M5	88.1

$$x_{mi} = \frac{x - m}{s} \qquad (11)$$

where x is the original data value, m is the mean of each dimension, and s is its standard deviation.

It can be seen from the formula 10 that under the condition of sample determination, the calculation result of the Euclidean distance is proportional to the corresponding weight. However, giving weights to individual variables characterizes the subjectivity of the decision maker to the variables, but the completely subjective Euclidean distance calculation lacks the professionalism and credibility in the field. Therefore, objective weights need to be given to individual variables.

Taking the analysis result as the objective basis for determining the weight of each variable, if the range R_{ij} is the value of the jth variable corresponding to the ith resource environment load indictor, the weight that the jth variable corresponding to the ith resource environment load indicator and the similarity between the reference condition and the target condition can be expressed as follows:

$$w_{ij} = \frac{R_{ij}}{\sum\limits_{i=1}^{p} R_{ij}} \qquad (12)$$

$$PCS_{M_jN_j} = 1 - d_{M_jN_j} \qquad (13)$$

According to the results of similarity calculation, the data of resource environment load corresponding to the process condition

with maximum similarity is used as the evaluation value of the new process condition. With the continuous enrichment and expansion of the process condition library, the accuracy of matching results can be further improved.

3 Results

3.1 Resource environment load data collection

Aluminum alloy materials are widely used metal material in the manufacturing industry, and it is of great significance to conduct environmental performance assessment during machining process. Therefore, in order to verify the accuracy and effectiveness of proposed method, an experiment which use VCML850 to mill aluminum alloy Al6061 on a CNC machine tool was conducted.

Due to the equipment is generally selected according to the process type, the resource environment load data is collected considering the process parameters, processing methods and other factors when processing aluminum alloy Al6061. Therefore, according to the systematic principle, quantitative principle, independence principle and operability principle of resource environment load data, noise, dust and carbon emission are selected as the resource environment load data in

TABLE 6 The matching results corresponding to N2.

Reference condition	Carbon emission		Noise		PM	
	$d_{M_jN_j}$	Similarity	$d_{M_jN_j}$	Similarity	$d_{M_jN_j}$	Similarity
M1- N2	0.622	0.378	0.638	0.363	0.726	0.274
M2- N2	0.363	0.638	0.393	0.607	0.476	0.524
M3- N2	0.370	0.630	0.408	0.592	0.460	0.540
M4- N2	0.309	0.691	0.335	0.665	0.419	0.582
M5- N2	0.204	0.796	0.217	0.783	0.266	0.734
...	...	...	...	...	...	...
M16- N2	0.242	0.758	0.197	0.803	0.198	0.802
...	...	...	...	...	...	...
M31- N2	0.788	0.212	0.738	0.262	0.622	0.378
M32- N2	0.702	0.298	0.662	0.338	0.508	0.492

TABLE 7 The matching results corresponding to N3.

Reference condition	Carbon emission		Noise		PM	
	$d_{M_jN_j}$	Similarity	$d_{M_jN_j}$	Similarity	$d_{M_jN_j}$	Similarity
M1- N3	0.761	0.239	0.746	0.254	0.651	0.349
M2- N3	0.734	0.266	0.711	0.289	0.600	0.401
...	...	...	...	...	...	...
M20- N3	0.274	0.726	0.291	0.709	0.341	0.659
M21- N3	0.237	0.763	0.185	0.815	0.181	0.819
M22- N3	0.208	0.792	0.260	0.740	0.306	0.694
M23- N3	0.237	0.763	0.185	0.815	0.183	0.817
...	...	...	...	...	...	...
M31- N3	0.303	0.697	0.276	0.724	0.291	0.709
M32- N3	0.264	0.736	0.303	0.697	0.347	0.653

TABLE 8 The resource environment load evaluation results for N2 and N3.

Process condition	N2			N3		
	Prediction value	Experimental values	Matched condition	Prediction value	Experimental values	Matched condition
Carbon Emission (g)	88.7	83.7	M5	185.5	172.7	M22
Noise (dB)	89	82	M16	102	94	M21
PM (g)	112.3	106	M16	84.7	76.3	M21

this case study. During the experimental, milling speed Vc, feed speed f, milling depth ap, milling width ae, two types of cutting condition (CC), dry cut and wet cut (represented by 1 and 2, respectively), were selected as the process condition elements. The resource environment load data under the different process conditions are shown in Table 2.

Further, the resource environment load database interface is shown in Figure 5. The data can be stored in the database after

TABLE 9 The accuracy verification results of prediction method.

Process conditions	N1	N2	N3	Average accuracy (%)
	Accuracy (%)	Accuracy (%)	Accuracy (%)	
Carbon Emission	92.5	94.1	92.6	93.0
Noise	91.5	91.5	91.5	91.5
PM	88.1	94.0	89.0	90.4

TABLE 10 Environmental performances of N1,N2,N3.

Category	N1		N2		N3	
	Result using predict data	Result using actual data	Result using predict data	Result using actual data	Result using predict data	Result using actual data
ADP fossil	1.73×10^{-13}	1.63×10^{-13}	3.40×10^{-13}	3.12×10^{-13}	5.73×10^{-13}	5.11×10^{-13}
AP	1.41×10^{-13}	1.33×10^{-13}	2.48×10^{-13}	2.33×10^{-13}	4.04×10^{-13}	3.76×10^{-13}
FAETP	2.53×10^{-14}	2.38×10^{-14}	4.43×10^{-14}	4.15×10^{-14}	7.23×10^{-14}	6.74×10^{-14}
GW	1.66×10^{-13}	1.57×10^{-13}	3.02×10^{-13}	2.81×10^{-13}	4.96×10^{-13}	4.56×10^{-13}
HTP	1.70×10^{-12}	1.60×10^{-12}	2.88×10^{-12}	2.71×10^{-12}	4.62×10^{-12}	4.38×10^{-12}
TETP	4.44×10^{-14}	4.17×10^{-14}	7.56×10^{-14}	7.12×10^{-14}	1.22×10^{-13}	1.15×10^{-13}

*ADP, Fossil: Abiotic Depletion; AP, acidification potential; FAETP, freshwater aquatic ecotoxicity pot; GW, global warming potential; HTP, human toxicity potential; TETP, terrestric ecotoxicity potential.

TABLE 11 The accuracy of total environmental impact using resource environment loading prediction data and actual data.

Process condition	The total environmental performances using prediction values	The total environmental performances using actual values	Accuracy (%)
N1	2.25×10^{-12}	2.12×10^{-12}	93.81
N2	3.89×10^{-12}	3.65×10^{-12}	93.39
N3	6.29×10^{-12}	5.91×10^{-12}	93.53

transmitting to the data processing analysis system. The role of the database is mainly to realize the management of the basic data of the resource environment load by using a graphical user interface, which can be more intuitive to manage the data. When it is necessary to evaluate the resource environment load of the actual process condition or optimize the process condition, the database can provide a reference base data inventory.

3.2 Resource environment load prediction results
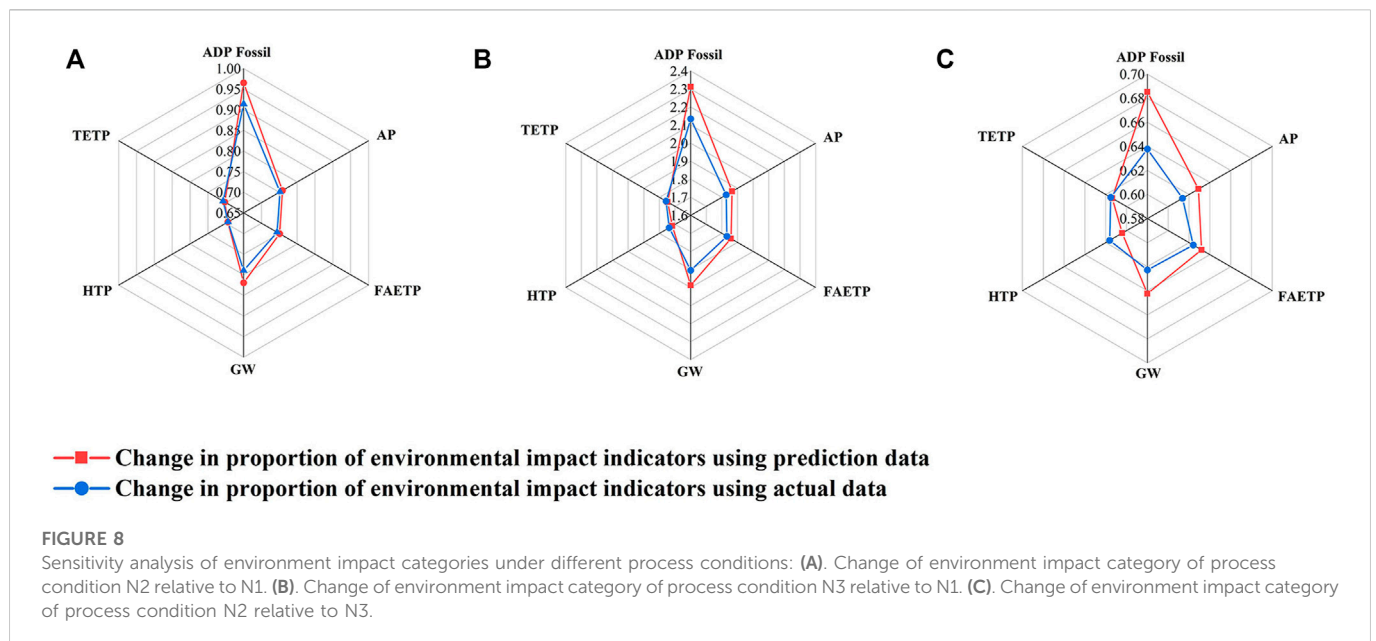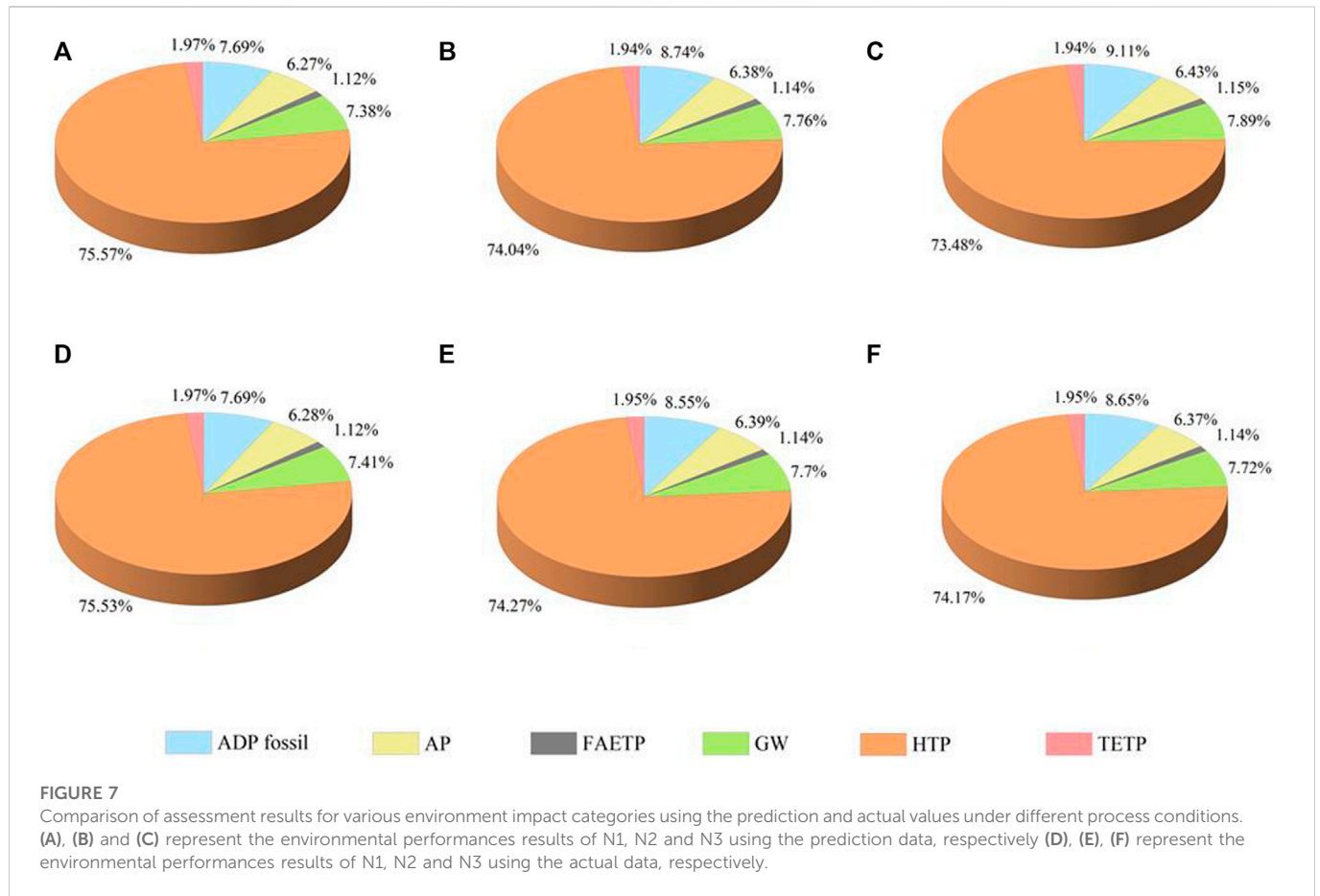
3.2.1 Significance analysis results

According to the framework in Section 2.2, it is first necessary to analyze the significance of the elements on the resource environment load in the process condition. Milling Al6061 process condition data is analyzed for significance and extreme range analysis, and the results are collated as shown in Table 3. Through the analysis of the range value, it can be seen that the influence of process condition elements on the carbon emission is shown as follows: $CC > ae > Vc > ap > f$ for carbon emission; For noise, $CC > Vc > ap > f > ae$; With regard to PM,

$Vc > f > CC > ap > ae$. Therefore, the reasonable process condition must be taken seriously to reduce the resource environment load.

According to the formula 12, the significance of variable i of each dimension on each resource environment load can be calculated. The weight of variable x_i corresponds to the resource environment load y_j is w_{ij}, and the weight set of each factor corresponding to the process condition is shown in Figure 6. For carbon emission, the maximum weight is given to CC with 41%, and the minimum weight of milling width is 12%; For noise, the CC has the greatest impact on it, with a weight of 40%, while the milling speed has the lowest impact, with a weight of 9%. As for PM, feed speed has the highest impact, accounting for 28%, while spindle speed has the lowest impact, with a weight of 6%.

3.2.2 Process condition similarity calculation results

Process condition similarity calculation is the premise and core of resource environment load prediction. Before calculating similarity, it is necessary to determine the raw data of the reference condition, and standardize the raw data according to the formula 11. Taking the reference condition sample M1 shown in Table 2 as an example, the information can be expressed as M1 = (90, 0.2, 0.8, 2.5, 1).

FIGURE 7
Comparison of assessment results for various environment impact categories using the prediction and actual values under different process conditions.
(A), **(B)** and **(C)** represent the environmental performances results of N1, N2 and N3 using the prediction data, respectively **(D)**, **(E)**, **(F)** represent the environmental performances results of N1, N2 and N3 using the actual data, respectively.

FIGURE 8
Sensitivity analysis of environment impact categories under different process conditions: **(A)**. Change of environment impact category of process condition N2 relative to N1. **(B)**. Change of environment impact category of process condition N3 relative to N1. **(C)**. Change of environment impact category of process condition N2 relative to N3.

With Al6061 as the processing material, the set of process condition N1 = (130, 0.26, 1.4, 3.25, 1), were selected as object process condition. The resource environment data under different process conditions stored in database are selected. Then, the weighted Euclidean distance results are used to represent the similarity between the object process condition to be predicted and the reference process

conditions. The matching result is shown in Table 4. According to the matching results, the reference process conditions with the greatest similarity to the condition N1 is M6 when predicting the carbon emission. The reference process conditions with the greatest similarity for noise and PM are both M5.

In order to demonstrate the accuracy of the proposed prediction method, the prediction values of each indicator are compared to the experimental values as shown in Table 5. The prediction accuracy of carbon emissions, noise, and PM for N1 are 92.5%, 91.5%, and 88.1% respectively. Besides, the Ecoinvent database was taken as reference to estimate the resource environmental data for N1. The result showed that the carbon emission is 46.3 g. Accordingly, the accuracy of the proposed method for predicting the carbon emission is more than the one of Ecoinvent database. However, Ecoinvent database lacks the noise and PM data which results in that these two types of resource environment load cannot be predicted. Therefore, the proposed prediction method has the higher accuracy for predicting the resource environment load and more types can be analyzed, comparing to the Ecoinvent database.

4 Discussion

4.1 Robust of the prediction method

In order to prove the robust of the proposed prediction method, another two sets of process conditions N2 = (150, 0.3, 1.8, 3.75, 1), and N3 = (130, 0.26, 1.4, 3.25, 2) were selected as object process conditions to test the effectiveness of the method. The weighted Euclidean distance results are used to represent the similarity between three process conditions to be predicted and the reference process conditions. The calculation results are shown in Tables 6, 7.

According to the matching results in Tables 6, 7, the reference process conditions with the greatest similarity to the conditions N2 and N3 are M5 and M22, respectively when predicting the carbon emission. When predicting noise, the reference process conditions with the greatest similarity with the conditions N2 and N3 are M16 and M21 respectively. When predicting PM, the reference process conditions with the greatest similarity with the conditions N2 and N3 are M16 and M21, respectively. The similarity matching results of the process conditions to be predicted, along with predicted and experimental values of their resource environment loads are shown in Table 8.

After experimental verification, Table 9 shows the accuracy verification results of the prediction method. The average prediction accuracy of carbon emissions, noise, and PM was 93%, 91.5%, and 90.4% respectively, all exceeding 90%. It can be seen that the proposed prediction method is efficient and robust for predicting the resource environmental data of different process condition.

4.2 Environmental impact analysis with the predicted resource environmental data

According to the existing resource environment load data obtained for the new process conditions, the environmental performances of the new process conditions are assessed by using the LCA methodology, which is a widely used method of conducting environmental impact assessments of products or processes standardized in ISO14040 and ISO14044 (International Organization for Standardization, 2006; La

Rosa et al., 2018). Accordingly, the environmental performances are evaluated by prediction data and experimental data, and the normalized results of six environmental impact categories are shown in Table 10.

Table 11 illustrates the results of total environment performance assessment using resource environment load predict data and actual data respectively for process conditions N1, N2 and N3. It could be seen that the total environmental impact assessment result using the prediction value is close to the assessment result using the actual value. The accuracy of the total environmental impact assessment results using the prediction values for the three scenarios N1, N2 and N3 are 93.81%, 93.39% and 93.53% respectively. The results show that the method has a high accuracy and the data which predicted by similarity matching can be used to conduct environmental impact assessment.

Based on the data in Table 10 and Figure 7 shows the comparison of the percentage of various environment impact categories. Taking the process condition N1 as an example, it is seen that the evaluated percentage for each environment impact category is almost equal to the actual one, as shown in the Figures 7A, 7D. The maximum environment impact category under process condition N1 is HTP, which accounts for about 75.6% of the total environmental impact. About 7.7% of the total environmental impact is consumed by the ADP fossil, which is the secondary maximum impact category. The impact of the GW and AP cannot be ignored due to environment performance of about 7.4% and 6.3% respectively, while the environment performance for the FAETP is the lowest. The process condition N2, N3 can be analyzed in the same way.

Figure 8 shows sensitivity analysis of environment impact categories under different process conditions using the data in Table 10. It can be drawn that the change proportion of environmental impact category under different process conditions presents the similar results. As can be seen from Figure 8A, the maximal variation indicates that the ADP Fossil is most sensitive to the change of conditions from N1 to N2. Moreover, the same conclusion is obtained corresponding to the change of conditions from N2 to N3. However, the influence of the change of conditions from N3 to N1 on several environment impact categories are similar. These analyses can provide guidance for adjusting process conditions to improve certain environment performance.

5 Conclusion

Resource environment load data are very important for predicting environmental performances of the metal machining process. In this paper, a method based on process condition is proposed to predict the resource environment load data. In the proposed method, the process condition is introduced to comprehensively describe the process type, materials, processing mode, equipment, process parameters and other information of the metal machining process. A resource environment load database based on process condition is developed to store the collected data. After that, a process condition-oriented resource environment load prediction method is proposed, which uses the weighted Euclidean distance method for evaluating the resource environment load data. The results shows that the proposed method is effectively applied to predict the resource environment load under changeable process condition, providing basic data for analyzing and optimizing process condition. In addition, for the evaluated results of environmental performances of the metal material machining process, the accuracy for predicting total environmental performances using the predicted

data is more than 93%. Considering the three different process conditions, it can be seen that the largest total environmental performances using the prediction values is under the N3 which agrees with the experimental values. The method is efficient and practical to evaluate the environment performances of different process conditions to help process designers make robust decisions in choosing a better process condition for machining the metal materials. Further, the future work may focus on the influence of quantities of the data sets on the prediction results and the comparison with different data-driven methods.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

Writing—original draft, ZX and HD; Writing—review and editing, YL and HD; methodology and investigation, JX, ZX, and JZ; conceptualization, project administration, supervision, ZX and YL All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

HD was employed by Shanghai Aerospace Equipments Manufacturer Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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