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Uncertainty Study and Parameter Optimization of Carbon Footprint Analysis for Fermentation Cylinder

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Abstract: With the rapid development of industry, problems for the ecological environment are increasing day by day, among which carbon pollution is particularly serious. Product carbon emission accounting is the core of sustainable green design. In this paper, the beer fermentation cylinder is taken as an example for low carbon design to get the best combination of design parameters when the carbon emission is the smallest. The life cycle assessment method is used to calculate the carbon footprint of products. In order to analyse the uncertainty and sensitivity of the method, an uncertainty analysis method using data quality characteristics as input of Monte Carlo is proposed. Sensitivity analysis is carried out by multivariate statistical regression and Extended Fourier Amplitude Sensitivity Test (EFAST). The system boundary of fermentation cylinder is determined and the carbon emissions of life cycle are calculated. The quality characteristics of life cycle inventory data (LCI) data are analysed and Monte Carlo simulation is carried out to quantify the uncertainty of LCI. EFAST is used to calculate the sensitivity of LCI and the results are compared with those of multivariate statistical regression to verify the feasibility of the method. Finally, response surface methodology (RSM) is used to optimize the design of parameters. It provides guidance for the establishment of product carbon emission model and low carbon design.

Keywords: carbon footprint; LCA; uncertainty analysis; sensitivity analysis; fermentation cylinder

1. Introduction

Since the beginning of the 21st century, with the progress of society and the rapid development of industry, a series of environmental problems have been brought about, especially carbon emissions. “Carbon Footprint” is a clear method and technology to determine and measure the carbon equivalent emissions of total greenhouse gas emissions in the supply chain process steps of each product or activity [1]. Most scholars use LCA method to calculate this value [2]. LCA strictly adheres to ISO14010, standards which provide the principles and scope of life cycle assessment and some methodological requirements for LCA research [3]. But LCA method also has some shortcomings [4], among which uncertainty is the main problem affecting the calculation results of carbon footprint, especially the input list. As the original calculation data, due to the uncertainty of data time, source, technology and other related factors, the calculation results bring certain errors.

At present, domestic and foreign scholars have made exploratory research on calculating carbon footprint of products based on LCA. Scholars Heijungs [5] proposed LCI model based on matrix and process and determined the propagation effect of multi-parameter uncertain fuzzy. This is the name of a Dutch author input. Sugiyama [6] used standard statistics to analyse the uncertainty of industrial LCI database. Zhu [7] used linear regression to analyse the inventory data and got the

influence of uncertainty on the final results and validated it with dishwasher as an example. Huang [8] made a quantitative evaluation and proposed to control the data quality of LCA by the CLCD. She conducted two simulation tests and then got the uncertainty of inventory data by Monte Carlo. Through sensitivity analysis, she got the key data with high sensitivity. Chen [9] established the analysis model of sensitivity and uncertainty of DQI-Monte Carlo and analysed the quality of carbon footprint data. She selected the key data affecting the reliability of the evaluation results and put forward suggestions to improve the quality of the data, optimized them and reduced the uncertainty of the carbon footprint evaluation results. Domestic and foreign scholars have little research on the carbon footprint of beer fermentation equipment. Cimini [10] analysed the carbon footprint of beer with different packaging specifications in the industrial production process and its impact on the environment and analysed the sensitivity of basic data. Alistair [11] simulated and optimized the fermentation process of beer and realized the model calculation of industrial beer fermentation process. Yang [12] calculates the carbon footprint of domestic beer from raw materials, factory production, packaging and other aspects by life cycle assessment, which lays the foundation for establishing the calculation model for the beer carbon footprint. Gao [13] systematically analysed the process of beer brewing process and carbon equivalent emissions from auxiliary materials, utilities, sewage treatment and internal logistics and obtained carbon equivalent emissions from beer production, packaging and transportation. However, the quantitative values of uncertainty and sensitivity of LCI have not been obtained from the above studies and little research has been done on the carbon footprint of beer fermentation equipment.

This paper makes up for the shortcomings of previous studies based on the above research. Firstly, the uncertainty and sensitivity of LCI are quantified and the data quality characteristics of LCI are also analysed. Then the analysis results are used as Monte Carlo input for simulation experiments. Meanwhile, multivariate statistical regression and EFAST methods are used for sensitivity analysis to obtain highly sensitive variables. In order to realize the low-carbon design of beer fermentation cylinder and analyse the influence of design parameters on the carbon footprint, the RSM method is used to carry out parameter optimization test and analysis and the optimal combination of design parameters of the beer fermentation cylinder with the smallest carbon footprint is obtained.

2. Carbon Footprint Analysis of Beer Fermentation Cylinder

2.1. The Calculating Process of Carbon Footprint

Carbon footprint of products refers to carbon equivalent emissions from raw material acquisition to the end of life throughout the life cycle [14]. The system boundary of beer fermentation cylinder is shown in Figure 1. Other smaller parts have little influence on the calculation results of carbon footprint, which can be neglected [15]. The 25-year service life can be selected as the functional unit for calculating the carbon footprint of beer fermentation cylinder. Since the energy consumption of beer fermentation stage cannot be distinguished from that of other stages, the energy consumption of fermentation cylinder accessories is taken as the basis for calculating carbon footprint.

2.2. Analysis of Carbon Footprint Calculation Results

Based on the field survey and literature collection, the carbon equivalent emission factor and the LCI of beer fermentation cylinder are obtained as shown in Table 1.

In this paper, LCA method is used to calculate the carbon footprint of products. PAS2050 is used as the calculation standard of carbon footprint. The raw material and energy consumption of the product, the direct emission of greenhouse gases in the manufacturing process and other factors are taken into comprehensive consideration. The raw material and energy acquisition, manufacturing, transportation, use, recycling and treatment stages of the product are quantitatively analysed and the carbon equivalent emission calculation formula of each stage is established.

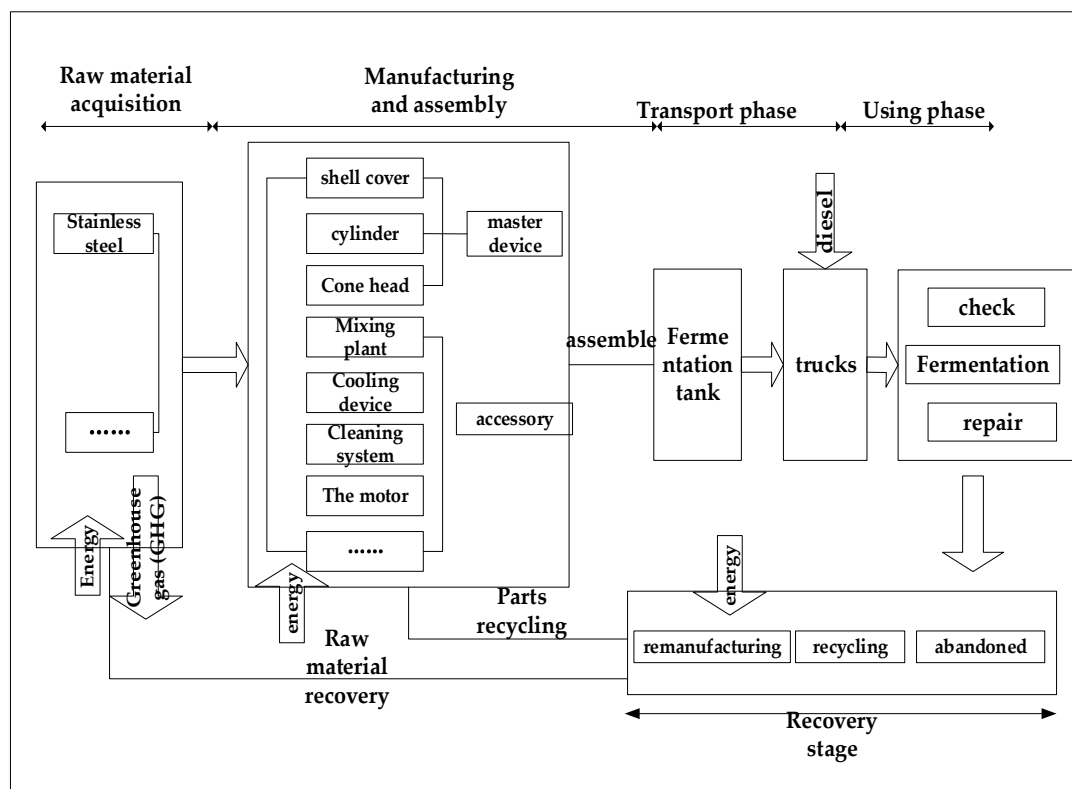


Figure 1. Boundary diagram of fermentation cylinder system.

Table 1. List of fermentation cylinder attachment data.

Tool	Power	Other	The Attachment	Power
Inverter welding machine	4800 w	Suitable electrode $\phi 1.6\text{--}\phi 3.2$	motor	1.5 w
The dryer	4–6 kw	Control the temperature + 5 – 250	Yeast pump motor	2.2 kw
Air compressor	3300 w	Displacement 300 L/min	Feed pump motor	18.5 w
Polishing machine	3 kw	Speed: 2800/min	Mechanical and electrical filter	3 kw
Cutting machine	7 kw	No-load loss 40 w	Additive motor	80 w
Rolling machine	5.5 kw	Auxiliary motor power 3 kw	Cold output pump	22 w
Vacuum pump	190	Frequency 50 Hz	CO ₂ filter press with motor	7.5 w

The carbon footprint of the raw material acquisition stage is expressed as G_M , suppose that n kinds of raw materials and m kinds of energy are consumed in this stage, then the carbon footprint model of this stage is shown in formula (1). Since in the material recovery stage, the material recovery and utilization can offset part of the carbon equivalent emissions in this stage, so the material utilization rate σ_{ij} is defined.

$$G_M = \frac{\sum_{i=1}^n M_i \times MEF_i + \sum_{j=1}^m E_j \times EF_j}{\sigma_{ij}} \quad (1)$$

In the formula, M_i is the physical quantity of class i material, E_j is the physical quantity of class j energy, MEF_i is the production emission factor of class i material and EF_j is the production emission factor of class j energy.

The carbon footprint in the manufacturing and assembly stage is expressed as G_P , which is mainly composed of the energy consumption in the processing process and the direct emission of greenhouse gases. It is assumed that the product consumes n kinds of energy and emits m kinds of greenhouse gases in the manufacturing and assembly process. The carbon footprint model of this stage is shown

in formula (2). Similarly, in the material recovery stage, the material recovery method has an offset effect on the carbon footprint of this stage.

$$G_P = \frac{\sum_{i=1}^n E_i \cdot EF_i + \sum_{j=1}^m O_j \cdot GWP_j}{\sigma_{ij}} \quad (2)$$

In the formula, E_i is the physical quantity of class i energy consumed in the process of manufacturing and assembly, O_j is the physical quantity of class j greenhouse gas emitted, EF_i is the energy emission factor and GWP is the global warming potential.

The carbon footprint of transportation stage is expressed as G_T , l types of transport vehicles produce different carbon equivalent emissions and the determinants of carbon equivalent emissions are the choice of transport vehicles, load and transport distance. The final carbon footprint calculation model of this stage is shown in formula (3).

$$G_T = \sum_{t=1}^l M_t \times D_t \times EF_t + \sum_{t=1}^l O_t \times GWP_t \quad (3)$$

In the formula, M_t is the load of the transport product, D_t is the transport distance, EF_t is the carbon equivalent emission factor of the transport product and O_t is the direct greenhouse gas emission.

The carbon footprint in the use stage is expressed as G_U and this process is mainly the energy consumption and the direct emission of greenhouse gases in the use of the product. The carbon footprint in the use stage is proportional to the actual daily power consumption E , the running time T_w and the local power emission factor EF . Similarly, another part of carbon equivalent emission comes from the direct emission of greenhouse gases in the use process. The carbon footprint calculation model of this stage is shown in formula (4).

$$G_U = E \cdot T_w \cdot 365 \cdot EF + \sum_{j=1}^m O_j \cdot GWP_j \quad (4)$$

The carbon footprint of the recovery processing stage is expressed as G_R , which mainly considers the recovery of r kinds of materials and energy consumption. The material recovery can make up the material consumption in the raw material acquisition stage, so the carbon footprint calculation model is shown in formula (5).

$$G_R = \sum_{i=1}^r E_i \cdot EF_i - \sum_{j=1}^r M_j \cdot MEF_j \quad (5)$$

In conclusion, the quantitative model of product carbon footprint can be expressed as (6):

$$G_{SUM} = G_M + G_P + G_T + G_U + G_R \quad (6)$$

The calculation results are shown in Table 2. It can be seen that the carbon equivalent emission in the use stage of the fermentation cylinder is the largest, followed by the raw material acquisition stage, manufacturing and assembly stage and transportation stage.

Table 2. Carbon footprint calculation results of beer fermentation cylinder.

Life Cycle Stage	Raw Material Acquisition Stage G_M	Manufacturing and Assembly Phases G_P	Trans-Port Phase G_T	Use Phase G_U	Recovery and Processing Stage G_R	Total Carbon Footprint per Unit Fermentation Cylinder G_{sum}
Carbon footprint calculation results/(kgCO _{2e})	1999.156	793.203	723.996	10,329.696	−1161.233	12,640.098

3. Uncertainty Analysis of LCA

Product life cycle data spans the whole process from raw materials to end of life. The data is huge, widely distributed, complex and difficult to collect. The results of carbon equivalent emissions directly depend on the quality of input data, so it is necessary to analyse the uncertainty and sensitivity of LCI.

3.1. Uncertainty Analysis of Data List

According to ISO 14040, data quality should include the following aspects: integrity, applicability, deviation, data distribution, consistency, accuracy of expert review, identification of anomalies, uncertainty, data collection methods and limitations [16]. This paper evaluates the inventory data by five indexes: data integrity, reliability, time, technical relevance and geographical relevance, each index is divided into levels 1 to 5 quantitative, quantitative formula is (7).

$$R = \frac{z - \min z_i}{\max z_i - \min z_i} \times 100\% \quad (7)$$

In the formula, z is the accumulative sum of the index score value of each quality of data, $\min z_i$ is the accumulative sum of the minimum score value of data quality and $\max z_i$ is the accumulative sum of the maximum score value of data quality.

According to the evaluation of formula (7), the data quality is within the range of (0,1) and the data quality is converted into the form of probability and statistical distribution as a random variable. In probability density function, the distribution of β has endpoint parameters a and b and the endpoint parameters limit the range of values.

There are also two shape parameters α and β that determine where the probability may occur. The shape parameters and range of different data distribution can simulate the function similar to the distribution, so the distribution is adopted and the probability distribution of data quality indicators is shown in Table 3.

Table 3. Probability distribution of data quality indicators.

Data Quality Fraction	Comprehensive Data Quality Index Values	Shape Parameter		Range	
		a	b	α	β
$0 \leq R \leq 12.5$	1	5	5	−10	+10
$12.5 \leq R \leq 25$	1.5	4	4	−15	+15
$25 \leq R \leq 37.5$	2	3	3	−20	+20
$37.5 \leq R \leq 50$	2.5	2	2	−25	+25
$50 \leq R \leq 62.5$	3	2	2	−30	+30
$62.5 \leq R \leq 75$	3.5	2	2	−35	+35
$75 \leq R \leq 87.5$	4	1	1	−40	+40
$87.5 \leq R \leq 100$	4.5	1	1	−45	+45
100	5	12	1	−50	+50

According to the characteristics of fermentation cylinder LCI, five indicators are selected as the characteristics of data quality. They are integrity, reliability, time, geographical location and technical relevance. the listing data is scored on a scale of 1–5. According to Table 3, the data quality of material consumption, energy consumption and corresponding carbon equivalent emissions in the whole life cycle of beer fermentation cylinder can be obtained, such as Table 4.

Table 4. Data quality of fermentation cylinder life cycle list.

	List Data	Variable	Data Quality Indicator Value	Composite Data Quality Indicator Value	(α, β)	R Value	Range
Material consumption	Stainless steel	X ₁	(2,1,2,3,3)	2	(3,3)	30%	(−20%,+20%)
	Paint	X ₂	(2,4,2,3,3)	2.5	(2,2)	45%	(−25%,+25%)
	Welding wire	X ₃	(2,4,2,3,3)	2.4	(2,2)	45%	(−25%,+25%)
The energy consumption	Electricity	X ₄	(3,4,1,2,2)	2	(3,3)	35%	(−20%,+20%)
	Water	X ₅	(3,5,1,2,1)	2	(3,3)	35%	(−20%,+25%)
Carbon equivalent emissions	Stainless steel	X ₆	(2,1,3,5,2)	2.5	(2,2)	40%	(−25%,+20%)
	Paint	X ₇	(2,1,3,5,2)	2.5	(2,2)	40%	(−25%,+20%)
	Welding wire	X ₈	(2,1,3,4,2)	2	(3,3)	35%	(−20%,+20%)
	Electricity	X ₉	(1,2,2,2,1)	1.5	(4,4)	15%	(−15%,+15%)
	water	X ₁₀	(1,2,2,2,1)	1.5	(4,4)	15%	(−15%,+15%)

Monte-Carlo simulation is carried out by using Crystal-Ball software. The uncertainty of 10 variables X₁, X₂, X₃, X₄, X₅, X₆, X₇, X₈, X₉, X₁₀ is analyzed. The simulation results are shown in Table 5.

Table 5. Uncertainty analysis results of fermentation cylinder data list.

Variable	Mean Standard Error	Kurtosis	Coefficient of Variation	Variance	Skewness	The Standard Deviation
X ₁	0.01	4.67	0.0057	0	−2.64	0.03
X ₂	0.01	1.57	0.0014	0	−0.139	0.02
X ₃	0.01	1.63	0.0049	0	0.3244	0.06
X ₄	0.01	2.28	0.0039	0	0.0831	0.04
X ₅	0.01	2.61	0.0019	0	0.3129	0.05
X ₆	0.01	3.12	0.0005	0	0.4313	0.05
X ₇	0.01	3.27	0.0017	0	0.2617	0.03
X ₈	0.01	4.91	0.0006	0	−0.3402	0.04
X ₉	0.01	3.06	0.0012	0	0.291	0.04
X ₁₀	0.01	2.51	0.0009	0	0.5421	0.03

The mean standard error, kurtosis, coefficient of variation, variance, skewness and standard deviation of each variable are presented from the Table 5 and coefficient of variation is an important index reflecting the uncertainty of variables. It can be seen that the coefficient of variation of X₁, X₃ and X₄ change obvious and the uncertainty is relatively large. The three variables correspond to the raw material stainless steel, welding wire and electric energy respectively. In the whole life cycle of beer fermentation cylinder, material consumption and energy consumption are relatively large, which have a great impact on the carbon footprint calculation results. The error of these factors should be taken into account when establishing the carbon equivalent emission model so as to calculate the carbon footprint of beer fermentation cylinder more accurately.

3.2. Sensitivity Analysis of Data Lists

Sensitivity analysis is a method to quantitatively describe the degree to which the output factors of the model are affected by the input factors [17].

In the process of calculating the carbon footprint of products, there are many data affecting the result. Multivariate statistical regression method [18] is adopted to calculate the influence degree of each input data on the calculation result of carbon footprint. The sensitivity index is calculated with EFAST method [19] and compared with the results of multivariate statistical regression analysis to verify the feasibility of the method. Taking the above beer fermentation cylinder list data as an

example, 20 groups of data are extracted for stepwise regression analysis and the regression equation is calculated by SPSS:

$$Y = 132.17 + 95.036X_1 + 6.549X_3 + 87.17X_4 + 61.223X_5 + 35.059X_6 + 0.512X_9 + 0.013X_{10}$$

A significant level is $\alpha = 0.05$ and stepwise regression analysis are shown in Table 6.

Table 6. Regression coefficient table.

Factors	Unstandardized Coefficients	Standardized Coefficient	t	p
constant	132.17		2.255	
X ₁	95.036	0.639	56.711	0.891
X ₃	6.549	0.325	13.336	0.456
X ₄	87.17	0.216	10.118	0.370
X ₅	61.223	0.069	6.549	0.275
X ₆	35.059	0.015	1.124	0.042
X ₉	0.512	0.018	2.217	0.131
X ₁₀	0.013	0.042	4.649	0.275

From the Table 6, it can be seen that: X₁, X₃, X₄, X₅, X₆, X₈, X₉ and X₁₀ all have significant influence on Y and the sensitivity is relatively large. 8 factors are included in the model and the partial regression sum of squares of these factors accounted for a larger proportion compared with other factors. The ranking is: X₁ > X₄ > X₅ > X₆ > X₉ > X₃ > X₁₀ > X₈.

EFAST is a global sensitivity analysis method based on variance decomposition. The model $y = f(x_1, x_2, \dots, x_n)$ is converted into a function $y = f(s)$ and the Fourier transform on $f(s)$:

$$x_i = 0.5 + \frac{\arcsin[\sin(\omega_i s + \varphi_i)]}{\pi}, s \in [-\pi, \pi], \omega_i (i = 1, 2, \dots, m) \quad (8)$$

$$y = f(s) = \sum_{i=-\infty}^{\infty} [A_i \cos(is) + B_i \sin(is)] \quad (9)$$

In the formula, i is the Fourier transform parameter, A_i and B_i is the Fourier amplitude:

$$A_i = \frac{1}{N_s} \sum_{k=1}^{N_i} f(s_k) \cos(\omega_i s_k) \quad (10)$$

$$B_i = \frac{1}{N_s} \sum_{k=1}^{N_i} f(s_k) \sin(\omega_i s_k) \quad (11)$$

In the formula, N_s is the sample number, $i \in Z = \left\{ -\frac{N_s-1}{2}, \dots, -1, 0, 1, \dots, \frac{N_s-1}{2} \right\}$. The spectrum of Fourier series is defined as $\Delta_i = A_i + B_i$, the frequency ω_i is calculated, the model output variance V_i caused by the change of parameter x_i can be obtained:

$$V_i = 2 \sum_{i=1}^{+\infty} \Delta_i \omega_i \quad (12)$$

The total variance of the model $V(Y)$ results can be decomposed into:

$$VY = \sum_{i=1}^m V_i + \sum_{1 \leq i \leq j \leq m} V_{ij} + \sum_{1 \leq i \leq j \leq m} V_{1,2,\dots,m} \quad (13)$$

In the formula, $V_{ij}, V_{1,2,\dots,m}$ is the variance of the interaction of m parameter. The direct contribution of parameters x_i to the total variance of the model output can be expressed by the first-order sensitivity index S_i .

$$S_i = \frac{V_i}{V(Y)} \quad (14)$$

The total sensitivity index ST_i is:

$$ST_i = \frac{VY - V_i}{V(Y)} \quad (15)$$

The EFAST method is used to calculate the sensitivity index of each variable. The results of MATLAB programming are shown in Table 7.

Table 7. Sensitivity coefficients of variables in inventory data.

S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}
0.9524	0.086	0.2297	0.7259	0.7122	0.5781	0.0570	0.6627	0.4769	0.1521

According to the Table 7, the first-order sensitivity coefficient of each parameter is: $S_1 > S_4 > S_5 > S_6 > S_9 > S_3 > S_{10} > S_8 > S_2 > S_7$, the results of the three variables with higher sensitivity are the same as those of the multivariate statistical regression method, which proves the feasibility of the method.

4. Optimization Design of Fermentation Cylinder Design Parameters

4.1. Experiment Design of Fermentation Cylinder Parameter Optimization

In the process of calculating the carbon footprint of products mentioned above, the carbon equivalent emissions mainly comes from the material consumption and energy consumption at each stage. In the raw material acquisition stage, the fermentation cylinder material consumption mainly depends on the design parameters: ratio of diameter and height, cone angle, wall thickness and material density. Based on industry standards and the existing literature [20], the ratio of diameter and height of the fermentation cylinder ranges from 1:1.5 to 1:6 (0.17 to 0.67), the scope of cone angle from 60° to 90° , the maximum material density of the stainless steel is 8.03 t/m^3 , the minimum value is 7.5 t/m^3 and the wall thickness ranges from 6 mm to 12 mm. Different design parameters result in different fermentation cylinder quality, which indirectly leads to different carbon footprint. The design parameters of the fermentation cylinder are optimized to minimize the carbon equivalent emission in the raw material acquisition stage.

In this paper, Box-Behnken of RSM method is used for experimental design and the relationship between the parameters is analysed. The quadratic polynomial equation obtained by the least square fitting is shown in formula (16).

$$Y = \beta_0 + \sum_{i=1}^n \beta_i X_i + \sum_{i=1}^{n-1} \sum_{j=2}^n \beta_{ij} X_i X_j + \sum_{i=1}^n \beta_{ii} X_i^2 + \varepsilon \quad (16)$$

$i < j$

X_n is the independent variable, $\beta_0, \beta_i, \beta_{ii}$ and β_{ij} are the coefficients of intercept, linear, quadratic and interactive terms, n is the number of independent variables and ε is the error of variance.

4.2. Regression Model of Fermentation Cylinder Parameters

The carbon footprint at the raw material acquisition stage obtained by the above calculation is taken as the response value for the experimental design and the Design Expert 8.0.5 software (Stat-Ease, Inc, Minneapolis, American) is used for analysis. The regression formula of carbon footprint

of fermentation cylinders at the stage of raw material production with design parameters A (ratio of diameter and height), B (cone angle), C (thickness) and D (material density) is obtained as follows:

$$Y = 1811.768 + 9.482 \times A + 36.748 \times B + 17.860 \times C + 58.577 \times D + 26.963 \times AB \\ - 40.678 \times AC + 3.620 \times AD + 15.153 \times BC + 87.270 \times BD - 29.005 \times CD \\ - 38.292 \times A^2 - 116.850 \times B^2 + 3.338 \times C^2 - 112.257 \times D^2$$

The coefficients of interaction AB, AD, BC and BD are positive, AC and CD are negative. It shows that the interaction between A with B, D on output results is the synergistic effect, while the interaction between A with C and C with D on output results is an antagonistic effect.

The results of the confidence analysis of the quadratic regression model are shown in Table 8. The correlation coefficient is 92.90% and correlation coefficients for calibration is 85.80% and the variation coefficient is 4.89% < 10%. The signal to noise ratio is 5.882 > 4, indicating that the correlation between the predicted value and the experimental value was good and the reliability was high.

Table 8. Results of model reliability analysis.

Standard Deviation	Mean Value	Coefficient of Variation/%	Correlation Coefficient	Correlation Coefficients for Calibration	Prediction Correlation Coefficient	SNR
83.28	1705.50	4.89	0.9290	0.8580	−0.0371	5.882

Table 9 is the variance analysis of carbon footprint in raw material production stage of fermentation cylinder. Model F value is 2.69, Pro > F is less than 0.05. It shows that the model has high reliability. The model is significant in 95% confidence interval. It is suitable to analyse the influence of fermentation cylinder design parameters on carbon footprint in raw material acquisition stage. According to the analysis, A, D and D² are significant influence factors and the rest have no significant influence on the model. The influence of factors on the response value is A > D > B > C; The order of impact of the interaction terms is: BD > AD > AC > AC > CD > BC; and the influence of the quadratic term is: D² > A² > B² > C². In conclusion, the ratio of diameter and height has the most significant effect on the carbon footprint of the raw materials in the life cycle of the fermentation cylinder, followed by the material density and wall thickness and the cone Angle was the least significant.

Table 9. Analysis of variance of quadratic regression model of carbon footprint response surface.

Item	Sum of Squares	Freedom	Sum of Mean Squares	F Value	Pro > F
The regression model	261,200	14	18,653.75	2.69	<0.05
Ratio of diameter and height A	1078.82	1	1078.82	0.16	<0.05
Cone Angle B	16,205.28	1	16,205.28	2.34	0.1486
Wall thickness C	3827.76	1	3827.76	0.55	0.4698
Density D	41,174.71	1	41,174.71	5.94	<0.05
AB	2907.91	1	2907.91	0.42	0.5278
AC	6618.64	1	6618.64	0.95	0.3452
AD	52.42	1	52.42	0.0076	0.1320
BC	918.39	1	918.39	0.13	0.7214
BD	30,464.21	1	30,464.21	4.39	0.0547
CD	3365.16	1	3365.16	0.49	0.4975
A ²	9510.95	1	9510.95	1.37	0.2611
B ²	88,565.10	1	88,565.10	12.77	0.3228
C ²	72.28	1	72.28	0.010	0.9201
D ²	81,740.21	1	81,740.21	11.79	<0.05
residual	97,092.41	14	6935.17	2.69	0.0372

4.3. Response Surface Analysis

The effects of diameter-height ratio, cone angle, wall thickness and material density of beer fermentation cylinder on carbon footprint are shown in Figures 2–7. Figure 2 shows the effect of diameter-height ratio and cone angle of beer fermentation cylinder and their interaction on carbon equivalent emissions. When the cone angle is 75° , the carbon equivalent emission in the initial stage increases with the aspect ratio. When the ratio of diameter and height is 0.42 (about 1:2.4), the carbon equivalent emission decreases with the increase of the two factors. Figure 3 shows the effect of the aspect ratio, thickness and their interaction on carbon equivalent emissions. When the wall thickness of fermentation cylinder is 9 mm, the carbon equivalent emission in the initial stage increases with the aspect ratio. When the aspect ratio is 0.42 (about 1:2.4), the carbon equivalent emissions decrease as the two factors increase. Figure 4 shows the effect of aspect ratio, material density and their interaction on carbon equivalent emissions. When the material density is 7.77 t/m^3 , the carbon equivalent emissions in the initial stage increase with the aspect ratio. When the aspect ratio is 0.42 (about 1:2.4), the carbon equivalent emissions decrease as the two factors increase. Figure 5 shows the effect of cone angle and thickness on carbon equivalent emissions. When the wall thickness is 9 mm, the carbon equivalent emissions in the initial stage increase with the cone angle. When the cone angle is 75° , the carbon equivalent emissions decrease as the two factors increase. Figure 6 shows the effect of cone angle and material density on carbon equivalent emissions. When the material density is 7.77 t/m^3 , the carbon equivalent emissions in the initial stage increase with the cone angle. When the cone angle is 75° , the carbon equivalent emissions decrease as the two factors increase. Figure 7 shows the effect of wall thickness and material density on carbon equivalent emissions. When the material density is 7.77 t/m^3 the carbon equivalent emissions in the initial stage increase with the wall thickness. When the wall thickness is 9 mm, the carbon equivalent emissions decreases as the two factors increase.

Response surface methodology is used to design and analyse the influence of parameter design of beer fermentation cylinder on its carbon footprint and the optimal value of carbon equivalent emissions is obtained. Therefore, the designed fermentation cylinder raw material acquisition stage has the lowest carbon equivalent emissions of about $1650.00 \text{ kgCO}_{2e}$, when the diameter ratio is about 1:2.4, the cone angle is 75° , the wall thickness is 9.00 mm and the material density is 7.77 t/m^3 . However, according to industry standards, there is no stainless steel with material density of 7.77 t/m^3 . So stainless steel with a material density of 7.76 t/m^3 and a model of 4Cr13 is selected as the material of the fermentation cylinder. Through the analysis of the parameter design of beer fermentation cylinder, it is found that under the optimal combination of parameters, the carbon footprint of raw materials required for fermentation cylinder's whole life cycle is reduced by 349.16 kgCO_{2e} compared with that before optimization.

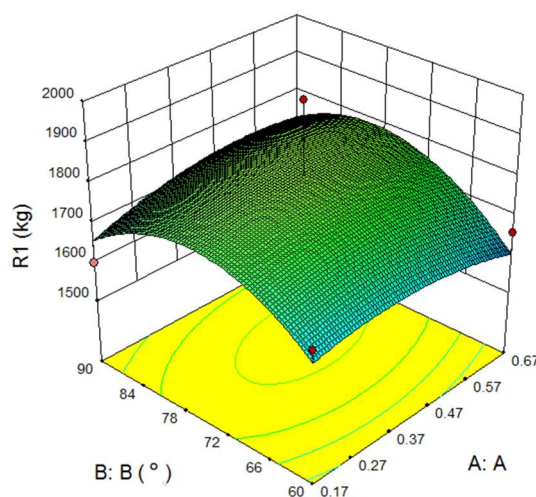


Figure 2. Response surface of diameter to height ratio and cone angle to carbon equivalent emissions.

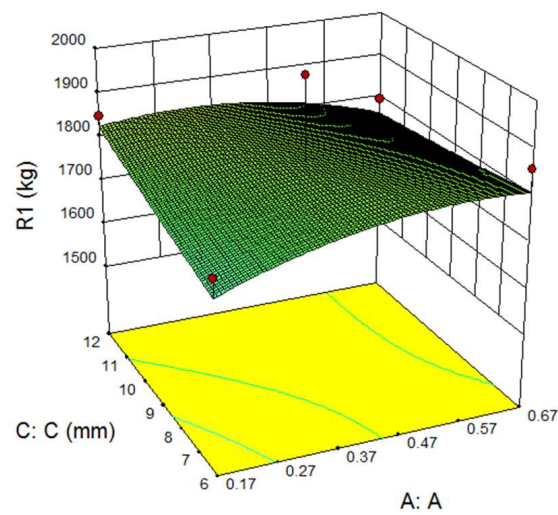


Figure 3. Response surface of diameter to height ratio and wall thickness to carbon equivalent emissions.

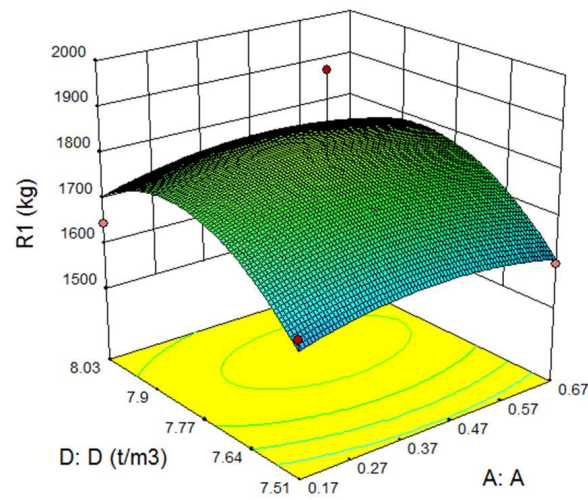


Figure 4. Response surface of diameter to height ratio and material density to carbon equivalent emissions.

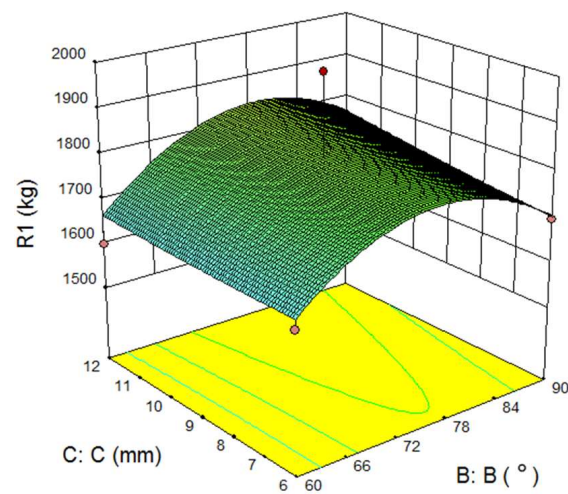


Figure 5. Response of cone angle and wall thickness to carbon equivalent emissions.

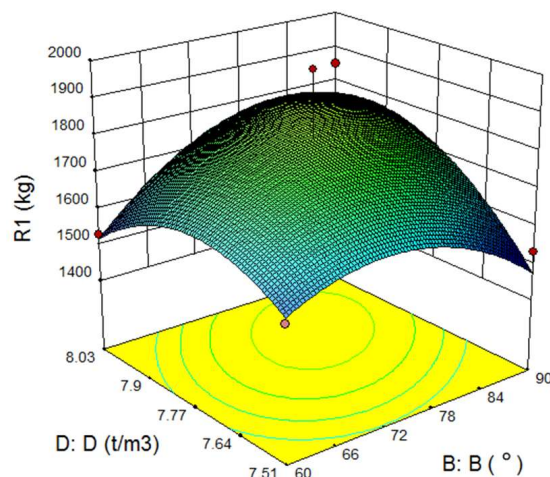


Figure 6. Cone angle and material density response surface to carbon emissions.

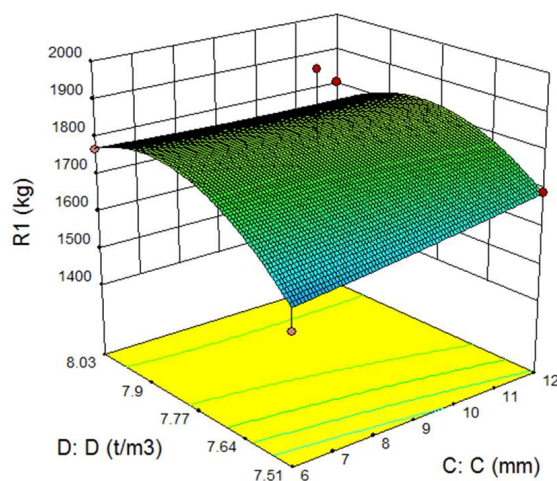


Figure 7. Wall thickness and material density response surface to carbon equivalent emissions.

5. Conclusions

In this paper, the LCA is used to calculate the carbon footprint of the product. The beer fermentation cylinder is taken as an example, the system boundary is determined and the carbon equivalent emissions from the raw material acquisition to the end of life stage are calculated. Due to the uncertainty of the LCI, the error is caused to the calculation results. The quality of LCI data is analysed to determine its probability distribution and then the results are simulated as Monte-Carlo input function to obtain variables with greater uncertainty. EFAST is used for sensitivity analysis and compared with multivariate statistical regression method, the sensitivity of data variables is obtained. In order to realize the low-carbon design of fermentation cylinder, the influence of parameters on carbon equivalent emissions is analysed. The optimum design of parameters is carried out by RSM. When the diameter-height ratio of fermentation cylinder is about 1:2.4, the cone angle is 75° , the wall thickness is 9 mm and the material density is 7.77 t/m^3 , the minimum carbon equivalent emissions of fermentation cylinder is obtained. It is $1650.00 \text{ kgCO}_{2e}$, which is 349.16 kgCO_{2e} less than before optimization. With the development of the actual production and research of products, the neglected problems in LCA have attracted more and more attention of scholars. These problems deserve our in-depth discussion and further study on the basis of this paper.

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