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

Hui Zheng 1,2,*, Meng Xing 1,2,*, Ting Cao 1,2 and Junxia Zhang 1,2

1 Department of Mechanical Engineering, Tianjin University of Science and Technology, Tianjin 300222, China; xiaoanshuye@sina.com (T.C.); zjx@tust.edu.cn (J.Z.)
2 Tianjin Key Laboratory of Integrated Design and Online Monitoring for Light Industry and Food Machinery and Equipment, Tianjin 300222, China
* Correspondence: tjzhenghui666@163.com (H.Z.); xingmeng0709@163.com (M.X.)

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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. Sugiyama [6] used standard statistics to analyse the uncertainty of industrial LCL 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.
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.

Table 1. List of fermentation cylinder attachment data.

| Tool                  | Power   | Other                  | The Attachment         | Power   |
|-----------------------|---------|------------------------|------------------------|---------|
| Inverter welding      | 4800 w  | Suitable electrode φ1.6-φ3.2 | motor 1.5 w          |         |
| machine               |         |                        |                        |         |
| 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        | CO₂ 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 $\sigma_{ij}$ is defined.

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

\[ GP = \sum_{i=1}^{n} E_i \cdot EF_i + \sum_{j=1}^{m} O_j \cdot GWP_j \]  
(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 \( GT \), \( l \) 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).

\[ GT = \sum_{i=1}^{l} M_i \times D_i \times EF_i + \sum_{i=1}^{l} O_i \times GWP_i \]  
(3)

In the formula, \( M_i \) is the load of the transport product, \( D_i \) is the transport distance, \( EF_i \) is the carbon equivalent emission factor of the transport product and \( O_i \) is the direct greenhouse gas emission.

The carbon footprint in the use stage is expressed as \( GU \), 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 \( Tw \) 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).

\[ GU = E \cdot Tw \cdot 365 \cdot EF + \sum_{j=1}^{m} O_j \cdot GWP_j \]  
(4)

The carbon footprint of the recovery processing stage is expressed as \( GR \), 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).

\[ GR = \sum_{i=1}^{r} E_i \cdot EF_i - \sum_{j=1}^{r} M_j \cdot MEF_j \]  
(5)

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

\[ G_{SUM} = GM + GP + GT + GU + GR \]  
(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 \( GM \) | Manufacturing and Assembly Phases \( GP \) | Trans-Port Phase \( GT \) | Use Phase \( GU \) | Recovery and Processing Stage \( GR \) | Total Carbon Footprint per Unit Fermentation Cylinder \( G_{sum} \) |
|------------------|--------------------------------------|--------------------------------|------------------|------------------|-----------------|--------------------------------------|
| Carbon footprint calculation results/(kgCO\(_2\)e) | 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).

\[ R = \frac{z - \text{min}z_i}{\text{max}z_i - \text{min}z_i} \times 100\% \]  \hspace{1cm} (7)

In the formula, \( z \) is the accumulative sum of the index score value of each quality of data, \( \text{min}z_i \) is the accumulative sum of the minimum score value of data quality and \( \text{max}z_i \) 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 \( \beta \) has endpoint parameters \( a \) and \( b \) and the endpoint parameters limit the range of values.

There are also two shape parameters \( \alpha \) and \( \beta \) 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.

| Data Quality Fraction | Comprehensive Data Quality Index Values | Shape Parameter | Range |
|----------------------|----------------------------------------|----------------|-------|
|                      |                                        | \( \alpha \)   | \( \beta \) |
| 0 ≤ R ≤ 12.5         | 1                                      | 5              | −10   |
| 12.5 ≤ R ≤ 25        | 1.5                                    | 4              | −15   |
| 25 ≤ R ≤ 37.5        | 2                                      | 3              | −20   |
| 37.5 ≤ R ≤ 50        | 2.5                                    | 2              | −25   |
| 50 ≤ R ≤ 62.5        | 3                                      | 2              | −30   |
| 62.5 ≤ R ≤ 75        | 3.5                                    | 2              | −35   |
| 75 ≤ R ≤ 87.5        | 4                                      | 1              | −40   |
| 87.5 ≤ R ≤ 100       | 4.5                                    | 1              | −45   |
| 100                  | 5                                      | 12             | −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 | Composite Data Quality Indicators Value | Composite Data Quality Indicator Value | (α, β) R Value | Range       |
|-------------------------------|----------|----------------------------------------|--------------------------------------|----------------|-------------|
| Material consumption         | X₁       | (2,1,2,3,3)                            | 2                                    | (3,3)          | 30% (-20%, +20%) |
| Paint                         | X₂       | (2,4,2,3,3)                            | 2.5                                  | (2,2)          | 45% (-25%, +25%) |
| Welding wire                 | X₃       | (2,4,2,3,3)                            | 2.4                                  | (2,2)          | 45% (-25%, +25%) |
| The energy consumption       | Electricity X₄ | (3,4,1,2,2)                          | 2                                    | (3,3)          | 35% (-20%, +20%) |
| Water                        | X₅       | (3,5,1,2,1)                            | 2                                    | (3,3)          | 35% (-20%, +25%) |
| Carbon equivalent emissions  | Stainless steel X₆ | (2,1,3,5,2)                          | 2.5                                  | (2,2)          | 40% (-25%, +20%) |
| Paint                        | X₇       | (2,1,3,5,2)                            | 2.5                                  | (2,2)          | 40% (-25%, +20%) |
| Welding wire                 | X₈       | (2,1,3,4,2)                            | 2                                    | (3,3)          | 35% (-20%, +20%) |
| Electricity water            | X₉       | (1,2,2,2,1)                            | 1.5                                  | (4,4)          | 15% (-15%, +15%) |
| X₁₀                           |           | (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 |
|----------|---------------------|----------|--------------------------|----------|----------|------------------------|
| X₁       | 0.01                | 4.67     | 0.0057                   | 0        | -2.64    | 0.03                   |
| X₂       | 0.01                | 1.57     | 0.0014                   | 0        | -0.139   | 0.02                   |
| X₃       | 0.01                | 1.63     | 0.0049                   | 0        | 0.3244   | 0.06                   |
| X₄       | 0.01                | 2.28     | 0.0039                   | 0        | 0.0831   | 0.04                   |
| X₅       | 0.01                | 2.61     | 0.0019                   | 0        | 0.3129   | 0.05                   |
| X₆       | 0.01                | 3.12     | 0.0005                   | 0        | 0.4313   | 0.05                   |
| X₇       | 0.01                | 3.27     | 0.0017                   | 0        | 0.2617   | 0.03                   |
| X₈       | 0.01                | 4.91     | 0.0006                   | 0        | -0.3402  | 0.04                   |
| X₉       | 0.01                | 3.06     | 0.0012                   | 0        | 0.291    | 0.04                   |
| X₁₀      | 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: \( X_1, X_3, X_4, X_5, X_6, X_8, X_9 \) and \( X_{10} \) 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: \( X_1 > X_4 > X_5 > X_6 > X_9 > X_3 > X_{10} > X_8 \).

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

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

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

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

\[
A_i = \frac{1}{N_s} \sum_{k=1}^{N_s} f(s_k) \cos(\omega_is_k)
\]

\[
B_i = \frac{1}{N_s} \sum_{k=1}^{N_s} f(s_k) \sin(\omega_is_k)
\]

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

\[
V_i = 2 \sum_{i=1}^{\infty} \Delta_i \omega_i
\]

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

\[
V_Y = \sum_{i=1}^{m} V_i + \sum_{1 \leq i < j \leq m} V_{ij} + \sum_{1 \leq i < j \leq m} V_{1,2,\ldots,m}
\]
In the formula, \( V_{ij}, V_{1,2,...,m} \) 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 \( S_i \).

\[
S_i = \frac{V_i}{V(Y)}
\]  

(14)

The total sensitivity index \( ST_i \) is:

\[
ST_i = \frac{VY - V_i}{V(Y)}
\]  

(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/m³, the minimum value is 7.5 t/m³ 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).

\[
Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \sum_{i=2}^{n-1} \sum_{j=1}^{i-1} \beta_{ij} X_i X_j + \sum_{i=1}^{n} \beta_{ii} X_i^2 + \varepsilon
\]  

(16)

\( X_n \) is the independent variable, \( \beta_0, \beta_i, \beta_{ij} \) and \( \beta_{ii} \) are the coefficients of intercept, linear, quadratic and interactive terms, \( n \) is the number of independent variables and \( \varepsilon \) 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 D^2 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: D^2 > A^2 > B^2 > C^2. 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   | 1078.82       | 1        | 1078.82             | 0.16    | <0.05   |
| height A                |               |          |                     |         |         |
| 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 $75^\circ$, 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 $75^\circ$, 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 $75^\circ$, 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 decrease 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 kgCO$_2$e, when the diameter ratio is about 1:2.4, the cone angle is $75^\circ$, 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$_2$e compared with that before optimization.

![Figure 2. Response surface of diameter to height ratio and cone angle to carbon equivalent emissions.](image-url)
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.

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 1,650.00 kg CO$_2$e, 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$^3$. 

Figure 5. Response of cone angle and wall thickness to carbon equivalent emissions.
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 1,650.00 kg CO$_{2e}$, 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$^3$.

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 kg CO$_{2e}$, which is 349.16 kg CO$_{2e}$ 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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**References**

1. Yu, X.; Dong, D.; Zhang, X. Product carbon footprint and its development status at home and abroad. *Econ. Res. Guide* 2010, 19, 182–183.
2. Bartocci, P.; Fantozzi, P.; Fantozzi, F. Environmental impact of Sagrantino and Grechetto grapes cultivation for wine and vinegar production in central Italy. *J. Clean. Prod.* 2016, 15, 267–270.
3. Jiang, C.; Zhang, L. Introduction to Life Cycle Assessment (ISO14040 series). *Sichuan Lin Kan Des.* 2002, 2, 54–59.
4. Guo, M.; Liu, H.; Zhang, Q.; Guo, B. Life Cycle Assessment of Fruit Aggregation and Its Application. *Comput. Integr. Manuf. Syst.* 2014, 20, 661–665.
5. Heijungs, R.; Tan, R. Rigorous proof of fuzzy error propagation with matrix-based LCI. *Int. J. Life Cycle Assess.* 2010, 15, 1014–1019. [CrossRef]
6. Sugiyama, H.; Fukushima, Y.; Hirao, M.; Hellweg, S.; Hungerbühler, K. Using Standard Statistics to Consider Uncertainty in Industry-Based Life Cycle Databases. *Int. J. Life Cycle Assess.* 2015, 10, 399–405. [CrossRef]
7. Zhu, L. *Uncertainty Analysis in the List of Product Life Cycle Assessment*; Hefei University of Technology: Hefei, China, 2012.
8. Huang, N.; Wang, H.; Fan, C.; Zhou, S.; Hou, P.; Yang, J. LCA data quality assessment and control methods based on uncertainty and sensitivity analysis. *J. Environ. Sci.* 2012, 32, 1529–1536.
9. Chen, S.; Li, F.; Cao, L.; Liu, Z.; Chen, Y. Data quality analysis combining uncertainty and sensitivity in product carbon footprint evaluation. *China Environ. Sci.* 2014, 34, 1067–1072.
10. Cimini, A.; Moresi, M. Carbon footprint of a pale larger packed in different formats: Assessment and sensitivity analysis based on transparent. *J. Clean. Prod.* 2016, 5, 4196–4213. [CrossRef]
11. Alistair, D.; Dimitrios, R.; Gerogiorgis, I. Mult-objective process optimization of beer fermentation via dynamic simulation. *Food Bioprod. Process.* 2016, 100, 255–274.
12. Yang, J.; Zhong, J.; Zhang, K.; Lu, J. Beer Carbon Footprint and Calculation Case. *Beer Technol.* 2013, 8, 6–14.
13. Gao, F.; Guo, Z. Carbon footprint of beer production based on life cycle calculation. *Beer Sci. Technol.* 2013, 3, 7–10.
14. Cao, H.; Li, H.; Song, S.; Du, Y.; Chen, P. Life Cycle Carbon Emission Assessment Method and Application of Machine Tools Based on Life Assessment. *Comput. Integr. Manuf. Syst.* 2011, 17, 2432–2437.
15. Wang, X.; Li, W.; Li, Y. Carbon Footprint Evaluation and implementation method of electromechanical products based on life cycle. *Mech. Des. Manuf.* 2016, 5, 1–4.
16. International Organization for Standardization. *ISO/DIS14040: 2006, Environmental Management—Life Cycle Assessment—Principles and Framework*; International Organization for Standardization: Geneva, Switzerland, 2006.
17. Cai, Y.; Xing, Y.; Hu, D. Review of Sensitivity Analysis. *J. Beijing Norm. Univ.* 2008, 44, 9–16.
18. Gao, X.; Wang, Z. Application of Multivariate Statistical Regression Model in the Distribution of Medical Fund. *Stat. Decis. Mak.* 2009, 9, 145–146.
19. Xing, H.; Yao, X.; Xu, X.; Chen, Y.; Feng, H.; Yang, G.; Chen, Z. Global sensitivity analysis of AquaCrop model parameters based on EFAST method. *China Agric. Sci.* 2017, 50, 64–76.
20. General Administration of Quality Supervision. *GB/T 25198-2010, Pressure Vessel Head*; General Administration of Quality Supervision: Beijing, China, 2010.

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