Research on the Co-pyrolysis of Biomass and Coal Based on BP Neural Network

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Abstract. This paper takes the statistics of coal pyrolysis data released by the Chinese Academy of Sciences as the research subject and integrates the BP neural network model. It conducts an empirical study on the prediction and optimization issues of product yields during the co-pyrolysis process of biomass and coal. The research reveals that n-hexane insoluble (INS) have an insignificant impact on the yields of tar, water, and char residue. Subsequently, the multi-factor analysis of variance (ANOVA) is employed to analyze the disparities between the experimental values and the theoretical calculated values. The conclusion drawn is that the tar, water, and char residue products exhibit statistically significant differences under certain mixing ratios. Particularly, a notable difference exists between the experimental and theoretical values of char residue, indicating that the existing model might require adjustment and optimization in predicting the yield of char residue. To optimize the yield of co-pyrolysis products, a multivariate regression model is established to analyze the influences of different mixing ratios on the yields of tar, water, and char residue, and the BP neural network model is utilized to predict the yields of pyrolysis products. This showcases the application potential of artificial intelligence in the field of chemical engineering, especially in handling complex chemical reaction systems.

Keywords: BP Neural Network Model, Multi-factor Analysis of Variance Method, Multivariate Regression Model, Prediction of Coke Residue Yield, Optimization of Co-pyrolysis Product Yield.

1. Introduction

With the rapid advancement of global industrialization, the consumption of traditional fossil energy is escalating at a fast pace [1]. This not only gives rise to the rapid exhaustion of resources but also triggers severe environmental pollution issues. Confronted with this dual challenge, the search for clean and renewable alternative energy sources has emerged as a focus in the global scientific research domain. Biomass, being the sole renewable carbon source, has garnered significant attention due to its abundant reserves, carbon neutrality, and renewability. Nevertheless, when utilized independently, biomass suffers from drawbacks such as low energy density, low calorific value, and low thermal efficiency, which constrains its large-scale application. Meanwhile, coal, as a vital constituent of the current global energy consumption framework, will continue to play a crucial role in the foreseeable future. However, the combustion of coal generates a considerable number of pollutants such as carbon dioxide, sulfur dioxide, and nitrogen oxides, exerting a serious impact on the environment. Hence, the co-utilization of biomass and coal, particularly through the co-pyrolysis technology, has emerged as a highly promising solution. The co-pyrolysis technology can not only ameliorate the disadvantages of biomass when used alone but also alleviate, to a certain extent, the environmental pollution caused by coal combustion. Through co-pyrolysis, solid, liquid, and gas three-phase products can be obtained, and these products possess extensive application prospects [2]. Simultaneously, the synergy effect during the co-pyrolysis process is also one of the current research hotspots, which holds great significance for enhancing the pyrolysis efficiency and optimizing the product distribution [3]. The conclusions drawn from this study are not only of great significance for the research and development of pyrolysis technology, but also provide a theoretical basis and practical guidance for process optimization and control in industrial applications. By further experimental verification and process optimization, it is possible to achieve more efficient energy recovery and superior environmental performance in commercial pyrolysis processes. Furthermore, by analyzing the effects of different mixing ratios on the yields of tar, water, and slag, valuable insights have been gained on how to adjust these ratios to optimize product yields. Therefore, this study has important reference value for related issues in co-pyrolysis of biomass and coal.

2. Theoretical analysis and research hypotheses

2.1. The Impact of the Mixing Ratio of n-Hexane Insoluble Matter (INS) and Raw Materials

Firstly, hexane insoluble matter [4] primarily refers to the solid products remaining subsequent to pyrolysis, and its formation is intricately associated with the carbonaceous structure within the raw materials, pyrolysis conditions, and the interaction among the raw materials. Biomass and coal exhibit marked disparities in chemical composition and structure. Biomass is rich in cellulose, hemicellulose, and other components prone to pyrolysis, while coal mainly consists of complex organic macromolecules and minerals. Hence, when the two are combined in varying proportions, it will directly influence the transformation and reconfiguration of the carbonaceous structure during the pyrolysis process [5]. Secondly, alterations in the mixing ratio will modify the concentration of hydrogen radicals and other active groups within the pyrolysis reaction system. Biomass releases a substantial amount of hydrogen radicals during the pyrolysis process, and these radicals can participate in the pyrolysis reaction of coal, facilitating the cleavage and reformation of carbon-hydrogen bonds in coal [6]. When the proportion of biomass escalates, the supply of hydrogen radicals concomitantly increases, which assists in the cracking of more macromolecular structures in coal into smaller molecules or fragments, thereby generating more volatile products and reducing the formation of hexane insoluble matter. Nevertheless, it is worthy of note that the ash and mineral content within biomass might also exert an impact on the formation of hexane insoluble matter. Certain mineral components may play a catalytic role during the pyrolysis process, promoting the generation of coke or altering its structure. Therefore, when the mixing ratio varies, the catalytic or inhibitory effect of minerals in biomass on the pyrolysis behavior of coal also necessitates consideration. Additionally, the mixing ratio may also impinge upon the secondary reactions of pyrolysis products. During the co-pyrolysis process, the volatile products generated from the initial pyrolysis might undergo further reactions (such as gas-phase reforming, polycondensation, etc.) with coke, thereby influencing the yield and properties of hexane insoluble matter [7]. A higher proportion of biomass may stimulate the generation of more volatile products, thereby augmenting the likelihood of these products undergoing secondary reactions with coke and modifying the yield and structure of hexane insoluble matter.

Based on the foregoing: The following hypotheses are proposed in this paper:

H1: The presence of n-hexane insoluble matter (INS) exerts a certain impact on the product distribution in the pyrolysis process, particularly on the yields of tar and water.

H2: The selection of raw materials and the mixing ratio are the crucial factors for the control of pyrolysis efficiency and product quality.

2.2. The influence of the proportion of biomass

Firstly, from the perspective of chemical reaction kinetics, the co-pyrolysis of biomass and coal constitutes a complex chemical reaction process, encompassing multiple reaction pathways. When the two are blended in varying proportions, the interaction between them alters the pyrolysis reaction path and rate of the original single material. Nevertheless, as the proportion of biomass increases, the ash and minerals it contains may exert catalytic or inhibitory effects on the pyrolysis process, thereby influencing the yield of the product. Secondly, from the viewpoint of the interaction mechanism, there exists a distinct synergy effect during the co-pyrolysis process of biomass and coal. The hydrogen element and alkali metal elements in biomass can facilitate the cleavage of carbon-hydrogen bonds in coal, thereby accelerating the pyrolysis process of coal. Concurrently, the minerals and carbon skeleton structure in coal may also have certain impacts on the pyrolysis of biomass [8-10]. The intensity of this synergy effect depends on the mixing ratio of biomass and coal. Under an appropriate mixing ratio, the synergy effect is the most pronounced and can significantly enhance the yield of pyrolysis products. However, when the mixing ratio is excessively high or low, the synergy effect may weaken or even vanish, resulting in no notable change in the product yield. Additionally, from the perspective of product distribution, different mixing ratios will also affect the types and quantities of co-pyrolysis products. A higher proportion of biomass may augment the yields of gas and tar as biomass is rich in components prone to pyrolysis. Nevertheless, an overly high proportion of biomass may also lead to an increase in the moisture content of the product, thereby reducing the calorific value and quality of the pyrolysis product. Hence, when conducting co-pyrolysis experiments, it is requisite to select an appropriate mixing ratio to obtain the optimal product yield and quality [11].

H3: A high proportion of biomass is beneficial for increasing the tar yield.

3. Research Design

3.1. Data Sources and Preprocessing

The data in this article is derived from the pyrolysis data of coal published by the Chinese Academy of Sciences. The following processing was carried out on the initial data in this article: (1) Eliminate the samples in the experimental samples whose mass is significantly different from that of other samples; (2) Eliminate the samples with missing data; (3) Eliminate the samples with improper results due to improper operation and other reasons; (4) Calculate the yield of pyrolysis products of each sample.

3.2. Method Introduction

Firstly, through data analysis in this paper, the specific influence of the mixing ratio of different raw materials on the product yield is studied, the key factors are identified, and the optimization direction for the production process is provided. The correlation between the physicochemical properties of the raw materials and the product yield is analyzed, and the reaction mechanisms under different conditions are evaluated. Subsequently, statistical methods (such as t-test) are adopted to assess whether there are significant differences between the experimental values and the theoretical calculated values, the possible reasons for the differences, such as experimental errors and the limitations of the theoretical model, are analyzed, and suggestions for improving the theoretical model are proposed. Finally, based on a large amount of experimental data, a BP neural network model is established and trained to learn the complex relationship between the input variables and the product yield. The prediction performance and accuracy of the model are analyzed, and its application value in the actual production process is evaluated.

4. Model establishment and solution

4.1. Analysis of the influence of hexane insoluble matter (INS) on the product yield

First, the data preprocessing is carried out as follows (Table 1).

Table 1. Data Preprocessing

	Date	Sample	Ratio	INS_g	Tar_Yield	Water_Yield	Char_Yield
0	2013-12-06	Huainan Coal (HN)	100	0.1246	0.0579	0.7599	0.0809
1	2013-12-06	Huainan Coal (HN)	100	0.4566	0.0579	0.7587	0.0809
2	2014-03-12	Shenmu Coal (SM)	100	0.0977	0.0914	0.7365	0.0719
3	2014-03-12	Shenmu Coal (SM)	100	0.1061	0.0914	0.7281	0.0719
4	2014-01-05	Nei Mongol Lignite (NM)	100	0.4244	0.1671	0.6244	0.0331
5	2014-01-05	Nei Mongol Lignite (NM)	100	0.0249	0.1671	0.6288	0.0331
6	2015-10-15	Heishan Coal (HS)	100	0.0839	0.0904	0.7348	0.0749
7	2015-10-15	Heishan Coal (HS)	100	0.0775	0.0904	0.7353	0.0749
8	2013-11-23	Cotton Stalk (CS)	100	0.1828	0.2608	0.3139	0.0944
9	2013-11-23	Cotton Stalk (CS)	100	0.4844	0.2608	0.3140	0.0944

Based on Figure 1 of this paper, the following conclusions can be drawn: There exists a moderate positive correlation (0.48) between the tar yield (Tar Rate) and n-hexane insoluble matter (INS), indicating that as INS increases, the tar yield also tends to rise. There is a slight negative correlation (-0.35) between the water yield (Water Rate) and INS, revealing that when INS increases, the water yield slightly drops. The correlation between the char residue yield (Char Rate) and INS is relatively low (-0.21), suggesting that the impact of INS on the char residue yield is not very significant.

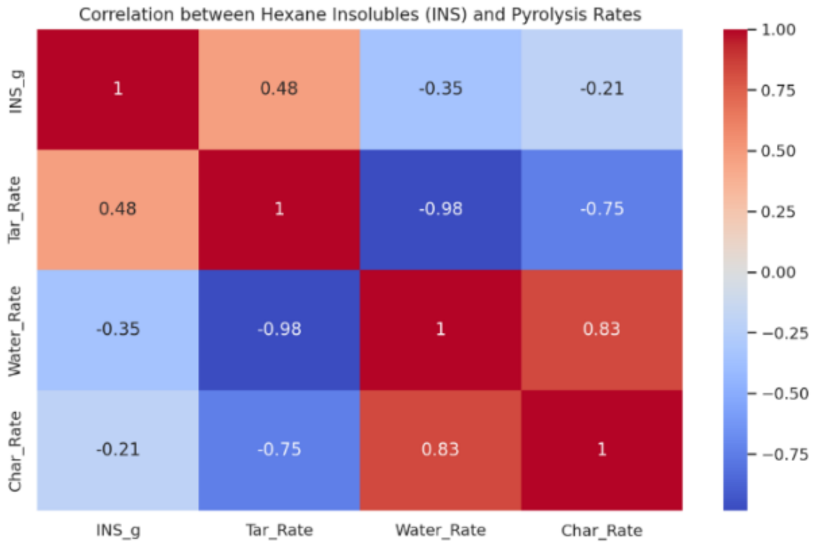

Figure 1. Correlation Analysis Chart

To explore the influence of hexane insoluble substances (INS) on the pyrolysis yield more deeply, this article uses Figure 2 to show the relationships between INS and tar yield, water yield, and char residue yield. From Figure 2 that: 1) The relationship between INS and tar yield: There is a moderate positive correlation (correlation coefficient is about 0.48). This shows that as INS content increases, the tar yield tends to increase. 2) The relationship between INS and water yield: There is a slight negative correlation (correlation coefficient is about -0.35). 3) The relationship between INS and char residue yield: The correlation is relatively low (correlation coefficient is about -0.21), indicating that the direct influence of INS on char residue yield is not significant. Nevertheless, the figure shows that at some data points, as INS increases, the char residue yield has a slight downward trend.

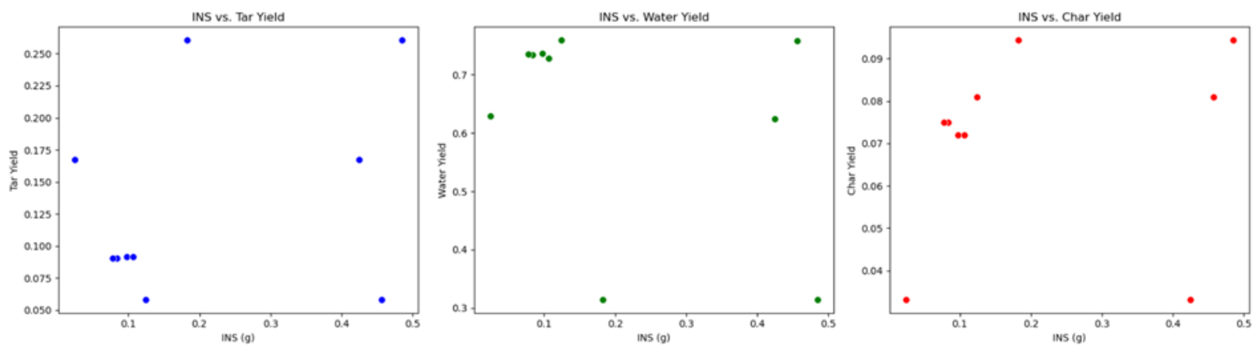

Figure 2. The relationship between INS and the yields of tar, water, and coke residue

Consequently, the presence of n-hexane insoluble matter (INS) exerts a certain impact on the product distribution in the pyrolysis process, particularly on the yields of tar and water. Through optimizing the INS content in the raw materials, it is feasible to effectively regulate the proportion of pyrolysis products, thereby attaining more efficient energy recovery and utilization. Hypothesis H1 is verified.

4.2. Analysis of the interaction effect of hexane insoluble matter (INS) and the mixing ratio

To explore whether there is an interaction effect between hexane insoluble matter (INS) and the mixing ratio and analyze its influence on the yield of pyrolysis products, a deeper data analysis is needed in this paper. This can include multi-factor analysis of variance (ANOVA), considering the effects of INS content, the mixing ratio and their interaction on different pyrolysis products like tar yield, water yield and char residue yield. The interaction effects are reported as follows: Tar yield (Tar Rate): The main effect of INS: P value = 1.000, indicating no significant effect on tar yield. The main effect of the mixing ratio: P value = 0.0136, indicating a significant effect. The interaction effect of INS and the mixing ratio: P value = 0.334, indicating no significant effect. Water yield (Water Rate): The main effect of INS: P value = 1.000, indicating no significant effect. The main effect of the mixing ratio: P value = 0.00366, indicating a significant effect. The interaction effect of INS and the mixing ratio: P value = 0.498, indicating no significant effect. Char residue yield (Char Rate): The main effect of INS: P value = 1.000, indicating no significant effect. The main effect of the mixing ratio: P value = 0.00448, indicating a significant effect. The interaction effect of INS and the mixing ratio: P value = 0.693, indicating no significant effect. In the dataset, both INS and the mixing ratio have 6 unique values. Based on this, the marking and color settings of the graph are adjusted appropriately, and the interaction diagram is generated in this paper.

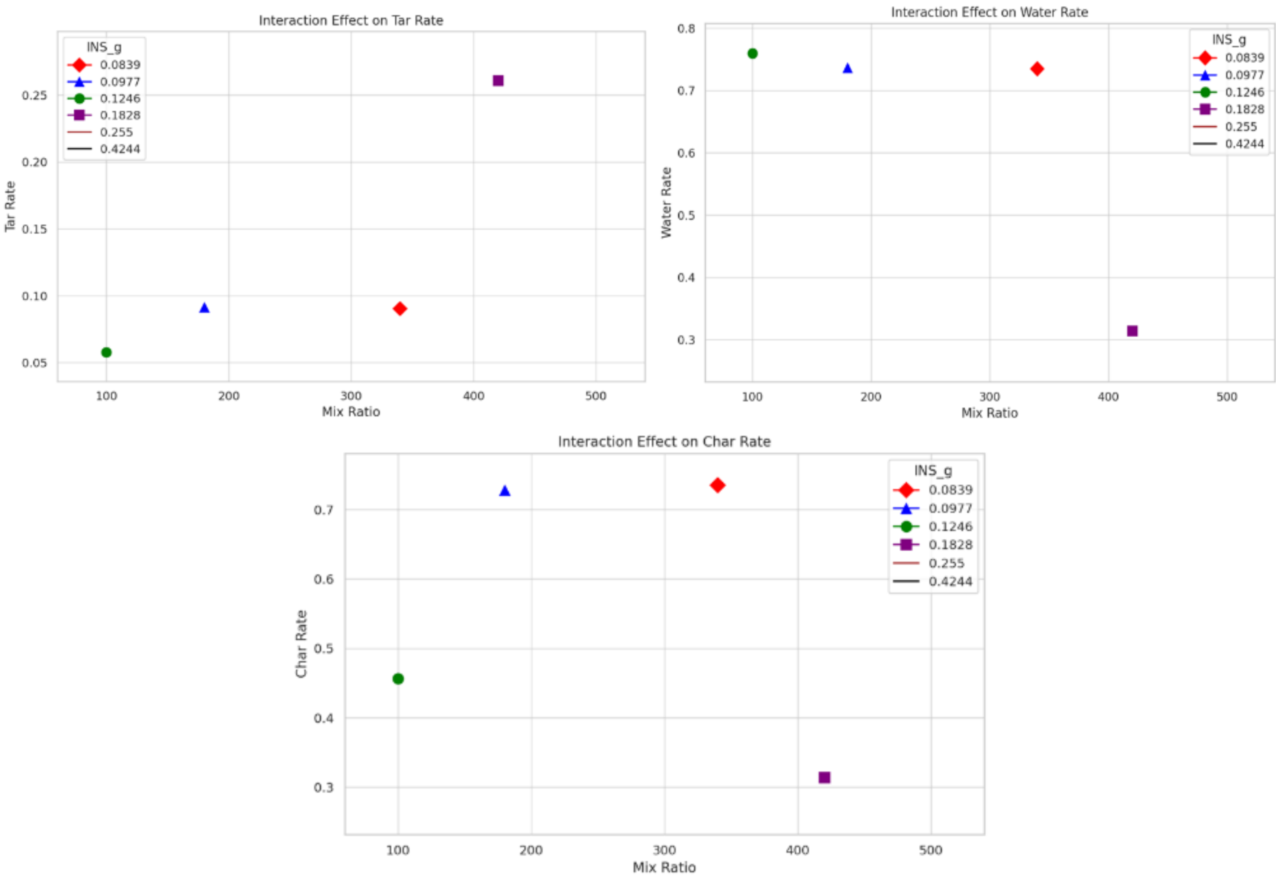

Figure 3. Interaction diagram of n-hexane insoluble matter (INS) ABC (From the first row on the left to the second row)

Figure 3 shows: There is a moderate positive correlation (0.48) between n-hexane insoluble matter (INS) and tar yield, indicating that a higher INS content boosts tar yield during pyrolysis, possibly due to more heavy components and complex organic structures in INS that can transform into tar. The strong positive correlation (0.87) between the mixing ratio and tar yield further highlights the significant influence of the raw material ratio on the pyrolysis product yield. Adjusting the mixing ratio appropriately can increase tar yield significantly, offering a control method for industrial applications. There is a very strong negative correlation (-0.86) between water yield and the mixing ratio, indicating that an increase in the mixing ratio often leads to a decrease in water yield. This may be because a higher proportion of certain raw materials generates less water during pyrolysis. The moderate negative correlation (-0.53) between char residue yield and the mixing ratio and the strong negative correlation (-0.75) between char residue yield and tar yield show the influence of raw material composition and reaction conditions on the yield of solid residues during pyrolysis. Therefore, the following conclusion can be drawn: The selection of raw materials and the mixing ratio are key factors for controlling pyrolysis efficiency and product quality. Optimizing these parameters can significantly improve the yield and quality of pyrolysis oil and other by-products. Hypothesis H2 is verified.

4.3. Optimal analysis of the co-pyrolysis mixture ratio

The co-pyrolysis process of biomass and coal, as a sustainable energy recovery technology, especially needs precise operating conditions and raw material ratios to maximize energy utilization and minimize environmental impacts. In this paper, through constructing a multivariate regression model, the aim is to explore and optimize the mixing ratio in the co-pyrolysis process for higher product utilization and energy conversion efficiency.

Table 2. Correlation Examination of N-Hexane Insoluble Matter (INS) (Multiple Linear Regression for Coefficients)

	x_1	x_2	x_3	x_4	a	b	c	d	e	f
x_1	1	0.1672	-0.039	0.2168	-0.0330	0.0346	-0.0295	0.3272	-0.3070	0.2792
x_2	0.1672	1	0.0377	-0.2458	0.1896	-0.2002	0.1665	0.0047	0.0171	-0.0418
x_3	-0.0398	0.0377	1	-0.1437	0.0745	-0.0669	0.0473	-0.1524	0.1472	-0.1412
x_4	0.2168	-0.2458	-0.1437	1	-0.4150	0.3595	-0.2397	-0.1316	0.1242	-0.0902
aa	-0.0330	0.1896	0.0745	-0.4150	1	-0.9967	0.9751	-0.2908	0.2989	-0.3297
bb	0.0346	-0.2002	-0.0669	0.3595	-0.9967	1	-0.9890	0.3038	-0.3121	0.3410
cc	-0.0295	0.1665	0.0473	-0.2397	0.9751	-0.9890	1	-0.3203	0.3283	-0.3529
dd	0.3272	0.0047	-0.1524	-0.1316	-0.2908	0.3038	-0.3203	1	-0.9981	0.9915
ee	0.3070	0.0171	0.1472	0.1242	0.298	-0.3121	0.3283	-0.9981	1	-0.9970
ff	0.2792	-0.04183	-0.1412	-0.0902	-0.3297	0.3410	-0.3529	0.9915	-0.9970	1

It can be observed from Table 2 that the correlations between each x and the respective coefficients are relatively low, and the outcome of the multiple linear analysis would be rather poor. To address this issue, a new regression equation needs to be determined based on the mechanism. One significant aspect worth noting in this table is that there exists a certain linear relationship among a, b, and c, and the same holds true for d, e, and f. Herein, the parameters a, b, c, d, e, and f are variables related to the combination x. Let's denote$a(x_1, x_2, x_3, x_4)$, $b(x_1, x_2, x_3, x_4)$, $c(x_1, x_2, x_3, x_4)$, $d(x_1, x_2, x_3, x_4)$, $e(x_1, x_2, x_3, x_4)$, $f(x_1, x_2, x_3, x_4)$.

Table 3. Correlation test of n-hexane insoluble matter (INS) with $\alpha_1$and α_2(Regression model integrating all variables)

	x_1	x_2	x_3	x_4	T	α_1	α_2
x_1	1	0.1486	-0.036	0.2003	-0.014	0.0325	-0.186
x_2	0.1486	1	0.0384	-0.2912	-0.039	-0.3266	-0.0920
x_3	-0.0366	0.0384	1	-0.1381	-0.0011	-0.0708	0.0382
x_4	0.20032	-0.2916	-0.1381	1	-0.0021	0.3924	0.3495
T	-0.0147	-0.0393	-0.0011	-0.0021	1	0.7775	0.7240
α_1	0.0325	-0.3266	-0.0709	0.392399	0.7775	1	0.7316
α_2	-0.1868	-0.0920	0.0383	0.3491	0.7240	0.7316	1

Retain two decimal places (Table 3). Some of the data exhibit a relatively strong correlation and a correlation analysis can be carried out. It is advisable to simply represent this linear relationship as follows for the time being:

$$\alpha_{1i} = \beta_1 + \beta_2 x_{1i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \beta_5 T_i + \varepsilon_i \tag{1}$$

$$\alpha_{2j} = \gamma_1 + \gamma_2 x_{1i} + \gamma_3 x_{3j} + \gamma_4 x_{4j} + \gamma_5 T_j + \varepsilon_j \tag{2}$$

The objective of regression is to minimize$\sum_{i=1}\varepsilon_i^2$ and $\sum_{j=1}\varepsilon_j^2$ respectively. Thus, the following model is constructed:

$$\begin{cases} min\sum_{i=1}{\varepsilon_i}^2 \\ \alpha_{1i} = \beta_1+\beta_2x_{1i}+\beta_3x_{2i}+\beta_4x_{3i}+\beta_5x_{4i}+\beta_6T_i+\varepsilon_i \end{cases} \tag{3}$$

$$\begin{cases} min\sum_{j=1}{\varepsilon_j}^2 \\ \alpha_{2j} = \gamma_1+\gamma_2x_{1i}+\gamma_3x_{2j}+\gamma_4x_{3j}+\gamma_5x_{4j}+\gamma_6T_j+\varepsilon_j \end{cases} \tag{4}$$

The solutions of Formulas (3) and (4) can lead to Table 4:

Table 4. Linear Regression Results of Formula (3) and (4)

	α_1	α_2
$\beta_1 or\gamma_1$	-81.0438914296219	-54.9392098407296
$\beta_2 or\gamma_2$	0.127428135520998	-3.17766498661371
$\beta_3 or\gamma_3$	-8.72122122790579	2.69905263685084
$\beta_4 or\gamma_4$	-1.51147210922572	4.77751156318683
$\beta_5 or\gamma_5$	0.107736874774200	0.0855854403467038
$\beta_6 or\gamma_6$	0.339444075584484	0.187536029875751
Correlation coefficient	0.7961	0.7278
Sum of Squares of Residuals	1.1666e+04	5.3647e+03

When the correlation coefficient is greater than 0.7, the result is acceptable. Nevertheless, it is noted that the confidence interval of the coefficient at this point contains 0, and certain adjustments need to be made to this outcome (Tables 5 and 6).

Table 5. Confidence intervals of parameters $\alpha_1$and α_2

	α_1 Parameter		α_2 Parameter	
$\beta_1 or\gamma_1$	-98.2836	-63.8041	-66.6300	-43.2483
$\beta_2 or\gamma_2$	-1.6680	1.9229	-4.3952	-1.9600
$\beta_3 or\gamma_3$	-12.8492	-4.5931	-0.1003	5.4984
$\beta_4 or\gamma_4$	-9.8498	6.8269	-0.8770	10.4320
$\beta_5 or\gamma_5$	0.0765	0.1389	0.0644	0.1067
$\beta_6 or\gamma_6$	0.3005	0.3785	0.1611	0.2139

Table 6. Values of the parameters $\alpha_1$and $\alpha_2$after adjustment

	α_1	α_2
$\beta_1 or\gamma_1$	-41.9096161648839	-20.5306533996748
$\beta_2 or\gamma_2$	12.7543829180532	-3.23987245553597
$\beta_3 or\gamma_3$	0.108626957388203	2.89296212257521
$\beta_4 or\gamma_4$	0.000523199399310967	0.0861854351885269
$\beta_5 or\gamma_5$	-8.51951956130856	0.000287505863408505
Correlation coefficient	0.8108	0.7381
Sum of Squares of Residuals	1.0824e+04	5.1625e+03

Table 7. Confidence intervals of adjusted parameters α_1、andα_2

Confidence interval	α_1 Parameter		α_2 Parameter	
$\beta_1 or\gamma_1$	-52.79629	-31.022	-27.1259	-13.9359
$\beta_2 or\gamma_2$	2.4720	23.036	-4.4283	-2.0514
$\beta_3 or\gamma_3$	0.0796	0.1375	0.1599	5.6259
$\beta_4 or\gamma_4$	0.00046	0.00057	0.0656	0.1066
$\beta_5 or\gamma_5$	-12.3794	-4.6595	0.0002	0.0003

The adjusted model:

$$\begin{cases} min \sum_{i=1} {\varepsilon_i}^2 \\ \alpha_{1i} = \beta_1 + \beta_2 x_{3i} + \beta_3 x_{4i} + \beta_4 {T_i}^2 + \beta_5 \frac{x_{2i}}{x_{3i}} + \varepsilon_i \end{cases} \tag{5}$$

$$\begin{cases} min \sum_{j=1} {\varepsilon_j}^2 \\ \alpha_{2j} = \gamma_1 + \gamma_2 x_{1j} + \gamma_3 x_{2j} + \gamma_4 x_{3j} x_{4j} + \gamma_5 {T_j}^2 + \varepsilon_j \end{cases} \tag{6}$$

Table 8. Comparison of the Model Before and After Adjustment

Regression equation	Correlation coefficient	Sum of Squares of Residuals	Parameter confidence interval
(3)	0.7961	1.0824e+04	Containing 0
(4)	0.8108	1.0641e+04	Not Containing 0
(5)	0.7278	5.3647e+03	Containing 0
(6)	0.7381	5.1625e+03	Not Containing 0

It can be discerned from Table 7 that the confidence interval excludes zero, and the result is more credible. As can be observed from Table 8, the adjusted regression equation features a larger correlation coefficient, a smaller residual sum of squares, and the confidence interval does not incorporate zero. It outperforms the original regression equation in all respects. In conclusion, the following relationship is established:

$$\alpha_1 = -41.909616 + 12.75438x_3 + 0.108627x_4 + 0.00052319939932T^2 - 8.519519\frac{x_2}{x_3} + \varepsilon \tag{7}$$

$$\alpha_2 = -20.530653 - 3.239872x_1 + 2.892962x_2 + 0.086185x_3x_4 + 0.0002875058634T^2 + \varepsilon \tag{8}$$

The square of the temperatures of the two was performed. The consideration was that the variation of the chemical process with temperature is often not linear but a nonlinear one with a more rapid increase in influence. It has also been known from the above conclusion that the impact of temperature on this type of reaction conforms to a quadratic function relationship.

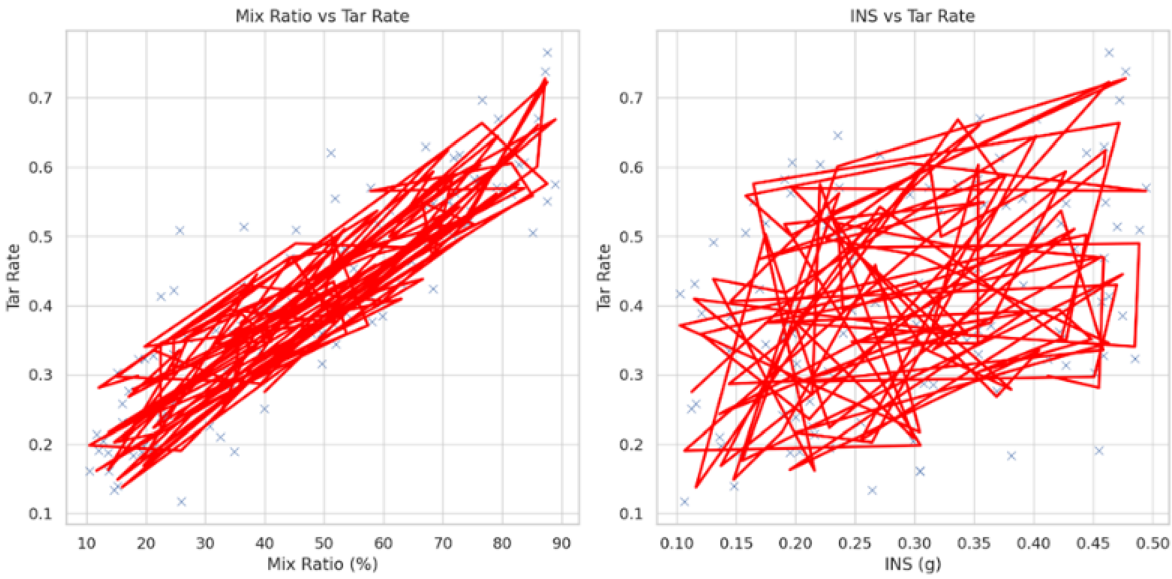

Figure 4. Graph of the Relationship between the Mixing Ratio and the Tar Yield (Left) and Graph of the Relationship between Hexane Insoluble and Tar Yield (Right)

Through Figures 4, the relationship between the mixing ratio, n-hexane insoluble matter (INS), and tar yield and their performance in the regression model can be seen more clearly: With the increase of the biomass ratio, the tar yield increases slightly. The regression line shows this trend clearly. The graph of the relationship between INS and tar yield: There is a more significant positive correlation between INS content and tar yield. This indicates that the increase in INS significantly affects the increase in tar yield. The regression line highlights the strong positive relationship.

Therefore, the following conclusions can be drawn: (1) Increasing the biomass ratio is beneficial for increasing the tar yield. However, the effect of the increase in the mixing ratio on the increase in tar yield is relatively mild. The balance between economic benefits and production efficiency needs to be considered in practical operations. (2) Raw materials with higher INS may contain more components that are difficult to convert, which may be converted into more useful products like tar during the pyrolysis process. Hypothesis H3 is proved.

4.4. Statistical Analysis of the Discrepancies between Experimental Values and Theoretical Calculated Values

To analyze whether there are significant differences between the experimental values and theoretical calculated values of the product yields of various co-pyrolysis combinations provided in the attachment and identify at which mixing ratios these differences are the most significant, the following steps are needed in this paper: Firstly, organize the data in the table, including the experimental and theoretical calculated values, for analysis. Next, the t-test statistical method will be used to compare the differences. These tests can help determine if the differences are statistically significant. For the combinations showing significant differences, the data at different mixing ratios will be further analyzed to identify specifically at which ratios the differences are the most significant.

For each product (tar, HEX, water, and coke residue), this article will undertake a paired sample t-test to compare the experimental values with the theoretical calculated values. The t-test results for each product are calculated as presented in Table 9:

Table 9. T-Test Results for Each Product

Mix_Ratio	Exp_Tar	Calc_Tar	Exp_HEX	Calc_HEX	Exp_Water	Calc_Water	Exp_Char	Calc_Char	
2	5/100	17.46	15.97	12.58	11.34	5.39	6.17	67.01	68.79
3	10/100	16.82	16.17	13.02	11.27	7.44	7.37	65.06	66.99
4	20/100	15.54	16.51	11.16	11.22	10.01	9.39	61.66	63.84
5	30/100	16.33	16.78	11.67	11.17	10.60	11.03	60.55	61.18
6	50/100	16.56	17.21	11.48	11.10	14.06	13.76	53.46	56.92

The following are the paired sample t-test results for different products: Tar: T statistic: 0.0305, P value: 0.9771. Results show no significant difference between experimental and theoretical values of tar. n-Hexane Soluble (HEX): T statistic: 2.3545, P value: 0.0781. Indicates marginal significance, suggesting a possible difference. Water: T statistic: -0.1751, P value: 0.8695. Results show no significant difference for water. Chart: T statistic: -4.4116, P value: 0.0116. Results show a significant difference for char. Conclusions: No significant differences in yields of tar and water. Deficiency in predicting char yield. Explore assumptions or other factors. n-Hexane Soluble (HEX) is close to significance. Further data needed. Similar experimental and calculated values under most mixing ratios. Especially in the 5%-50% range, the closeness is high, indicating strong applicability.

4.5. Analysis of predicting the yield of pyrolysis products by BP neural network model

In the field of pyrolysis technology, accurately predicting the yield of pyrolysis products is crucial for optimizing the production process, enhancing energy efficiency, and reducing environmental impacts. Especially in the co-pyrolysis of biomass and coal, different raw material mixing ratios, temperatures, and other reaction conditions complexly affect the final product distribution. Traditional physical and chemical models, though providing reliable predictions in some cases, often require detailed reaction mechanisms and complex parameter adjustments. Meanwhile, artificial intelligence technologies, especially BP (Back Propagation) neural networks, have become powerful tools for such problems due to their excellent nonlinear mapping ability and adaptability. The BP neural network can establish a prediction model by learning the complex relationship between inputs (like raw material ratios, temperatures, etc.) and outputs (such as the yields of tar, water, gas, and char slag). This model doesn't need to pre-define the specific chemical mechanism of the reaction but automatically recognizes these relationships through training data, making the BP neural network highly suitable for handling prediction tasks in the optimization of chemical processes.

The neural network model can be specifically categorized into the following four steps: Step 1: (Generally, the larger the number of nodes in the hidden layer, the better the fitting effect); Step 2: Utilize the processed data to train the network, as detailed below: A. Establish the model and conduct training using the trainlm function; B. Specify the learning rate as 0.065; C. Set the maximum training epochs to 5000; D. Define the standard error as 0.025; E. Initiate the training of the network. Step 3: Employ the trained BP network to simulate the original data; Step 4: Conduct a comparison and test between the simulation results and the original data. If the error is less than 0.025, the training concludes. Based on the aforementioned steps, the following results are obtained by programming through the neural network toolbox:

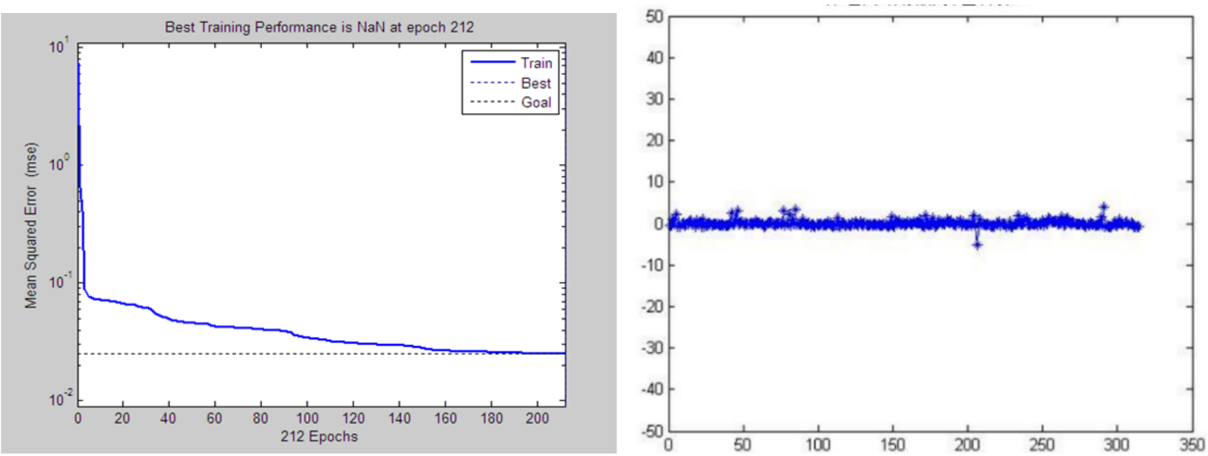

Figure 5. Schematic Illustration of Error Decline (Left)and Error Analysis Chart (Right)

It can be known from Figure 5(Left) that after 200 iterations, the mean square error has been less than 0.025. Therefore, the training is over and the neural network training is completed. In order to more intuitively reflect the effect of the network, the relative error graph is made in this paper, as shown in Figure 5(Left). It can be discerned from Figure 5(Right) that the relative error primarily fluctuates around 0, with only a few relatively large errors. Consequently, the trained neural network can effectively evaluate the model performance. In this research, the BP neural network model was employed to predict the yield of co-pyrolysis products of biomass and coal. Through the training of a considerable amount of experimental data, the model successfully acquired the complex nonlinear correlations among the raw material ratio, reaction conditions, and product yield. The prediction outcomes indicate that the model is capable of providing precise and reliable yield predictions under a broad range of operating conditions, and the error rate is conspicuously lower than that of traditional prediction approaches.

5. Conclusion

The existence of n-hexane insoluble matter (INS) exerts a certain impact on the product distribution during the pyrolysis process, particularly on the yields of tar and water. Through optimizing the INS content in the raw materials, it is feasible to effectively adjust the proportion of pyrolysis products, thereby attaining more efficient energy recovery and utilization. Raw materials with higher INS might contain more components that are difficult to transform, which could be converted into more useful products like tar during the pyrolysis process. Specifically, there is no significant disparity between the experimental values and the theoretical calculated values for the yields of tar and water. Under the majority of mixing ratios, the experimental values are close to the calculated values, demonstrating the excellent predictive capability of the calculation model for the actual pyrolysis reaction. Especially within the range of 5% to 50% of the mixing ratio, the proximity between the experimental values and the calculated values is relatively high. Meanwhile, as the proportion of biomass rises, the tar yield also increases, but the increment is relatively moderate.

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