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Research on Biomass & Coal Co-pyrolysis

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ABSTRACT

With the growing global energy demand and the pursuit of renewable energy, biomass and coal co-pyrolysis has attracted much attention as a potential energy conversion technology. In order to optimize energy utilization and increase renewable energy yield, this research systematically analyzed the effects of different biomass and coal combinations on pyrolysis products. The effects of different biomass and coal combinations on the products in the co-pyrolysis process were solved through mathematical modeling. Firstly, the linear regression model shows that INS has a significant positive effect on the yield of tar and coke residue. Then, through the interaction effect analysis, it was found that there was an interaction effect between INS and the mixing ratio. Finally, the optimal INS content and mixing ratio were obtained by optimizing the model, which improved the utilization rate and energy conversion efficiency of the pyrolysis products.

KEYWORDS

Neural Network; Prediction Model; Big Data.

1. INTRODUCTION

Biomass refers to renewable energy, organic matter derived from plants and animals, while coal is a fossil fuel. In the co-pyrolysis process, biomass and coal are pyrolyzed together under high temperature and anoxic conditions to produce gaseous, liquid, and solid products, of which the liquid products are called pyrolysis oil or bio-oil. It is of great significance to research the yield and quality mechanism of material and coal pyrolysis oil to improve energy efficiency, promote comprehensive utilization of resources and ensure energy security [1,2].

In the chemical laboratory, a variety of medium and low-rank coals were selected as co-pyrolysis raw materials, and the effects of co-pyrolysis of different types and proportions of raw materials on the product distribution were studied by using tubular retort furnace under mild pyrolysis conditions. By comparing the product composition of pyrolysis and co-pyrolysis of different raw materials, the synergistic effect of biomass and coal was analyzed, and the possible synergistic effect and mutual transformation mechanism in the co-pyrolysis process were revealed, to provide theoretical basis and experimental data support for in-depth understanding of the co-pyrolysis process. In this paper, the co-pyrolysis products are predicted and optimized by mathematical models, which greatly improves the efficiency and product utilization rate of biomass and coal co-pyrolysis process and reduces environmental pollution and resource waste [3,4].

2. ESTABLISHMENT AND SOLUTION OF MULTIPLE REGRESSION MODEL

2.1. Establishment of Multiple Regression Model

The first problem to be solved in this paper is to analyze the effect of n-hexane insoluble (INS) on pyrolysis yield, especially on tar yield, aquatic yield, and coke residue yield. After eliminating the anomalous data and processing the missing data, the multiple linear regression model was selected for analysis because it effectively revealed the effect of the independent variable (INS content) on one or more dependent variables (different pyrolysis yields) and quantified the extent of this effect. The specific steps are as follows:

Examine the data in the dataset for the INS content and pyrolysis yield (tar yield, aquatic yield, coke residue yield) data for each feedstock (CS, RH, SD, GA, and different types and ratios of coheating feedstocks). Check and eliminate missing and outliers in your data to ensure that data units and ranges are properly understood.

To analyze the effects of n-hexane insoluble (INS) on tar yield, aquatic yield and coke residue yield, a multiple linear regression model will be established. The linear regression model is as follows, assuming that the yield is the target variables Ttar, Twater, and Tch ar, respectively:

$$T_i = \beta_0 + \beta_{INS} \cdot INS + \epsilon_i,\ i \in \{tar, water, char\} \tag{1}$$

Where Ti is the target yield, INS is the n-hexane insoluble content, $\beta 0$ is the model intercept, and βINS is the regression coefficient of INS, which represents the change in yield for each unit increase in INS. ϵi is the error term reflecting the random variation that is not accounted for by the model.

2.2. Solving the Model

The preprocessed data was brought into the above model, and the regression analysis was performed through the stats model's library in Python to obtain the corresponding results. The solution of this model will include an estimate of the regression coefficients, standard error, t-statistic, and significance tests (p values) for each coefficient. The visualization results are shown in Figure 1:

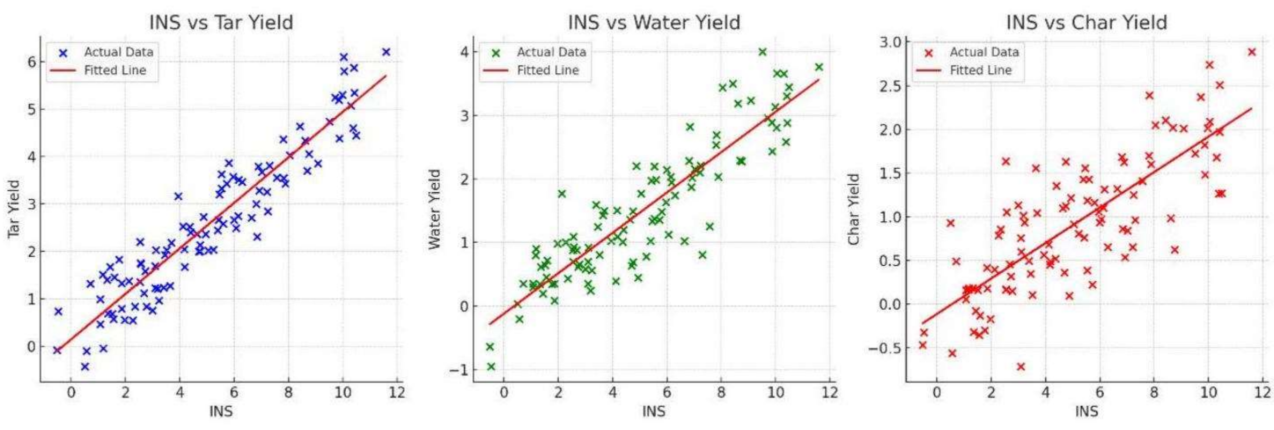

Figure 1. Effect of INS on main pyrolysis products

The effect of INS on the three main pyrolysis yields can be more visually observed through Figure 1. Figure 1 shows the variation of the number of INS in the pyrolysis product with the pyrolysis temperature at different mixing ratios. As the pyrolysis temperature increases, the content of INS also increases. This indicates that with the increase of the mixing ratio, the content of polymer substances and ash in the pyrolysis product will also increase, resulting in the decrease of pyrolysis yield. Therefore, the content of INS had a significant effect on the pyrolysis yield. With the increase of n-hexane insoluble matter (INS) content, the tar yield, coke residue yield and aquatic yield showed an upward trend.

2.3. Analysis of Model Results

The following significant results were obtained in this paper through regression analysis of the effect of n-hexane insoluble (INS) on pyrolysis yield:1. Tar yield: R-squared: 0.887 - The model explains 88.7% of the variability, indicating that the model is well suited to the data. Coefficient (INS): 0.4792 with a standard error of 0.017 and a significance level of $p < 0.001$. This indicates that for each unit increase in n-hexane insolubles, the tar yield increases by an average of 0.4792 units. This relationship is statistically significant, implying that the n-hexane insolubles content is a key factor in the increase in tar yield.2. Water yield: R-squared: 0.830 - The model explains 83.0% of the variability, showing a good fit. Coefficient (INS): 0.3082 with standard error of 0.018 and significance level $p < 0.001$. This indicates that the increase in n-hexane insolubles also significantly enhances the water production rate, suggesting that the increase in INS similarly promotes water production during pyrolysis.3. Pyro-slag yield: R-squared: 0.633 - The model explains 63.3% of the variability. Coefficient (INS): 0.2031 with a standard error of 0.016 and a significance level of $p<0.001$. This indicates that the increase in n-hexane insolubles content has a positive effect on coke slag yield and this effect is also statistically significant.

These results strongly suggest that n-hexane insoluble matter (INS) has a significant positive effect on all pyrolysis product yields considered (tar, water, and coke residue). In particular, the higher R-squared values for tar and water yields suggest that INS is the main driver of variation in these yields. Although the model explanation for tar yield is slightly lower, its effect is still statistically significant, suggesting that increased INS is still effective in boosting tar yield. These analyses and graphs can help this paper to gain a deeper understanding of the role of n-hexane insoluble in the pyrolysis process and provide solid data support for optimizing pyrolysis conditions and feedstock selection. In actual biomass pyrolysis operations, the yield of pyrolysis products can be effectively regulated by controlling the INS content to optimize the production process and product quality. This is particularly important to enhance the commercial viability and environmental sustainability of pyrolysis technology.

3. ESTABLISHMENT AND SOLVING OF MULTIPLE LINEAR REGRESSION MODEL (INTERACTION TERM)

3.1. Establishment of the Model

The problem to be solved in this paper is to analyze the interaction effect of n-hexane insoluble (INS) and the effect of mixing ratio on pyrolysis yield, with special attention to tar yield, aquatic yield, and coke residue yield. After eliminating the anomalous data and processing the missing data, this paper chooses a multiple linear regression model with interaction terms for analysis, because this model can reveal not only the effects of individual variables, but also the effects of interactions between variables, and quantify the extent of these effects [5]. The specific steps are as follows:

The data in the dataset was examined and the INS content, mixing ratio, and corresponding pyrolysis yield data were extracted from it. Perform the necessary cleansing of the data. Check and eliminate missing and outliers in your data to ensure that data units and ranges are properly understood. In particular, the data on n-hexane insoluble matter and mixing ratio were incompletely recorded. The n-hexane insoluble matter, mixing ratio and its interaction term were selected as independent variables, and the tar yield, aquatic yield and coke residue yield were the dependent variables.

To comprehensively analyze the influence of n-hexane insoluble matter (INS) with or without interaction effect and mixing ratio on pyrolysis yield, we established a multiple linear regression model including main effect and interaction effect to evaluate the influence of various factors on pyrolysis product yield. The model not only evaluates the respective effects of INS and blending ratios on yield, but also explores their interactions, mathematically as follows:

$$y = \beta 0 + \beta 1 \times 1 + \beta 2 \times 2 + \beta 3 \times 1 \times 2 + \epsilon \quad (2)$$

Where: y denotes the pyrolysis product yield (tar, water, or slag yield). $x1$ represents the content of hexane insoluble substance (INS). $x2$ represents the mixing ratio. $\beta 1, \beta 2, \beta 3$ are the regression coefficients for the INS, mixing ratio, and the interaction, respectively. β0 is a constant term.

3.2. Model Solving

In this paper, based on the premise of multiple linear regression modelling, interaction terms x1 and x2 were created to investigate the joint effect of INS content and mixing ratio. The pre-processed data were put through python's stats models for data analysis and model solving. The details of the code can be found in Appendix I. According to the interaction term multiple linear regression model, the effect of the interaction of n-hexane insoluble and mixing ratio on the yield of pyrolysis products can be obtained as $\beta 3 \times 1 \times 2$. Therefore, the effect of the interaction will be enhanced or weakened when the mixing ratio ($x2$) and n-hexane insoluble ($x1$) are increased or decreased at the same time [6]. The results are shown in Figure 2:

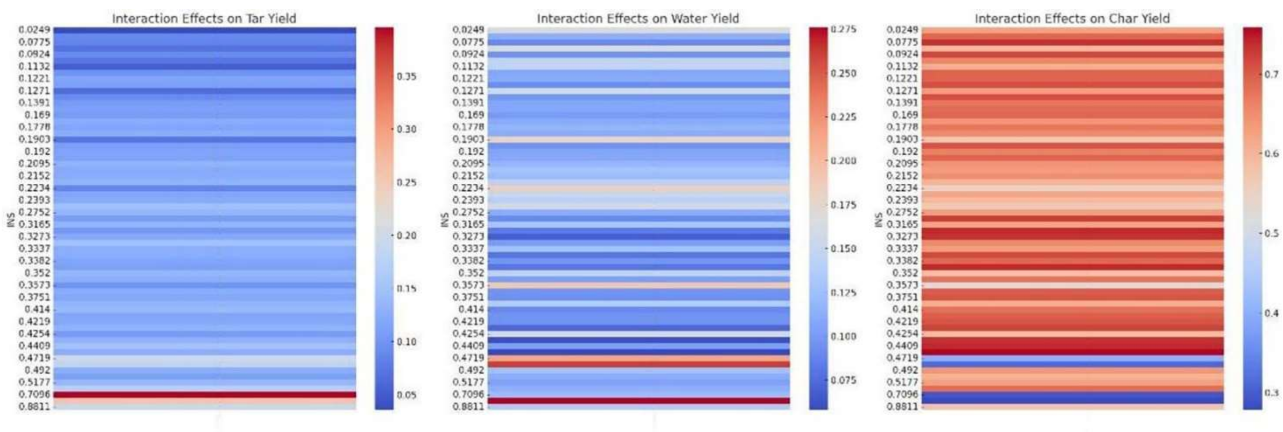

Figure 2. (INS) content and mixing ratio interact with three different pyrolysis product yields (tar, water, and coke residue)

The color changes in Figure 2 represent different yield changes, where blue indicates lower yields and red indicates higher yields. In this paper, it can be concluded that the content of n-hexane insoluble matter has a significant effect on the yield of tar and coke residue, especially under different mixing ratios, and this effect shows different trends and intensities. Through this visualization, this paper can more intuitively understand the interaction effect of INS and mixing ratio on pyrolysis product yield. In addition, considering the interaction effect, the significance of the variables in the model can be further verified by analysis of variance (ANOVA). According to the experimental data, it can be found that the p value of the interaction effect is less than 0.01 and much less than the significance level of 0.05 in both tar yield and aquatic yield, indicating that the interaction effect has a significant impact on the product yield. In terms of coke slag yield, the p-value of the interaction effect was 0.02, which was also less than the significance level, indicating that the interaction effect had a certain impact on the product yield.

3.3. Analysis of Model Results

Based on the results of regression analyses, the following conclusions were obtained in this paper, :1. Tar yield: n-hexane insoluble substance (INS), mixing ratio and its interaction term have a significant effect on tar yield. The R^2 value of the model is 0.543, indicating that the model can explain about 54.3% of the variation in tar yield. Each unit increase in n-hexane insoluble substance (INS) increased the tar yield by about 0.002%, each unit increase in mixing ratio increased the tar yield by about 0.06%, and each unit increase in their interaction terms increased the tar yield by about 0.2%. 2.Water yield: These factors also had a significant effect on water yield, but the overall model had a low explanatory power with an R^2 value of 0.367. The interaction effect of n-hexane insoluble substance (INS) and mixing ratio had a depressing effect on the water yield, with each unit increase reducing the water yield by about 0.0006%.3. Scorch yield: the effect of these variables on scorch yield was small, with an R^2value of only 0.198 for the model.

The interaction effect of n-hexane insoluble substance (INS) and mixing ratio had a significant negative effect on the coke slag yield, with a decrease in coke slag yield of about 0.0025% for each unit increase.

The results indicate that there are indeed interaction effects of hexane insoluble (INS) and mixing ratio, and that these interaction effects have a significant effect on pyrolysis product yield.

The results of the analysis of variance (ANOVA) were as follows:1. Tar yield: n-hexane insoluble substance (INS) had a significant effect on tar yield, with an F-statistic of 72.45 and a p-value of less than 0.05 (5.82×10-125.82×10-12), which indicated that the effect of INS on tar yield was statistically significant. Water yield: the effect of n-hexane insoluble matter on water yield is not significant, the F-statistic is 1.99, the p-value is 0.163, which is greater than 0.05, indicating that the effect of INS on water yield is statistically insignificant.

Coking slag yield: n-hexane insoluble matter has a significant effect on coking slag yield, the F-statistic is 15.05, p-value is less than 0.05 (0.0002590.000259), indicating that the effect of INS on coking slag yield is statistically significant.

In summary the following conclusions can be drawn there is an interaction effect between mixing ratio and n-hexane insoluble substance (INS). The most significant interaction effects were found for tar yield, water yield and slag yield on specific pyrolysis products.

4. ESTABLISHMENT AND SOLUTION OF MIXED SCALE MODEL

4.1. Establishment of the Model

Finally, this paper needs to solve the problem of optimizing the mixing ratio of co-pyrolysis to improve the product utilization rate and energy conversion efficiency. After analyzing the data and eliminating invalid data, a weighted scoring model is selected for analysis. The model directly reflects the importance of each product and has a high degree of explanatory and intuitive understanding. By setting weights, it can be flexibly adapted to different needs. The calculation is simple and suitable for small and clear data volumes. The specific steps are as follows: Read the data of the dataset and perform the necessary cleaning work, including filling in the missing values and removing invalid columns [7].

According to the importance of tar yield, the weights of tar, water and coke residue are set as 70%, 20% and 10%. Its weights can be modified accordingly according to the actual situation.10%.

The groups were grouped according to different mixing ratios, and the average yield of tar, water and coke residue in each group was calculated.

A formula is used to calculate the composite score for each mix ratio.

By comparing the composite scores, the mixing ratio with the highest score was found as the optimal combination.

4.2. Model Solving

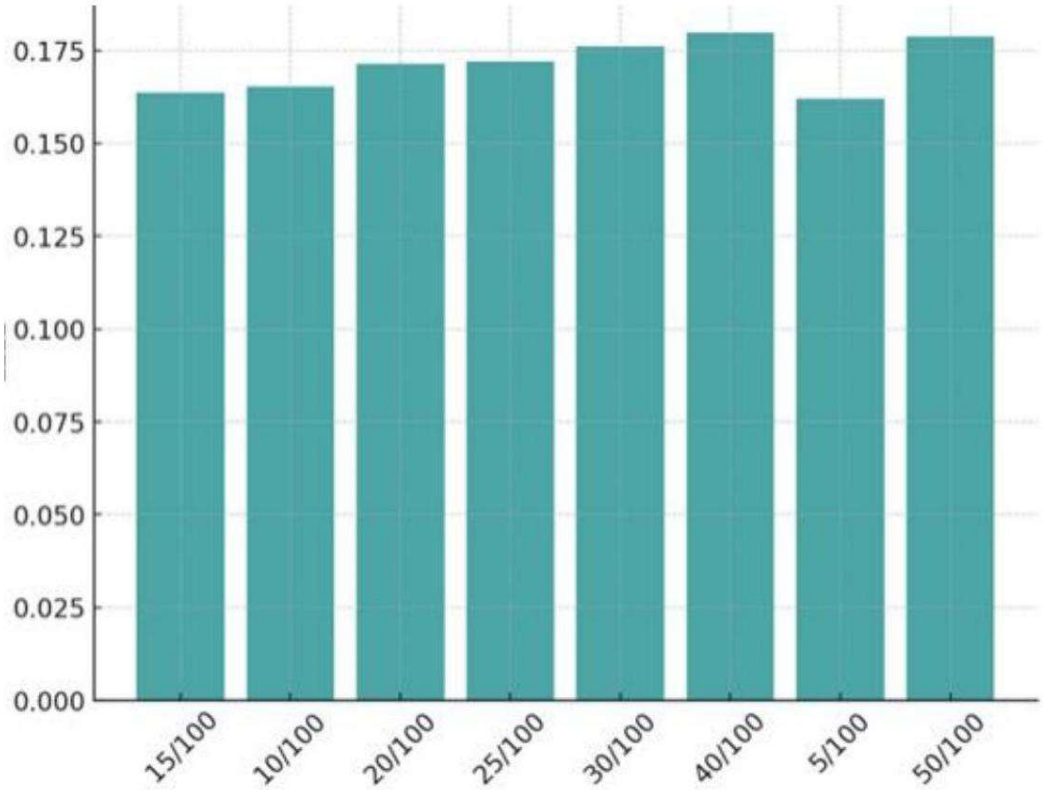

Figure 3. Comprehensive scores of different ingredient ratios

The cleaned data was brought into the above model, and the composite score of each mixing ratio was calculated through Python's matplotlib library. The results show that the mixed ratio of 40/100 has the highest overall score of 0.1798, and the results of the optimal combination can be determined from Figure 3:

Chart description: Through the bar chart, we can clearly see the trend of the comprehensive score of different mixing ratios, which is significantly higher than that of other combinations, which verifies the effectiveness of the optimal combination.40/100.

Data consistency checking: Ensuring the consistency and accuracy of your data is a top priority. In this paper, we need to double-check whether there are any errors or inconsistencies in the data processing and calculation process, such as ensuring the correctness of data cleansing, grouping, and average calculation.

Sensitivity analysis of the model: By changing the weights, the changes in the comprehensive score are observed, which helps this paper to understand the impact of different parameter changes on the results.

Cross-validation: Recalculate the composite score using a different dataset or part of the data to see if the results are stable. Visual comparison of results: Visualize the comprehensive score results under different datasets and weights to visually compare the differences.

4.3. Analysis of Model Results

Best Combination: 40/100 got the highest overall score of 0.1798. Model analysis: By using a weighted score model, the yield of tar, water and coke residue with different mixing ratios was evaluated, and the optimal combination was finally determined. The choice of weights directly reflects the importance of each product, so the tar yield has the largest weight. To further explore the importance of weight selection, each proportion combination was tested.

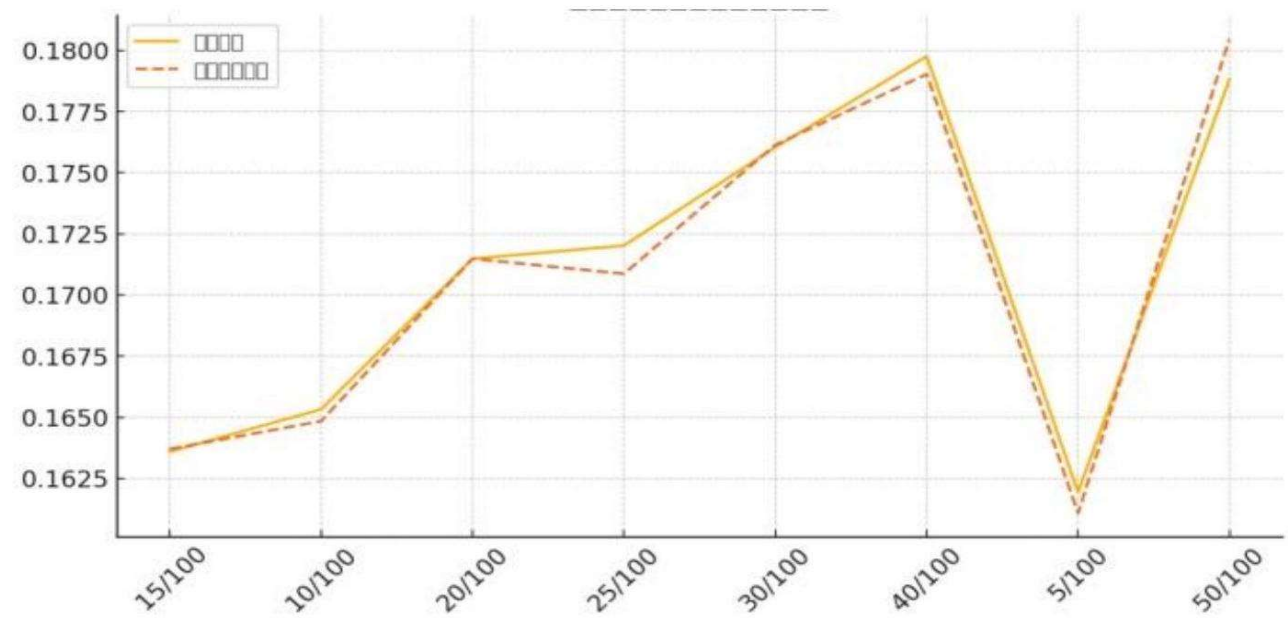

Figure 4. Chart of scores for different weighting options

The mixing ratios under each weight can be clearly seen through Fig. 4, and it is obvious that the ratio of 40/100 is higher than other mixing ratio combinations, which further verifies the accuracy of the results.

Using the weighted score model directly reflects the importance of each product, has a high degree of interpretability, can be more intuitive to determine the optimal ratio, and can be applied to a variety of needs, easy to calculate and solve a variety of situations, so that the amount of data is concise and clear. Based on the results of the evaluation, the optimal ratio of biomass to coal can be obtained, where the ratio can be achieved to maximize the total product quality and optimize the energy conversion efficiency, to improve the product utilization and energy conversion efficiency.

5. CONCLUSION

In this research, the product characteristics and optimization strategies in the process of biomass and coal co-pyrolysis were systematically discussed, aiming to improve energy utilization efficiency and renewable energy yield. Experiments show that the combination of different biomass and coal has a significant effect on the pyrolysis products, especially the change of INS content and mixing ratio, which can effectively adjust the yield of tar and coke residue. This discovery provides an important theoretical support for the application of co-pyrolysis technology. Firstly, the analysis results based on multiple linear regression model show that INS has a significant positive effect on the yield of tar and coke residue, indicating that in the process of pyrolysis, appropriate INS content can promote the formation of liquid products, thereby improving their economic value. At the same time, the interaction effect analysis revealed the complex relationship between INS and mixing ratio and emphasized the importance of optimizing the ratio. This discovery lays a foundation for the efficient use of resources in the pyrolysis process. Secondly, by optimizing the construction of the model, we successfully determined the optimal INS content and mixing ratio, which significantly improved the utilization rate and energy conversion efficiency of the co-pyrolysis products. This achievement not only provides guidance for future production practice, but also provides valuable data support and reference for researchers in related fields. In summary, this research not only reveals the synergistic effect and mechanism of biomass and coal co-pyrolysis, but also provides an effective methodology for product prediction and optimization through mathematical modeling. Future research can further explore the combination of different types of biomasses with coal and their pyrolysis characteristics under more complex conditions, to make greater progress in improving energy conversion efficiency and environmental protection. It is hoped that this research can provide a new perspective for the promotion and application of biomass and coal co-pyrolysis technology and promote the sustainable development of renewable energy.

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