

Research on the coporolysis problem of biomass and coal

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Abstract. With the growth of the global population and the acceleration of industrialization, energy needs are increasingly urgent. To meet this challenge, biomass and coal co-pyrolysis technology has become the focus of attention, which not only provides a new approach for energy conversion, but also has great potential economic and environmental value.

Keywords: Biomass, co-pyrolysis, data visualization, multi-objective optimization, Kruskal-Wallis H test.

1. Introduction

This paper aims to study the pyrolysis problem of biomass and coal through the data visualization method.

For problem 1, data preprocessing and abnormal data are eliminated to ensure the quality and reliability of data. Then we explored the influence of n-hexane insoluble material (INS) on tar yield, aquatic yield and coke residue yield, observed the distribution and change trend of data points, and the influence of INS on pyrolysis yield was evaluated by visual analysis.

For question 2, a graph between mixing proportion and INS and pyrolysis yields was established, and a linear model including continuous and categorical variables was set for three different pyrolysis yields, and analyzed with ANOVA. An interaction effect analysis model was developed to explore the influence of hexane insoluble material (INS) and mixing ratio (H) on tar yield, aquatic product yield and coke residue yield. The results show that the ratio and the hexane insoluble content are significant in the tar yield and the coke residue ratio; the insoluble content is not.

For problem 3, a multi-objective optimization model is established, and the objective function is defined to maximize the tar yield based on the relationships obtained from problem 1 and problem 2 as constraints. Using the particle swarm optimization algorithm to solve the model and explore the appropriate mixing ratio to maximize product utilization and energy conversion efficiency.

Aiming at question 4, the data was visualized, and then the difference between the experimental values and the theoretical calculated values of the product yield was analyzed by Kruskal-Wallis H test method, and the subgroup analysis was conducted to obtain the significant difference table of ten different combinations. The results show that the theoretical and experimental values are essentially not significantly different.

For problem 5, a prediction model was established by using the random forest prediction model, predicting the yield of the pyrolysis product, and comparing the predicted value with the experimental value. Through the construction, training and validation of the model, it provides a reliable prediction basis for the optimization and regulation of the pyrolysis process.

1.1. Problem background

With the continuous growth of global population and the acceleration of industrialization, energy demand shows an increasing trend. However, traditional fossil fuels, such as coal and oil, are facing increasingly tense situations, and their limited reserves and unsustainable exploitation and utilization

methods have attracted wide attention. At the same time, with the increasingly serious environmental problems, including climate change, air pollution, water shortage, etc., people's demand for finding clean and renewable energy is also increasingly urgent [1].

In this context, biomass and coal copyrolysis technology has attracted much attention. As a renewable resource, biomass has a wide range of sources and rich species, and its advantage of sustainable utilization has become one of the important choices to replace the traditional energy[2]. In contrast, coal, as one of the main representatives of traditional energy sources, is rich in reserves, but its high carbon emissions and environmental pollution are also causing growing concerns[3].

Biomass and coal copyrolysis technology organically combines these two resources, through the common pyrolysis in high temperature and hypoxic environment, the organic substances in biomass and the carbon in coal are transformed, producing various products such as gas, liquid and solid[4, 5]. Among them, liquid products, namely pyrolytic oil or bio-oil, are considered to have great potential economic value and environmental benefits. This technology can not only effectively reduce the dependence on traditional fossil energy, but also reduce greenhouse gas emissions, reduce the degree of environmental pollution, and promote the development of energy utilization to a cleaner and more sustainable direction.

In addition to the impact on the energy structure and environmental protection, the development of biomass and coal copyrolysis technology will also bring a series of economic and social benefits[6]. This includes promoting the upgrading and transformation of relevant industrial chains, enhancing employment opportunities and economic growth, and improving regional development and the ecological environment. Therefore, strengthening the research and application of biomass and coal co-pyrolysis technology is not only of great significance for solving energy and environmental problems, but also has a far-reaching impact on promoting economic development and the realization of sustainable development goals.

1.2. Problem Restatement

Problem 1: Analysis of the influence of hexane insoluble material (INS) on pyrolysis yield. According to the data in Annex I, it is necessary to analyze whether hexane insoluble material (INS) has a significant effect on the pyrolysis yield (tar yield, aquatic product rate, coke residue yield), and explain it by image.

Question 2: The hexane insoluble material (INS) and mixing ratio were analyzed accordingly. In pyrolysis experiments, it is necessary to determine whether there is an interactive effect between hexane insoluble material (INS) and mixing ratio, and whether they have an important effect on the yield of pyrolysis products. If there is an interaction effect, it is necessary to determine on which pyrolysis products the interaction effect of sample weight and mixing ratio is most significant.

Problem 3: the establishment of the characteristics and composition optimization model of the heating solution products. According to the characteristics and composition of the copyrolysis products in Annex I, it is necessary to build models to optimize the thermal mixing ratio of the copyrolysis to improve the product utilization rate and energy conversion efficiency.

Problem 4: significance analysis of experimental value and theoretical calculation value of product yield of heating solution combination. For the data in Annex II, it is necessary to analyze whether there is a significant difference between the experimental values and the theoretically calculated values of each copyrolysis combination. If there are differences, subgroup analysis is used to determine which proportion these differences are represented by subgroup analysis.

Problem 5: the establishment of the prediction model of the pyrolysis product yield. Based on the experimental data, corresponding models need to be built to predict the yield of the pyrolysis products.

2. Problem analysis

2.1. Analysis of Question 1

For problem 1, the data in Annex I need to be preprocessed to ensure the quality and reliability of the data. The preprocessing process includes missing value processing, outlier detection and processing, data conversion, etc. With these steps, we can clean the data, reduce the noise, and provide a reliable basis for subsequent analysis. The effect of n-hexane insoluble material (INS) on tar yield, aquatic product yield and coke residue yield were analyzed visually. Establish the scatter plot or line diagram, the horizontal axis indicates the insoluble content of n-hexane, the vertical axis indicates the various yields, and observe the distribution and trend of data points. Further use the statistical method of correlation coefficient to evaluate the significant effect of INS on the yield of pyrolysis, and interpret it by the images to strengthen the confidence of the analysis conclusions.

2.2. Analysis of the Problem 2

In view of question 2, the relationship between mixing ratio and INS and pyrolysis yield was established, and the interaction effect of mixing ratio and INS on tar yield, aquatic yield and coke residue yield was discussed. Combining the linear model and ANOVA ANOVA, the importance of interaction effects was analyzed in depth to determine the extent and significance of its effect in product yield.

2.3. Analysis of the Problem 3

In view of problem 3, the optimization model optimizes the mixing ratio of co-heating to improve the product utilization rate and energy conversion efficiency. The multi-objective optimization model is established to maximize the pyrolysis yield, and the particle swarm optimization algorithm is used to solve the model, explore the appropriate mixing ratio, and realize the optimization of energy conversion efficiency.

2.4. Analysis of the Problem 4

Aiming at question 4, the data in Annex II were visualized, and the significant difference between the experimental values of the product yield was analyzed by Kruskal-Wallis H test method. Through subgroup analysis of the data from different combinations, the difference between the experimental and theoretically calculated values can be determined to reveal the credibility of the experimental results and the accuracy of the theoretical model.

2.5. Analysis of the Problem 5

For problem 5, the random forest prediction model is used to establish the corresponding prediction model to predict the yield of pyrolysis products. Through model construction, training and validation models, the pyrolysis product yield under different conditions is predicted to provide a reliable prediction basis for the optimization and regulation of the pyrolysis process.

3. Model hypothesis

When building models of biomass and coal, some basic assumptions are usually made to simplify the problem and the complexity of the model. The following are the model assumptions:

(1) The data given by the topic is true and reliable.

(2) The chemical reaction in the pyrolysis process is homogeneous reaction: it is assumed that the chemical reaction in the pyrolysis process is carried out under homogeneous conditions, that is, the reactants are evenly distributed in the reaction system, without considering the influence of the phase interface and inhomogeneity on the reaction rate.

(3) The temperature and pressure in the pyrolysis process remain constant: assuming that the temperature and pressure in the pyrolysis process remain constant, excluding the influence of the change of temperature and pressure on the reaction rate and product distribution.

(4) The reaction in the pyrolysis process is a rapid equilibrium reaction: assuming that the reaction in the pyrolysis process reaches a rapid equilibrium state, that is, the reaction reaches the maximum degree of transformation, and the relationship between the reaction rate and the concentration of the reactants can be described by the equilibrium constant.

(5) The composition of biomass and coal is fixed: assume that the composition of biomass and coal remain unchanged in the pyrolysis process, without considering the influence of the change of composition on the reaction.

(6) The distribution coefficient of pyrolysis products is constant: assuming that the distribution coefficient of pyrolysis products remains constant under different conditions, without considering the influence of temperature, pressure and other factors on the distribution coefficient.

4. Evaluation of the model

4.1. The advantages of the model

(1) Comprehensive: The model considers the influence of various factors on the yield of pyrolysis products, including the insoluble content of hexane, mixing ratio, interaction effect, etc., and comprehensively analyzes the key factors in the pyrolysis process from multiple perspectives.

(2) Interpretability: the model building process is clear, and the theories and methods involved are easy to understand and explain. The diagram and detailed description can intuitively understand the influence of each factor on the yield of pyrolysis products, providing guidance for further research and practice.

(3) Prediction accuracy: Random forest prediction model is used to predict the yield of pyrolysis products, which has high prediction accuracy and stability. The model is able to fully exploit the information in the data to effectively fit the yield of the pyrolysis products and make accurate predictions for the unknown data.

(4) Optimizability: By establishing the optimization model, the mixing ratio of the copyrolysis can be optimized to maximize the yield of the pyrolysis products and the energy conversion efficiency. The particle swarm optimization algorithm can be used to solve the complex optimization problems quickly and effectively, which provides guidance and reference for the practical production.

(5) Reliability: The reliability of the model results is evaluated and validated through statistical analysis and hypothesis testing. The model is highly scientific and practical, and can provide strong support for the research and application of biomass and coal copyrolysis technology.

4.2. The shortcomings of the model

(1) Limitation: In the process of establishment, the model may be based on some assumptions, such as linear relationship assumption, data independence and identical distribution assumption, etc. These assumptions may deviate from the real situation, thus affecting the applicability and reliability of the model.

(2) Parameter adjustment: In the process of model optimization, the selection and adjustment of parameters may require certain experience and professional knowledge, while different parameter Settings may lead to different optimization results, with certain subjectivity and uncertainty.

(3) Model complexity: Some models may have high complexity, such as the use of complex optimization methods such as particle swarm optimization algorithm, which may increase the computational cost and implementation difficulty of the model, and limit its feasibility in practical application.

(4) Model interpretability: Some models may lack intuitive interpretability, such as black-box models like random forest. Although they can provide high prediction accuracy, the interpretation of

the decision process and influencing factors within the model is not intuitive enough, which may reduce the credibility and acceptability of the model.

5. Conclusions

(1) Optimize model parameters and hyperparameters: through the system parameter tuning and model evaluation, select the optimal combination of model parameters and hyperparameters to improve the performance and stability of the model. Cross-validation, grid search and other methods can be used to comprehensively search and evaluate the model with parameters.

(2) Improve the interpretability of the model: For complex black-box models, more explanatory models or technologies can be improved, such as local interpretability model, model explanatory algorithm, etc., to improve the intelligibility and interpretability of the model, and enhance the credibility and acceptability of the model in practical application.

(3) Strengthen model validation and evaluation: adopt more rigorous and comprehensive model validation and evaluation methods, including cross-validation, set-aside validation, self-service method, etc., to ensure the generalization ability and stability of the model, and make a comprehensive evaluation and comparison of the prediction effect of the model.

Reference documentation

- [1] Zhang Yunfei. Action strategy to enhance China's new energy competitiveness under the goal of "double carbon" —— In-depth study and implement General Secretary Xi Jinping's important discourse on the energy revolution [J]. National governance, 2023, (17): 14-9.
- [2] Yu Mei Shuang, Hou Shuo. Progress in biomass gasification [J]. Liaoning Chemical Industry, 2024, 53 (04): 606-11.
- [3] Zhang Yingying, Cui Xiaozheng, Wang Zhikang, et al. Control of the emission of unconventional pollutants from coal combustion [J]. Clean Coal Technology, 2023, 29 (10): 1-16.
- [4] Niu Zhiyuan, Liu Guijian. Characteristics and mechanism of non-catalytic synergistic effect of coal-biomass copyrolysis [J]. Journal of Solar Energy, 2024, 45 (04): 286-95.
- [5] Song Ruizhen, Yang Xiaoyang, Zhang Peng, et al. Progress on carbonization characteristics of hydrothermal carbon and functionalization modification of low-rank coal and biomass [J]. Clean Coal Technology, 2024, 30 (03): 72-85.
- [6] Luo Rui, Wang Zhiwei, Chen Huadong, et al. Analysis and synergistic effect of coal and biomass [J]. Clean Coal Technology, 2023, 29 (S2): 196-205.
- [7] CAI Quanfu, He Lihong, Wang Zhijun, et al. Optimization of silicon steel process parameters based on neural network and particle swarm algorithm [J]. Electrical Steel, 2024, 6 (02): 37-40.
- [8] Feng Qian. Multi-objective Optimization and Application based on improved particle swarm algorithm [D]; University of Science and Technology Beijing, 2022.
- [9] SECREST B R, LAMONT G B, IEEE, et al. Visualizing particle swarm optimization - Gaussian particle swarm optimization; proceedings of the IEEE Swarm Intelligence Symposium, Indianapolis, In, F Apr 24-26, 2003 [C]. Ieee: NEW YORK, 2003.
- [10] Zhong Yubin, Fan Shuheng. A fuzzy multicluster particle swarm algorithm based on factor space [J]. Journal of Guangzhou University (Natural Science Edition), 2023, 22 (06): 77-81.
- [11] VAN ZYL J P, ENGELBRECHT A P. Set-Based Particle Swarm Optimisation: A Review [J]. Mathematics, 2023, 11(13): 36.
- [12] VARGHA A, DELANEY H D. The Kruskal-Wallis test and stochastic homogeneity [J]. J Educ Behav Stat, 1998, 23(2): 170-92.
- [13] NIEDOBA T, SUROWIAK A, HASSANZADEH A, et al. Evaluation of the Effects of Coal Jigging by Means of Kruskal-Wallis and Friedman Tests [J]. Energies, 2023, 16(4): 17.
- [14] MARTIN J B, YEO D. Critical random forests [J]. ALEA-Latin Am J Probab Math Stat, 2018, 15(2): 913-60.

- [15] MANTAS C J, CASTELLANO J G, MORAL-GARCÍA S, et al. A comparison of random forest based algorithms: random credal random forest versus oblique random forest [J]. *Soft Comput*, 2019, 23(21): 10739-54.