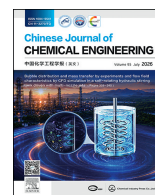




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Full Length Article

Prediction of pyrolysis products distribution for end-of-life wind turbine blades using attention-based feature fusion



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ABSTRACT

Pyrolysis can effectively recover glass fibers from end-of-life wind turbine blades (WTBs) while producing reusable pyrolysis oil and syngas. The nonlinear dynamics involved in the pyrolysis of end-of-life WTBs bring challenges in accurately predicting the product distribution. This paper proposes an attention-based feature fusion prediction framework for pyrolysis product distribution of end-of-life WTBs. Firstly, a physics-informed neural network (PINN) incorporating the Arrhenius equation is proposed. Then, a product distribution prediction model for the fast pyrolysis of end-of-life WTBs is developed by integrating the extreme gradient boosting algorithm, multilayer perceptron, and the PINN, with an attention mechanism introduced to dynamically weight their output. Based on this, a dynamic weighted feature fusion algorithm is proposed to predict the pyrolysis product distribution of end-of-life WTBs. Finally, the superiority of the proposed method is demonstrated through fast pyrolysis experiments of end-of-life WTBs. The experimental results show that the proposed method achieves a notable improvement in prediction accuracy, reducing the root mean square error and mean absolute error by 86% to 99% compared to existing approaches.

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1. Introduction

With the rapid advancement of wind power generation, the treatment of end-of-life wind turbine blades (WTBs) is becoming increasingly critical [1,2]. End-of-life WTBs are primarily composed of glass fiber-reinforced thermosetting polymer composite materials, which allows them to be recycled using industrial technologies [3,4]. Scholars have proposed several methods for processing end-of-life WTBs, including landfill, mechanical recycling [5], chemical treatment [6,7], incineration [8], and pyrolysis [9]. It should be noted that pyrolysis has gradually become the mainstream method for processing end-of-life WTBs due to its lower energy consumption and higher recycling efficiency for valuable materials [10]. Pyrolysis is a thermal decomposition process of carbonaceous materials conducted under anaerobic conditions [11,12]. The pyrolysis technology can break down the

cross-linked molecular chains of the polymer matrix, enabling the high-quality separation of glass fibers from end-of-life WTBs while producing oil, carbon, and syngas [13].

Product prediction is a fundamental topic in the study of the pyrolysis process, which is crucial for optimizing the parameters of industrial pyrolysis reactors [14]. The primary methods for predicting product distribution in pyrolysis include experimental analysis-based methods and machine learning-based methods [15–17]. Compared with experimental analysis-based methods, machine learning-based methods can develop product prediction models under various pyrolysis conditions with greater accuracy [18]. Recently, some machine learning models have been used for predicting the product distribution of fast pyrolysis, such as random forest (RF) [19], artificial neural network (ANN) [20], support vector machine (SVM) [21], extreme gradient boosting (XGB) [22], and multilayer perceptron (MLP) [23]. However, the pyrolysis process of end-of-life WTBs exhibits nonlinear dynamics, which can affect the accuracy of existing machine learning methods in predicting the product distribution of pyrolysis. Moreover, existing methods rely solely on data fitting to establish the relationship

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between system inputs and outputs, with limited incorporation of the physical laws governing the pyrolysis process. Therefore, it is meaningful to develop an effective method to improve the accuracy of product prediction of fast pyrolysis of end-of-life WTBs.

The physics-informed neural network (PINN) is a neural network model that integrates system operation mechanisms into the training process of neural networks [24]. Unlike traditional machine learning models that rely solely on data-driven methods, PINN incorporates physical constraints and reaction mechanisms into the neural network, enabling the results to more accurately reflect industrial processes [25,26]. By combining experimental data with reaction mechanisms, PINN has higher accuracy in simulating the dynamic characteristics of complex systems. PINN has seen rapidly expanding applications as an emerging model in various fields, such as wind power generation [27], photovoltaic power generation [28], material science [29], power system [30], and batteries [31]. The existing results demonstrate the superiority of PINN over other machine learning models. To the best of the authors' knowledge, there are no references on product distribution prediction of fast pyrolysis using PINN.

Inspired by the discussions above, we introduce the PINN to predict the product distribution of the fast pyrolysis of end-of-life WTBs. This is the first time that PINN has been applied to the fast pyrolysis of end-of-life WTBs. We establish a dynamic weighted feature fusion model (DWFFM) incorporating XGB, MLP, and PINN as submodels to predict the product distribution of fast pyrolysis. Our main motivation is to enhance the accuracy of the product prediction model. Unlike traditional methods that rely on a single machine learning model, our approach not only overcomes the limitations of capturing nonlinear dynamics but also offers a novel perspective on parameter optimization for the fast pyrolysis of end-of-life WTBs. The contributions of this paper can be summarized in the following points.

- 1) A novel PINN-based method for product distribution modeling is proposed to achieve interpretable modeling of the fast pyrolysis of end-of-life WTBs. By integrating the reaction mechanism, the proposed PINN method can ensure physical consistency and enhance the interpretability of product distribution modeling in fast pyrolysis.
- 2) To overcome the limitations of single-model predictions, an attention-based dynamic weighted feature fusion framework is proposed. By combining the advantages of XGB, MLP, and PINN submodels to enhance prediction accuracy. Then, a dynamic weighted feature fusion algorithm is presented.
- 3) A detailed experimental comparative analysis is provided to demonstrate the superiority of the proposed method. The experimental results show that the proposed attention-based product prediction model effectively reduces the root mean squared error and mean absolute error within a range from 86% to 99%.

The rest of this paper is structured as follows. Section 2 provides an attention-based dynamic weighted feature fusion framework for fast pyrolysis of end-of-life WTBs. Section 3 presents experimental verification to demonstrate the superiority of our method, while Section 4 concludes the paper.

2. Research Methods

The scheme of pyrolysis system for end-of-life WTBs is presented in Fig. 1. The pyrolysis system primarily consists of four stages: pretreatment, pyrolysis reaction, product separation, and product treatment and utilization. During the pretreatment stage, end-of-life WTBs are cut and crushed, then subjected to gradual

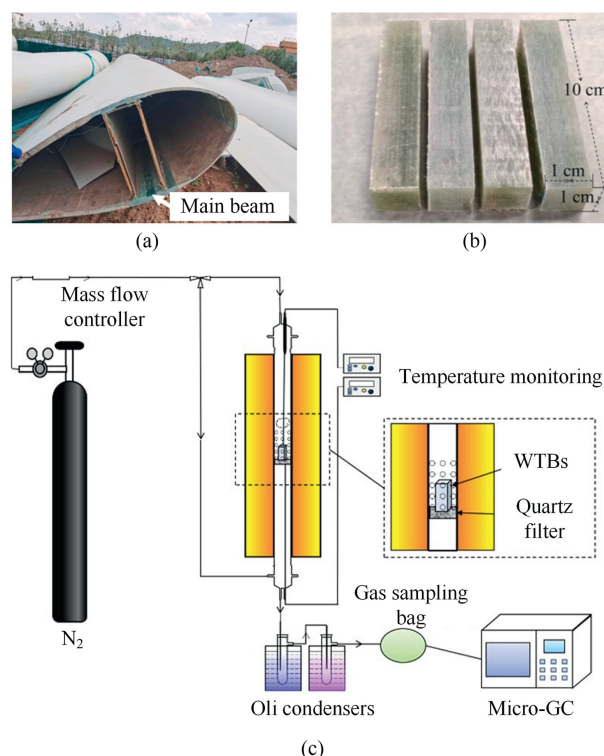


Fig. 1. (a) The industrial end-of-life WTBs. (b) The slicing of end-of-life WTBs for the pyrolysis tests. (c) The industrial process of fast pyrolysis of end-of-life WTBs.

heating under anaerobic conditions. The three-phase products generated from the pyrolysis of end-of-life WTBs are separately recovered and reused through separation devices. Pyrolysis oil can be utilized as a chemical raw material, pyrolysis gas can be recycled as furnace fuel or used for power generation, and glass fibers can be employed to manufacture low-load composite materials. The main focus of this paper is on the distribution of the three-phase products, specifically glass fibers, pyrolysis oil, and pyrolysis gas, generated during the pyrolysis reaction.

In this section, we propose the DWFFM based on an attention mechanism to predict the product distribution of fast pyrolysis of end-of-life WTBs.

2.1. PINN-based product distribution model

According to Ref. [32], the primary component of end-of-life WTBs is glass fiber-reinforced thermosetting polymer composite material. The key process in the rapid pyrolysis of these WTBs is the fracture of cross-linked molecular chains within the polymer matrix. The rate of the chain-fracture reaction depends on the pyrolysis temperature, with the reaction kinetics exhibiting an exponential dependence on temperature. Therefore, the Arrhenius equation can be applied to describe the thermodynamic behavior of pyrolysis for end-of-life WTBs. The Arrhenius law and n -th reaction rate can be expressed as follows:

$$r(T) = A \exp\left(-\frac{E_a}{RT}\right) \quad (1)$$

$$\frac{d\alpha(t)}{dt} = A \exp\left(-\frac{E_a}{RT}\right) (1 - \alpha(t))^\beta \quad (2)$$

where E_a denotes the activation energy, $r(T)$ denotes the reaction rate, T denotes the temperature, R denotes the gas constant, A

denotes the pre-exponential factor, and β denotes the reaction order that controls the nonlinear behavior of the conversion rate.

By substituting Eqs. (1) and (2) into the PINN, which consists of L hidden layers with N neurons each, and using the ReLU activation function to model the nonlinear characteristics of the reaction process. The total loss function includes two parts: data loss and physical constraint loss. Quantify the discrepancy between predicted yield and experimental yield based on mean squared error (MSE). Then, the data loss L_{data} can be expressed as follows:

$$L_{\text{data}} = \sum (\hat{y}_{\text{predict}} - y_{\text{data}})^2 \quad (3)$$

The physical constraint loss L_{phys} , which ensures that the conversion rate predictions satisfy the kinetic equation, can be expressed as follows:

$$L_{\text{phys}} = \sum \left[\frac{d\alpha(t)}{dt} - A \exp\left(-\frac{E_a}{RT}\right) (1 - \alpha(t))^\beta \right]^2 \quad (4)$$

Then, the total loss function L_{total} can be derived as

$$L_{\text{total}} = \lambda L_{\text{data}} + (1 - \lambda) L_{\text{phys}} \quad (5)$$

where λ is a tunable scalar controlling the trade-off between data fidelity and physical regularization. The value of λ is determined through cross validation. When the experimental data contains high noise levels, increase λ to enhance the data fitting capability. Conversely, when the sample size is insufficient or physical constraints need to be reinforced, decrease λ to improve the model's interpretability.

Compared to conventional machine learning models, the PINN integrates the pyrolysis mechanism into the training process, enhancing prediction accuracy by elucidating the underlying mechanisms that govern the influence of process variables on product distributions.

2.2. Attention-based dynamic weighted feature fusion

This subsection dynamically weights the XGB, MLP, and PINN models using an attention mechanism and subsequently develops a dynamic weighted feature fusion algorithm to predict the

product distribution of end-of-life WTBS during fast pyrolysis. Among these three models, XGB excels at handling structured data, MLP effectively models intricate nonlinear relationships, and PINN enhance prediction consistency by incorporating constraints imposed by physical laws. The combined advantages of these models collectively establish a solid foundation for the reliability of the proposed feature fusion algorithm and the accuracy of predicting fast pyrolysis product distributions.

The XGB algorithm is based on gradient boosting decision trees [33], and its general prediction formula is expressed as follows:

$$\hat{y}_i = \sum_{k=1}^{\alpha} g_k(x_i) \quad (6)$$

where α is the total number of trees, and $g_k(x_i)$ denotes the prediction of the k -th tree. The objective function comprises a training loss and a regularization term, which can be expressed as follows:

$$L(\theta) = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^{\alpha} \Omega(g_k) \quad (7)$$

The regularization term $\Omega(g_k)$ penalizes model complexity and can be expressed as follows:

$$\Omega(g_k) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^{\beta} w_j^2 \quad (8)$$

where γ denotes the tree-complexity coefficient, λ denotes the L2 regularization coefficient, β denotes the number of leaves, and w_j denotes the weight of each leaf node.

MLP is a feedforward neural network capable of modeling nonlinear relationships [34], and the output of its l -th layer can be expressed as follows:

$$h^{(l)} = \sigma(A^{(l)} h^{(l-1)} + b^{(l)}) \quad (9)$$

where σ represents a nonlinear activation function, $A^{(l)}$ represents the weight matrix, and $b^{(l)}$ represents the bias vector. The final output can be expressed as follows:

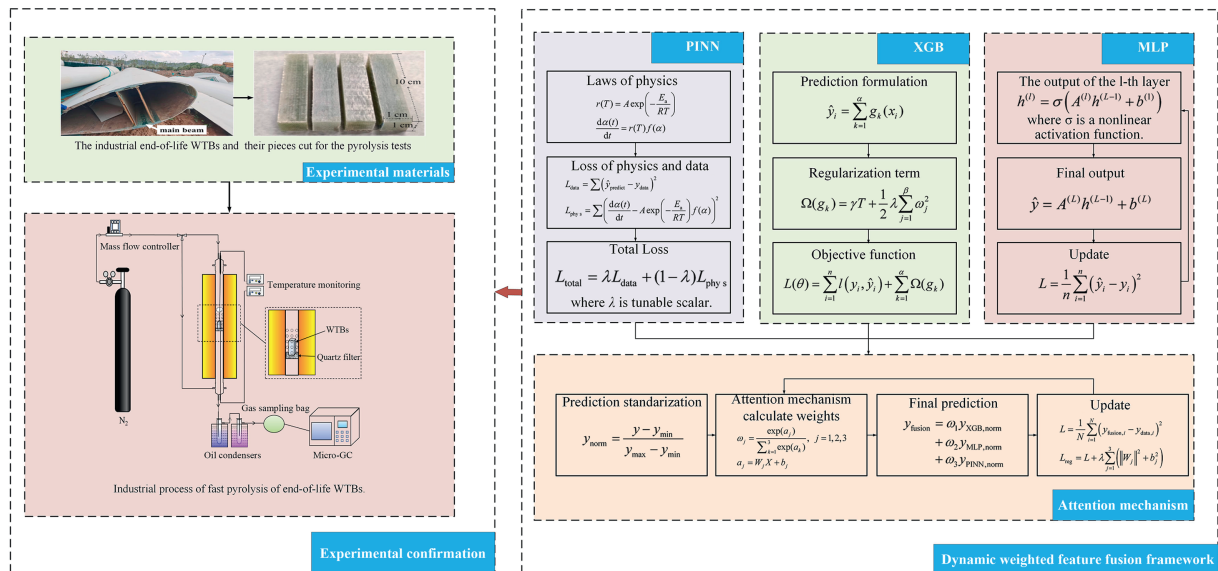


Fig. 2. Attention-based dynamic weighted feature fusion framework for fast pyrolysis of end-of-life WTBS.

$$\hat{y} = A^{(L)}h^{(L-1)} + b^{(L)} \quad (10)$$

where L is the number of hidden layers. Then, the MLP network is trained by minimizing the MSE. The loss function $\mathbb{L}$ can be expressed as follows:

$$\mathbb{L} = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2 \quad (11)$$

where $\hat{y}_i$ denotes the predicted value and y_i denotes the true value for the i -th sample.

Furthermore, each submodel (XGB, MLP, and PINN) is independently trained to predict the three-phase yields of fast pyrolysis of end-of-life WTBs. The resulting submodel prediction outputs, denoted as y_{XGB} , y_{MLP} , and y_{PINN} , are normalized using min-max scaling to ensure comparability. The formulation of y_{norm} can be expressed as follows:

$$y_{\text{norm}} = \frac{y - y_{\min}}{y_{\max} - y_{\min}} \quad (12)$$

It follows from Eq. (12) that the outputs are normalization maps to the interval $[0, 1]$.

To enable dynamic weighting, the normalized predictions are concatenated with the original input X and true experimental yields y_{data} to form a comprehensive training dataset. The dataset can be expressed as follows:

$$\text{Data}_{\text{fusion}} = [X, y_{\text{XGB|norm}}, y_{\text{MLP|norm}}, y_{\text{PINN|norm}}, y_{\text{data}}] \quad (13)$$

It is easy to see that Eq. (13) trains a fully connected attention neural network, which generates three weights ω_1 , ω_2 , and ω_3 , representing the contributions of XGB, MLP, and PINN, respectively. The attention network evaluates submodel relevance based on input features and performance, with raw outputs a_j normalized via the softmax function. Softmax can concentrate weights on a dominant submodel and suppress contributions from others, particularly when raw attention scores differ substantially. Although linear or sigmoid-based normalization provides greater flexibility, it can result in unbounded or less interpretable weights, potentially causing unstable training. The formulations of a_j and ω_j can be derived as

$$a_j = W_j X + b_j \quad (14)$$

$$\omega_j = \frac{\exp(a_j)}{\sum_{k=1}^3 \exp(a_k)}, j = 1, 2, 3 \quad (15)$$

where X represents input parameters, W_j and b_j represent trainable parameters. The attention mechanism is trained by minimizing an MSE loss function to quantify the discrepancy between fusion predictions and experimental yields, and to enhance generalization and prevent overfitting, an L2 regularization term is included. The formulation of L_{reg} can be expressed as follows:

$$L_{\text{reg}} = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2 + \lambda \sum_{j=1}^3 (\|W_j\|^2 + b_j^2), \quad (16)$$

where λ is coefficient used to control the strength of regularization. The Adam optimizer updates parameters W_j and b_j , with the learning rate tuned through cross-validation to ensure balanced convergence. Then, the fusion prediction y_{fusion} can be derived as

$$y_{\text{fusion}} = \omega_1 y_{\text{XGB|norm}} + \omega_2 y_{\text{MLP|norm}} + \omega_3 y_{\text{PINN|norm}}. \quad (17)$$

It follows from Eq. (17) that the proposed DWFFM can leverage strengths of the each submodel, dynamically adapting to input data characteristics to deliver accurate and physically consistent pyrolysis yield predictions. The flowchart of the attention-based dynamic weighted feature fusion framework is shown in Fig. 2. Based on this, Algorithm 1 is presented to execute the proposed DWFFM.

Algorithm 1 Attention-based dynamic weighted feature fusion algorithm

```

1: Input: Input data  $X$ , true experimental yields  $y_{\text{data}}$ , hyperparameters
2: Output: Fusion prediction  $y_{\text{fusion}}$ 
3: Train XGB, MLP, and PINN independently on  $((X, y_{\text{data}}))$  to obtain predictions  $(y_{\text{XGB}}, y_{\text{MLP}}, y_{\text{PINN}})$ 
4: Compute  $y_{\text{norm}}$  according to Eq. (12)
5: Construct fusion dataset:
    $\text{Data}_{\text{fusion}} = [X, y_{\text{XGB|norm}}, y_{\text{MLP|norm}}, y_{\text{PINN|norm}}, y_{\text{data}}]$ 
6: Initialize attention neural network with parameters  $W_j, b_j$  for  $j = 1, 2, 3$ 
7: For each epoch do
8:   Compute  $a_j, \omega_j, \mathcal{L}_{\text{reg}}$ , and  $y_{\text{fusion}}$  according to Eqs. (14)–(17)
9:   Update  $W_j, b_j$  using Adam optimizer
10: End for
11: Return  $y_{\text{fusion}}$ 

```

3. Results and Discussion

In this section, we validate the effectiveness of the proposed DWFFM through pyrolysis experiments conducted on end-of-life WTBs. Then, by comparing our method with existing results, we demonstrate the superiority of the proposed DWFFM.

3.1. Modeling dataset generation

The predominant component of end-of-life WTBs is glass fiber reinforced polymer, comprising approximately 60% to 70% glass fibers and 30% to 40% epoxy resin matrix. High-purity nitrogen is introduced as an inert carrier gas to purge the reactor system, thereby ensuring that the pyrolysis process occurred under oxygen-deficient conditions. The key input parameters included the temperature, ranging from 300 °C to 550 °C, and the heating rates, set at 10, 20 °C and 40 °C·min⁻¹, to investigate their impacts on the thermal kinetics of the process. The conversion rate is measured using thermogravimetric analysis and is expressed as follows:

$$\alpha = \frac{m_0 - m_t}{m_0 - m_{\text{ash}}} \times 100\% \quad (18)$$

where m_0 represents the initial sample mass, m_t represents the residue mass at time t , and m_{ash} represents the final ash mass.

The primary output parameters of the pyrolysis process are the yields of liquid, solid, and gas phases. The liquid phase yield included the condensates of water and organic liquids, while the solid phase yield is composed of pyrolytic char and glass fiber residue. Then, the gas phase yield consisted of non-condensable gases such as hydrogen, methane, and carbon monoxide. The input and output parameters are critical in evaluating the efficiency and dynamics of the pyrolysis reaction under various experimental conditions.

Based on multiple pyrolysis experiments conducted on end-of-life WTBs, a dataset suitable for predicting product distribution

using machine learning models is obtained. This dataset, comprising 153 entries, is created after recording experimental data and applying preprocessing steps, including outlier elimination using the Grubbs test and correction of conversion rate calculations. In addition, the dataset is partitioned to ensure the test's validity and reliability, with 70% allocated for training, 20% for validation, and 10% for testing.

3.2. Performance indices

The performance indicators, including mean absolute percentage error (MAPE), root mean squared error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2), are used to evaluate the predictive accuracy of the model. The calculation formulas of MAPE, RMSE, MAE, and R^2 are as follows:

$$\text{MAPE} = \frac{1}{T} \sum_{t=1}^T \frac{|y(t) - \hat{y}(t)|}{y(t)} \quad (19)$$

$$\text{RMSE} = \sqrt{\left(\frac{1}{T} \sum_{t=1}^T [y(t) - \hat{y}(t)]^2 \right)} \quad (20)$$

$$\text{MAE} = \frac{1}{T} \sum_{t=1}^T |y(t) - \hat{y}(t)| \quad (21)$$

$$R^2 = 1 - \frac{\sum_{t=1}^T [y(t) - \hat{y}(t)]^2}{\sum_{t=1}^T [y(t) - \bar{y}]^2} \quad (22)$$

where $\hat{y}(t)$ denotes the predicted value at time t , and $\bar{y}$ denotes the mean value of $y(t)$ series.

Additionally, we employ the Diebold-Mariano (DM) test to gauge the superiority of prediction outcomes compared to various

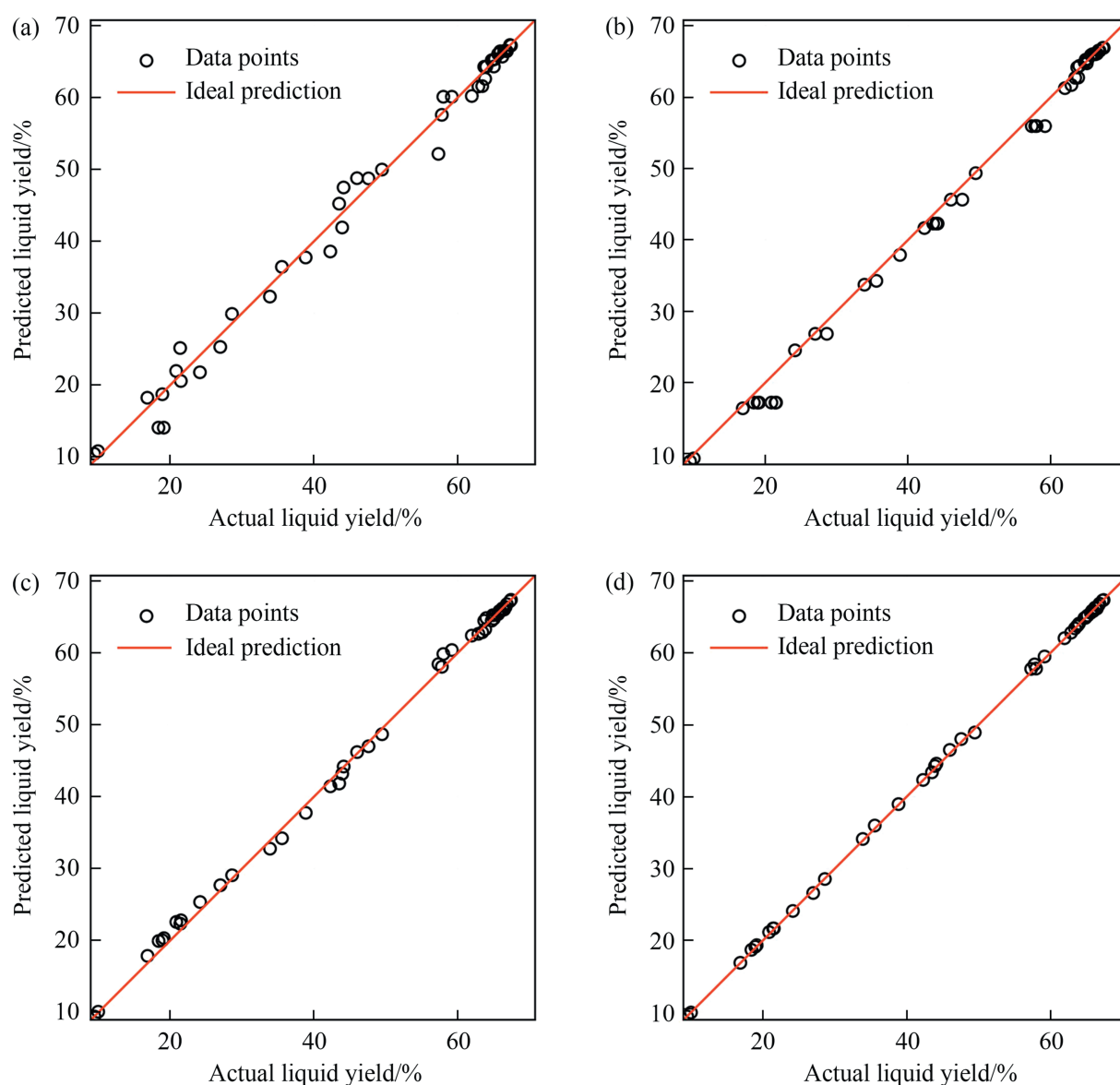


Fig. 3. Scatter plot of liquid yield. (a) SVM. (b) RF. (c) ANN. (d) DWFFM.

prediction techniques. For the DM test, the mean squared error is adopted as the loss function, ensuring consistency with the evaluation criteria used throughout this study. The loss function $L(\cdot)$ is defined as follows:

$$L(\varepsilon_t, \hat{\varepsilon}_{i|t}) = (y(t) - \hat{y}_{i|t})^2 \quad (23)$$

Then the null hypothesis H_0 can be expressed as follows:

$$H_0 = E[L(\varepsilon_t, \hat{\varepsilon}_{i|t})] = E[L(\varepsilon_t, \hat{\varepsilon}_{j|t})] \quad (24)$$

where $\hat{\varepsilon}_{i|t}$ represents the prediction result of a particular method at the time t , while $E(\cdot)$ represents the expected operation. According to the alternative hypothesis, there is a difference in the prediction accuracy between the two models, unlike the null hypothesis. The alternative hypothesis H_1 can be expressed as follows:

$$H_1 = E[L(\varepsilon_t, \hat{\varepsilon}_{i|t})] \neq E[L(\varepsilon_t, \hat{\varepsilon}_{j|t})] \quad (25)$$

The loss deviation d_t can be expressed as follows:

$$d_t = L(\varepsilon_t, \hat{\varepsilon}_{i|t}) - L(\varepsilon_t, \hat{\varepsilon}_{j|t}) \quad (26)$$

It follows from Eq. (26) that the DM statistics can be expressed as follows:

$$DM = \sqrt{T} \left(\frac{\bar{d}}{\hat{\sigma}} \right) \xrightarrow{d} N(0, 1) \quad (27)$$

where $\hat{\sigma}$ represents an estimate of the standard deviation of d_t , and $\bar{d}$ represents the sample mean of d_t .

3.3. Comparison with existing methods

In this subsection, we compare the proposed DWFFM with existing methods, including RF [19], ANN [20], and SVM [21]. The scatter plots for the predicted liquid, solid, and syngas products from these methods are shown in Figs. 3–5, respectively. The specific data regarding the performance indicators of oil, char, and

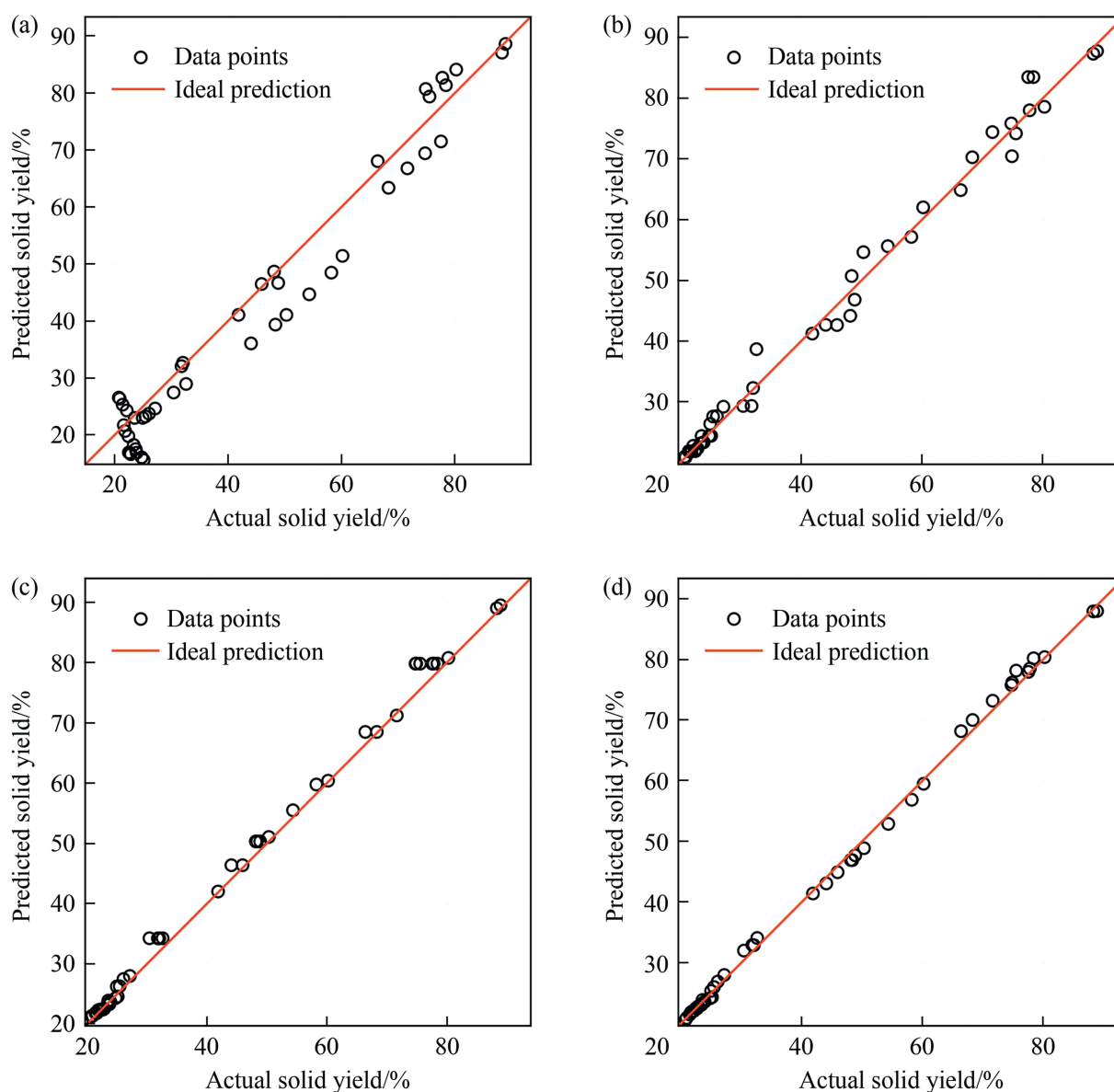


Fig. 4. Scatter plot of solid yield. (a) SVM. (b) RF. (c) ANN. (d) DWFFM.

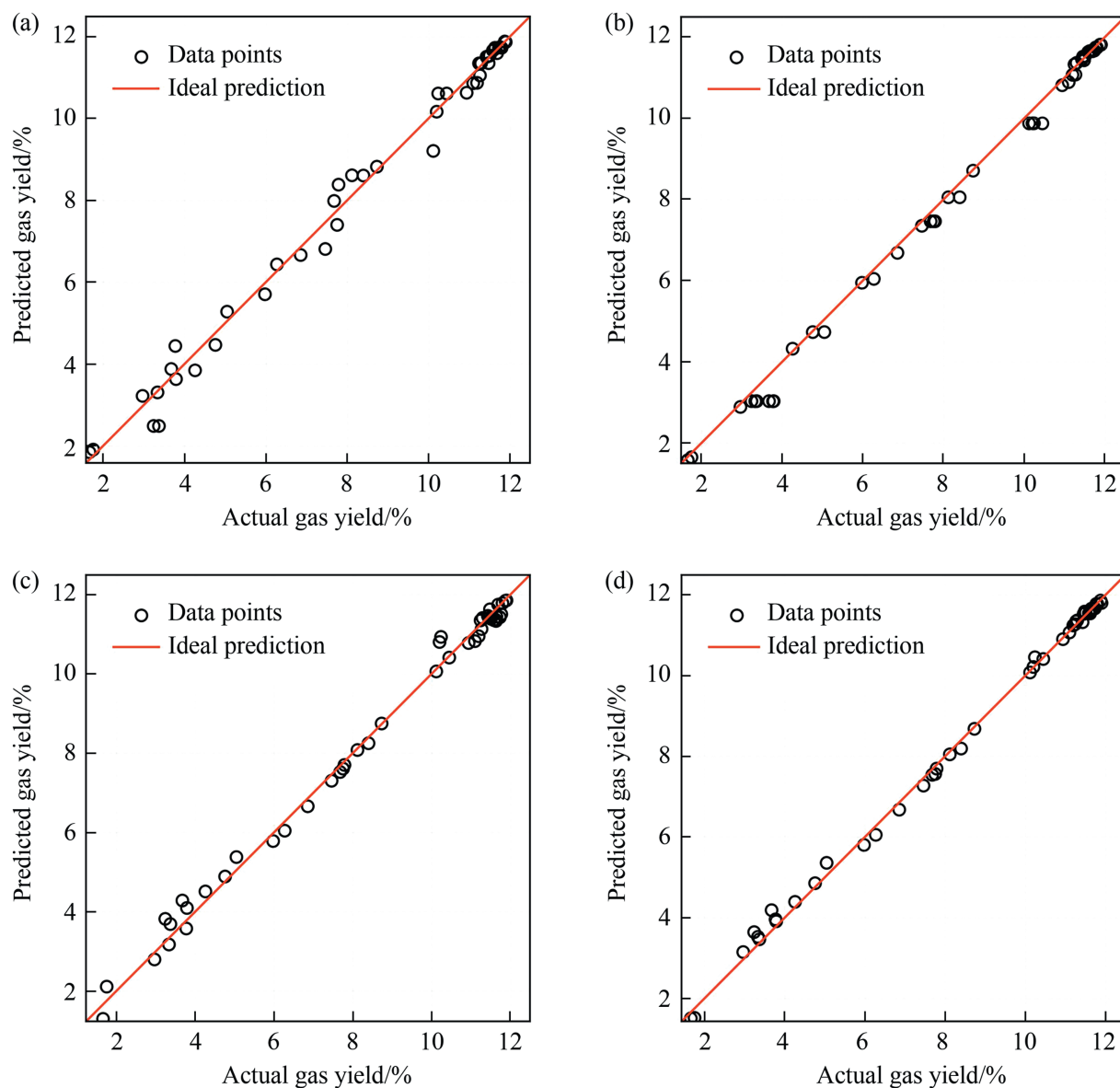


Fig. 5. Scatter plot of gas yield. (a) SVM. (b) RF. (c) ANN. (d) DWFFM.

Table 1
Performance indicators of liquid yield.

Method	SVM	RF	ANN	DWFFM
RMSE	1.675	2.466	0.305	0.021
MAE	1.256	1.295	0.208	0.017
MAPE	2.639	2.414	0.455	3.845
R^2	0.874	0.894	0.931	0.991

Table 2
Performance indicators of solid yield.

Method	SVM	RF	ANN	DWFFM
RMSE	1.467	2.094	0.212	0.026
MAE	1.086	1.105	0.152	0.021
MAPE	5.251	6.029	0.574	4.593
R^2	0.887	0.901	0.940	0.993

Table 3
Performance indicators of gas yield.

Method	SVM	RF	ANN	DWFFM
RMSE	0.517	0.371	0.176	0.023
MAE	0.348	0.197	0.149	0.018
MAPE	11.731	6.091	5.642	4.281
R^2	0.933	0.939	0.941	0.995

syngas products are presented in Table 1, Table 2, and Table 3, respectively.

It follows from Figs. 3–5 that the proposed DWFFM provides a more precise representation of the pyrolysis process of end-of-life WTBs. In addition, the statistical metrics summarized in Table 1, Table 2, and Table 3 confirm that the proposed DWFFM offers

Table 4
Results of Diebold–Mariano test.

Method	SVM	RF	ANN	DWFFM
DM test	10.336	10.285	6.335	2.734

superior capability in capturing the nonlinear dynamics during the fast pyrolysis of end-of-life WTBs. Specifically, the SVM model, RF model, and ANN model exhibit relatively large prediction errors for the liquid prediction, where the values of RMSE and MAE for the SVM model are 1.675 and 1.256, respectively. The RF model exhibits relatively limited accuracy for the char prediction, where the values of RMSE and MAE for the RF model are 2.094 and 1.105, respectively, along with lower R^2 values. On the contrary, the DWFFM achieves the lowest RMSE and MAE, demonstrating its strong capability to minimize prediction errors. The RMSE of DWFFM for liquid prediction is 0.021, which represents a reduction of 98.75% compared to SVM, and with a reduction of 96.84% and 95.92% in MAE and MAPE, respectively. For char prediction, an R^2 value of 0.993 is achieved by DWFFM, exceeding ANN by 5.64%. The RMSE is reduced from 0.352 for RF to 0.042 for DWFFM, with the MAE decreasing by 85.37% relative to RF. In comparison to SVM, the RMSE of DWFFM is reduced by 95.57%, reaching 0.040, and the MAE decreases from 0.775 to 0.040 for syngas prediction. Moreover, the high R^2 value shows that DWFFM has an excellent fitting degree to the actual data. It follows that the DWFFM has a more powerful nonlinear fitting and prediction capability in predicting the product distribution of the fast pyrolysis, which is a significant advantage over other traditional methods.

3.4. Diebold–Mariano test

To conduct a comprehensive evaluation of the simulation results, the DM test is performed in this subsection. It is employed to quantify the predictive discrepancies between the outputs of various methods and the actual values. Table 4 provides a summary of the scientific findings of the DM tests.

As shown in Table 4, the SVM and RF models recorded the highest statistics, with values of 10.336 and 10.285, respectively. This indicates that there is a significant difference between the values of the SVM model and the RF model and the true values. On the contrary, the proposed DWFFM achieves the lowest statistic of 2.734, reflecting the smallest loss discrepancy from actual values and demonstrating more stable and consistent predictive performance. The DM test results illustrate that the DWFFM outperforms the alternative models, confirming the effectiveness of the DWFFM in enhancing prediction accuracy.

Moreover, due to the parallelizable architecture of each sub-model in DWFFM, the proposed algorithm can adapt to dynamic changes in computing resources during model training, maintaining stable computational efficiency under resource constraints. The method proposed in this paper can effectively predict the distribution of pyrolysis products from end-of-life WTBs under various conditions. It also allows for the adjustment of parameters such as temperature and heating rate based on actual industrial requirements, providing valuable guidance for optimizing the pyrolysis process parameters of end-of-life WTBs.

4. Conclusions

In this paper, a product prediction model for the fast pyrolysis of end-of-life WTBs has been investigated. A PINN-based product distribution model has been proposed for fast pyrolysis of end-of-life WTBs. A DWFFM has been developed using an attention

mechanism to predict the product distribution of fast pyrolysis of end-of-life WTBs. An algorithm for determining the output parameters of DWFFM has been proposed. Compared to existing methods, the proposed DWFFM effectively reduces the RMSE and MAE within a range of 86% to 99%, depending on the specific pyrolysis product type, as demonstrated in the experimental comparisons. Additionally, the DM test verifies DWFFM's superior consistency and stability. Future work will extend the proposed DWFFM to predict the pyrolysis product distribution of other new energy materials. In addition, exploring the integration of DWFFM with control methods in the field of automation represents a promising future research direction, as it can help optimize the pyrolysis parameters of end-of-life WTBs.

CRedit Authorship Contribution Statement

Qiliang Zhang: Writing – review & editing, Supervision, Methodology, Investigation. Dekai Jiang: Writing – review & editing, Writing – original draft, Investigation. Chenxu Li: Methodology, Investigation. Baoxin Zhang: Investigation. Bin Hu: Investigation. Mingxin Xu: Investigation, Data curation. Kai Li: Investigation. Qiang Lu: Validation, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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