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Review of Biomass Gasification and Pyrolysis Process Based on Long Short-Term Memory Network

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Abstract. With the global energy crisis become escalated day by day, finding an effective way of exploring the renewable energy has become an important direction as its widely resources, comparatively low environment impact. This paper has concluded the biomass pyrolysis and gasification process based on long- and short-term memory (LSTM) method, including the LSTM principle, current application, faced challenges and future development. LSTM as a kind of special recurrent neural network, which could effectively solve the gradient vanish and explosion problem in time-series data. Research shows that, LSTM has an excellent performance in terms of reaction condition and optimization, which could be able to capture the relationship between complex variables, the pyrolysis efficiency could be improved, and prediction accuracy could over 90%. During the data preprocessing and model training stage, it is vital to make sure the quality of data, including data normalisation, outlier handling and time series splitting, etc. Through these steps, a better prediction accuracy could be achieved by LSTM. At the same time, the real application cases of LSTM used in biomass pyrolysis process have been discussed, it is shown that the combination of LSTM and other machine learning techniques could obviously improve the system stability and product quality. In addition, this paper has also looked forward to the enhancement of model explainability and the prospect of uncertainty quantification, which is helpful to improve the LSTM application and practical value.

Keywords: Long-and short-term approach, machine learning, biomass energy conversion, biomass pyrolysis, gasification.

1. Introduction

With the global energy crisis become escalated day by day, finding an effective way of exploring the renewable energy has become an important direction for science and industry. In various energy, biomass has been emphasized because of its wide range of source and comparatively low environment impact. Biomass include the plant, creatures and other organic energy which can be transferred into useful energy form by various bioconversion technologies. To solve these questions, scholars has

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gradually paid their attention to advanced computer techniques, in which machine learning algorithm compact with machine learning can be used for pyrolysis process control and optimization[1]. Machine learning as an effective data driven techniques, not only could analysis quantities of experiment data, but can also recognize the complex relationship between data, providing accurate model prediction.

Among various machine learning algorithm, Long and short-term memory network. LSTM network has drawn increasing attention recently. The related publication numbers have shown an increasing tendency as shown in figure.1. LSTM is kind of special recursive neural network; it has shown an excellent performance when tackling the time series problem [2]. The traditional neural network will have gradient vanish or gradient explosion problem, the problem could be solved by LSTM by introducing the memory cell and gate control strategy. Therefore, a good adaptability has been shown by LSTM in terms of gas generation, reaction condition optimization and process adjustment.

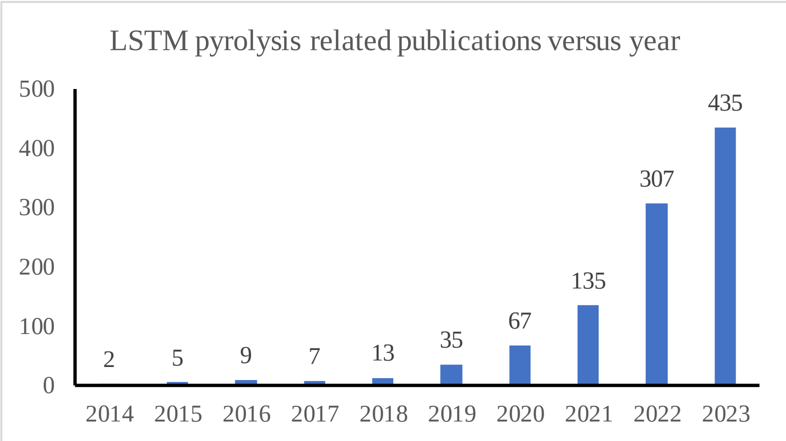

Figure 1. LSTM pyrolysis related publications versus year

On the one hand, the data properties could be automatically input during the model training process, and the complex designed model are not needed; On the other hand, LSTM could achieve a balance in model complexity and accuracy, especially adaptive to non-linear input-output relationship. Which has made a vast application prospects of LSTM in bioconversion technology, which could dramatically improve the pyrolysis efficiency.

Although several advantages have been shown to biomass pyrolysis, there still exist several challenges. First of all, LSTM is high rely on the data quantity, especially the historical data for ensuring the model accuracy. Secondly, LSTM has a comparatively low interpretability, which cause the research hard to understand how the model could make a specific prediction outcome. The risk could be increased of the applications used in scientific research and industrial scenarios. Therefore, increase the interpretability is a crucial direction, so that a more solid support could be offered to engineering.

In this review paper, the detailed application, faced technology challenge and future research directions will be discussed as a reference to related industries.

2. Basic Principle of LSTM

LSTM is an efficient Recurrent Neural Network (RNN) architecture, which aims to solve the gradient vanish and gradient explosion problem when tackling the long time series data. These problems occur during the process of propagation through time, the accumulation of gradient calculation may cause the too small or too large gradient, it makes the model low effective or failed completely. LSTM has first been raised by Hochreiter and Schmidhuber in 1997, this has been originally designed to overcome these limitations and providing an effective solution to time series model [3].

The core of LSTM is its unique memory cell and three important gate control mechanism, input gate, forget gate and output gate. The introduce of these mechanisms, could make the LSTM flexible decide which information need to be reserved or forgotten, so that the long-term dependency could be

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effectively captured. More specifically, input gate could control the input information flow in, forget gate decide which information need to be abandoned, and output gate decide which information could be selected for ongoing usage [4].

From mathematical aspect, the control operation of these gates could be realized by a series of differentiable function. The output value of each gate locates between 0 and 1, which could make the control of information flow acquire high flexibility. For example, the calculation equation of forget gate is:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{1}$$

In which, $\boldsymbol{f_t}$ is an active state of forget gate, $\boldsymbol{W_f}$ is weighting matrix, $\boldsymbol{h_{t-1}}$ is the hidden state of previous state, $\boldsymbol{x_t}$ is the current input, $\boldsymbol{b_f}$ is bias entry, $\boldsymbol{\sigma}$ is the sigmoid active function. This process could make sure the model could dynamically adjust the information storage and forget strategy, so that model study ability and prediction accuracy could be improved.

When passing the LSTM cell, the importance of model to past input could be reflected by the state storage in memory cell. In this way, LSTM could be able to effectively capture and use the context information in data series analysis. Based on research, LSTM shows an advanced performance in practical usage, especially in terms of nature language tackling, time series pretest and speech recognition [5].

3. The application of LSTM in biomass pyrolysis

The application of LSTM in biomass pyrolysis mainly represent in reaction condition prediction and optimization. Biomass pyrolysis is a process in which biomass could be converted into combustible gas, grease and carbon, this process could be affected by various of factors, including reaction temperature, pressure and gas compositions.

3.1. Data preprocessing and model training

Before the application of LSTM, it is vital to make sure the data quality and effectiveness. Research usually needs to normalise, clean, broken up the origin data. During the biomass pyrolysis, the various properties of reactant, such as temperature, pressure and pyrolysis gas composition. For example, by eliminating the extreme value and filling the eliminate value, researchers could build up a high-quality data set, which is important to consecutive model training [6].

Normalization is another necessary step, in which origin data should be zoomed in a unified scope, to avoid the data bias because of the differences in units of measurements. In addition, time series broken up is to divide the data set into training set and test set, to be more effectively in model training and consecutive performance evaluation. By these data treatment steps, the LSTM model could be made sure to study effectively, so that prediction accuracy could be improved [7].

3.2. Data preprocessing and model training

A comparatively high accuracy could be achieved during the LSTM integrated biomass pyrolysis process prediction based on precise model training. Various research results showed, the accuracy of LSTM prediction could over 90%, which makes the control accuracy dramatically increased. For example, in practical research, the temperature and composition change in predicting the pyrolysis process by real-time monitoring. LSTM not only improve the system stability, but also obviously improved the pyrolysis product efficiency and quality.

In addition, the adaptability and topicality are also important advantage during the biomass pyrolysis process. LSTM could dynamically adjust the prediction of pyrolysis conditions based on the dynamically changed input data. For example, in research, the parameters could be fast calibrated based on the dynamical change of input data, this property could realize the fast response of pyrolysis, which could make sure the effective convert of biomass. More specifically, based on Zhong, H., et al research, this developed LSTM model frame has shown a good applicability to different species and temperature, it could save approximate 30% of calculation working load comparing with traditional computational fluid dynamic method [8].

3.3. Practical case analysis

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4. Future direction and research

Long- and short-term network has opened numerous avenues, especially in biomass pyrolysis area. The future research should focus on several critical areas, to improve the effectiveness of LSTM and further optimize the bio energy conversion process.

4.1. Integration with other machine learning techniques

A prospect direction is to combine the LSTM with other machine learning methods, such as convolutional neural network (CNN) or hybrid model. These models could make use of the advantage of different algorithm. For example, combining the CNN with LSTM could extract the spatial property by convolutional layer, at the same time, the ability of tackling the complex input data could be improved. For example, when treat the temperature monitoring and energy resource consumption, multi-sensor's real-time input. This method not only could analysis the time series data, such as the historical temperature change, but also could generate the spatial data from CNN analysis sensor, such as the temperature distribution among different location.

In Fachrizal et.al' s research, authors have compared two kind of hybrid deep learning (HDL) model, CNN-LSTM and LSTM-CNN model's performance prediction in the direction of power flow in a single feeder. For CNN-LSTM model, the CNN has been firstly used for local feature extraction of input data [9]. Then these properties could be input to LSTM, LSTM time series modelling ability could be used as shown in figure.2.

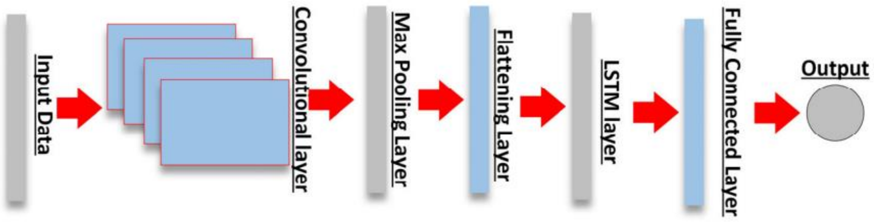

Figure 2. Structure of CNN-LSTM model [9]

But the opposite situation in LSTM-CNN model, first, LSTM has been used to build up model for time series data, and CNN's spatial feature extraction capability [9], as shown in figure.3.

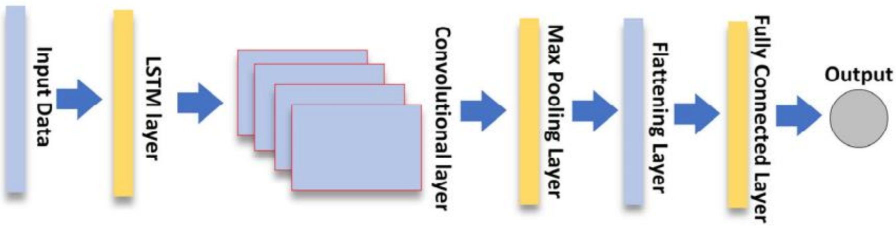

Figure 3. Structure of LSTM- CNN model [9]

Both of these two models have combined advantages of CNN and LSTM, which means they can perform better in input data time features, so that prediction ability can be improved. For RMSE value test, LSTM-CNN model has shown a comparatively better performance for which lowest RMSE has achieved to 2.991. For MAE value, The lowest MAE could be achieved by LSTM-CNN value as 1.985, and LSTM-CNN has shown a better performance than CNN-LSTM [9] The overall determination coefficient are all above 0.91, CNN-LSTM shows a comparatively better performance than LSTM-CNN.

4.2. Enhancing model interpretability

As the complexity of long and short-term continuously increase, its internal decision process become more and more important. In various application areas, including the financial prediction and biomedical analysis, therefore, the critical factor is to make sure its stability and confidence level. Therefore, the future research needs to focus on how to improve the explainability, to better satisfy the real application requirement.

The development of explainability, such as LRP (Layer-wise Relevance Propagation) and attention mechanism, has been widely used for machine learning transparency improvement. LRP is an effective technology, it could recall the model prediction result to input feature, and demonstrate the ultimate contribution of each feature, so that researchers could understand which features have taken a critical role in specific prediction. This method is especially effective in explaining the financial data series. Therefore, it could help analyst to recognize the major driven of market fluctuation, providing a support to risk management. According to Wehner and his coworkers, an interpretable online lane change prediction method was developed using a layer-normalised LSTM model. In this research, digital twins of German motorways were used to make real-time lane change predictions and the LRP method was extended to interpret the layer-normalised components of the LSTM model, providing a reliable and understandable interpretation of lane change predictions, demonstrating that the algorithms can be applied in practice. that both interpretability and high prediction performance can be achieved in the practical application of the algorithm [10].

In addition, the integration of attention mechanism could also dramatically enhance the explainability of LSTM model. In Attention-Based LSTM (AL-LSTM), the attention mechanism could make the model distribute the different weighting based on the different input feature, so that the prediction accuracy and transparency can be improved. This method not only could improve the model performance, but also could provide a more important background information for decision making by visualizing the weighting, so that the understanding of prediction can be more straight forward. For example, based on Ilaria Gandin et.al research, MIMIC III data set (an electronic health record database) have been used to extract a cohort of 10,616 cardiovascular patient, at the same time, a 10-hour sequence of 48 clinical parameters has been considered to predict the mortality rate within 7 days. The attention mechanism can be realized in LSTM model to identify the features that drive the model's decisions over time [11]. LSTM model has realized an area under the curve (AUC) value of 0.790, it shows there is a nice correspondence between attention weighting and prediction factor. This research has shown that attention mechanism could make the deep learning modelling to have more explainability [11].

4.3. Scenario analysis and uncertainty quantification

Biomass is a complex conversion process, its product quality and quantity have an obvious uncertainty with a variation of operation condition fluctuation and inlet composition, which could make a huge impact to final pyrolysis result. Pyrolysis is a complex process as shown in equation (2) and include quantities of uncertainties. This uncertainty will not only affect the biomass conversion efficiency, but also will damage the quality of biomass at the final stage. Therefore, it is vital to introduce the uncertainty quantification (UQ) into biomass pyrolysis prediction model, so that the robustness and reliability of model can be better evaluated under different conditions.

$$-\frac{dM}{dt} = k(t)M^n \tag{2}$$

In which, M represents the quantity of material, $k(t)$ represents the temperature dependency reaction rate constant, n is the reaction order.

One of the future research directions could focus on the integration of uncertainty quantification method in LSTM model for improving the prediction ability of biomass pyrolysis. This process not only focus on the training of historical data, but also include the simulation of various operation conditions. By system analysing of the change of different variables, the adaptability of model to real world can be enhanced. For example, based Tong et al research in 2022, the steam-temperature prediction based on LSTM covers the uncertainty analysis to quantify the reliability of prediction. This method not only help to recognize the critical factor that affecting the prediction precision, but also offering an important support for model performance optimization [12].

A stronger model can be developed by introducing the uncertainty quantification method into LSTM frame, so that a more precise prediction can be made when facing the uncertainty. For example, research shows that, the prediction to biomass pyrolysis could be dramatically increased when facing the parameter uncertainty. This Dynamically Adaptive Data Model (DADM) will allow the real time adjustment to model parameters; therefore, the fluctuation of biomass composition and operation conditions could be better tackled [12].

5. Conclusion

In conclusion, LSTM has a vast application prospect in biomass pyrolysis and other areas with a huge potential of improvement and creative. LSTM has shown a great potential in time series modelling in predicting and analysing the biomass conversion. Based on research, LSTM shows an excellent performance in capturing the mutual relationship between complex reaction conditions, which could effectively improve the process control precision, overcome the limitation of traditional method.

In this review, the prediction model of LSTM has shown a high accuracy above 90%, especially in real time monitoring, the prediction in temperature and gas composition, the average deviation is just 5.6%. This high extent of precision mainly relies on the effective data preprocessing method, which includes the normalisation, outlier handling and rational time series segmentation. In addition, LSTM could effectively adapt the varying data input, which could perform an excellent in dynamic model parameter tunings, and the efficiency of biomass conversion process can be dramatically increased.

In conclusion, the usage of LSTM in biomass pyrolysis process optimization has provided an important inspiration to bio energy conversion techniques development. The continuous research of model explainability and uncertainty quantification will provide a more robust and reliable solutions to biomass energy conversion process, this will provide a helpful movement to facing the global energy challenge without any doubt.

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