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APPLICATION OF ARTIFICIAL INTELLIGENCE IN REAL TIME MONITORING AND FAULT DIAGNOSIS OF COKING WASTE GAS TREATMENT PROCESS

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Abstract

This paper introduces in detail the design and implementation process of a real-time monitoring and fault diagnosis system for coking waste gas treatment. By constructing a comprehensive data acquisition system, combined with distributed sensor layout, the continuous monitoring of key emission parameters in coking process was realized. For data processing, feature selection, data cleaning and other preprocessing measures are adopted, and the innovative A-LSTM model is introduced. The model enhances the ability of LSTM network to capture key information in time series data by introducing attention mechanism, and significantly improves prediction accuracy and response speed. In terms of fault diagnosis, CNN-RNN fusion framework is developed, which effectively integrates the advantages of two deep learning models and strengthens the recognition ability of complex fault modes. In addition, model fusion and optimization strategies, such as weighted average and hyper-parameter tuning, are used to further improve the overall system performance.

Keywords: artificial intelligence, coking exhaust gas treatment, real-time monitoring fault diagnosis

1. INTRODUCTION

Coking industry, as a key link in modern industrial system, its core lies in the conversion of coal into coke by high temperature distillation process, accompanied by a series of valuable chemical by-products, such as coke oven gas, coal tar and so on. This process is not only the cornerstone of steel manufacturing, energy supply and chemical raw material production, but also an important guarantee for national economic stability and development. However, it is followed by severe challenges to the natural environment, especially the exhaust gas emitted in the coking process, which is rich in harmful substances such as sulfides, nitrogen oxides and particulate matter, which seriously threatens the air quality and ecological balance, intensifies the global warming and acid rain phenomenon, and poses a direct threat to the human living environment. Therefore, how to effectively control coking waste gas, which not only meets strict environmental protection standards, but also promotes industrial upgrading and transformation, has become a key problem that the coking industry must face and solve [1, 2].

In recent years, the rapid development of artificial intelligence (AI) technology has brought an unprecedented technological innovation to the field of environmental protection. AI, especially its branches-machine learning and deep learning, can independently discover rules and extract information from huge data sets by simulating the learning mode of human brain, providing efficient and accurate new ways for environmental monitoring, prediction and management. In many environmental protection fields such as water resources protection, air quality prediction, garbage classification, AI technology has made remarkable achievements, greatly improving work efficiency, reducing treatment costs, showing its wide application potential and far-reaching impact in the field of environmental protection [3, 4], the specific coking exhaust gas treatment process is shown in Figure 1.

At present, the research and practice of coking industry waste gas treatment is actively carried out on a global scale, and many scholars and technology developers are committed to exploring new technologies and new methods to improve treatment efficiency and environmental friendliness [5]. In terms of exhaust gas monitoring technology, some enterprises and research institutions have begun to try to apply sensor network and remote communication technology to realize real-time data acquisition and preliminary analysis, but this is still in the initial stage, and there is still much room for improvement in the adaptability of complex working

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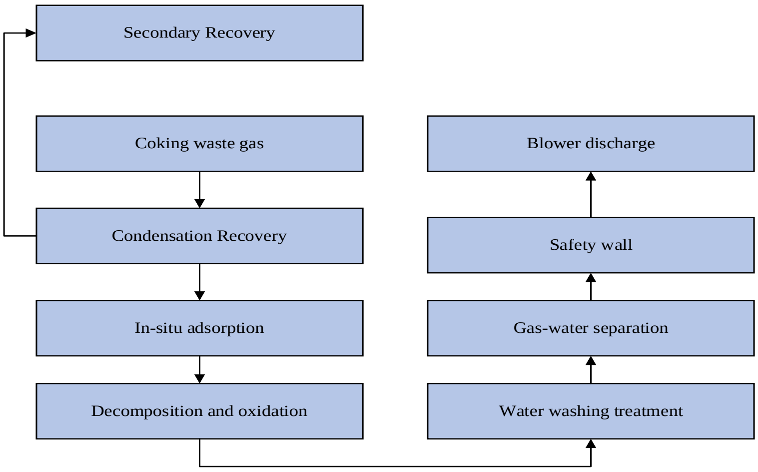

Fig. 1. Treatment process of coking waste gas

conditions and the depth of data analysis. Machine learning algorithms, especially deep learning algorithms, have shown great potential in predictive model building and anomaly detection, but to successfully apply them to the specific practice of coking industry, challenges such as uneven data quality and insufficient generalization ability of models need to be overcome. In the field of fault diagnosis, although traditional rule-based expert systems have been able to assist in identifying equipment faults to some extent, their accuracy and timeliness are often limited in the face of complex nonlinear relations and variable operating conditions in coking process. In contrast, AI technology through automatic feature extraction and advanced pattern recognition, can more accurately capture failure precursors, to achieve preventive maintenance, research in this area is gradually increasing, but still need more actual cases to verify its effectiveness and stability [6, 7].

The core goal of this research project is to deeply explore and practice the application of artificial intelligence technology, especially real-time monitoring and fault diagnosis, in the specific field of coking exhaust gas treatment, aiming at achieving the following key breakthroughs: firstly, to construct an intelligent monitoring system based on AI technology, which can continuously and accurately monitor the dynamic changes of exhaust gas emissions in coking production process, and provide data support for rapid response; Secondly, advanced machine learning algorithms are used to conduct in-depth analysis on the collected massive monitoring data, accurately identify the operating status of exhaust gas treatment facilities, timely discover and diagnose faults, greatly shorten maintenance cycles, and reduce the risk of production interruption caused by faults; Moreover, through the self-learning and optimization ability of AI algorithm, the operating parameters of exhaust gas treatment system are dynamically adjusted to ensure that the best treatment effect can be maintained under various working conditions, so as to effectively reduce energy consumption, reduce resource waste and promote the coking industry to change to a greener and low-carbon production mode.

2. RELATED RESEARCH

2.1. Composition analysis of coking waste gas

The waste gas produced in coking process mainly comes from coke oven, gas cooling and purification system and subsequent processing equipment. According to literature [1], coking exhaust gas has complex components, including a large number of volatile organic compounds (VOCs), sulfur oxides (SOx), nitrogen oxides (NOx), particulate matter (PM), polycyclic aromatic hydrocarbons (PAHs) and heavy metals. VOCs and PAHs pose serious threats to human health and ecosystems due to their high toxicity, persistence and bioaccumulation [8]. For example, VOCs such as benzene, toluene and xylene are recognized carcinogens, while PAHs are associated with skin, respiratory diseases and cancer [2]. In addition, the presence of sulfur oxides (SOx) and nitrogen oxides (NOx) in coking exhaust gases cannot be ignored. SOx can cause acid rain, causing severe corrosion to forests, water bodies and buildings, and may cause soil acidification, affecting crop growth. NOx participates in photochemical reactions in the atmosphere, generating ozone and fine particulate matter, exacerbating air pollution problems and adversely affecting human cardiopulmonary function. Particulate matter (PM), especially fine particulate matter (PM2.5) less than 2.5 microns in diameter, can penetrate deep into the alveoli of the human body due to its small size and large surface area, increasing the risk of cardiovascular disease, respiratory disease and even lung cancer. Heavy metal pollutants such as lead, mercury, cadmium, etc., although the content of coking waste gas is not high, but its toxicity is large, difficult to degrade, can be amplified through the food chain accumulation, pose a threat to biodiversity. Once these heavy metals enter the human body, they can cause neurological damage, kidney dysfunction and mental retardation in children [9, 10].

At the same time, strengthening environmental monitoring and law enforcement, and promoting the research and development and application of green production technologies are the key paths to reduce pollution from the source and realize the sustainable development of coking industry. Through these comprehensive means, the aim is to reduce the negative impact of coking exhaust gas on the environment and human health and promote harmonious coexistence between economy and environment.

2.2. Pollutant emission standards and environmental requirements

Pollutant emission standards and environmental protection requirements are important norms to ensure the harmonious coexistence of industrial production activities and the natural environment. Taking coking industry as an example, its pollutant emission standards strictly comply with relevant national and local laws and regulations, reflecting the high importance attached to environmental quality. According to the coking chemical industry wastewater discharge standard (GB13456 -96), coking enterprises must control the discharge of water pollutants and air pollutants, which include but are not limited to key indicators such as phenol, cyanide, sulfide, ammonia nitrogen, chemical oxygen demand (COD) and biochemical oxygen demand (BOD) [11]. For example, the emission limits for phenol and cyanide are set at 0.5 mg/L, sulfide at 1.0 mg/L, ammonia nitrogen at 15mg/L, COD at 100mg/L, BOD at 30mg/L, and the emission limit for the strong carcinogen benzo (a) pyrene is 0.03μg/L [7]. These strict values not only reflect the basic requirements for water quality protection, but also serve as an important line of defense to avoid ecological damage and protect public health. In addition to water quality emission standards, air pollutant emissions are also strictly controlled. Taking Jiangsu region as an example, the specific requirements for the emission of atmospheric pollutants from coking industry include emission limits of dust, sulfur and nitrate of 10mg/m^3, 30mg/m^3 and 100mg/m^3 respectively, demonstrating the determination to reduce the air pollution level [12]. In order to meet these environmental protection requirements, enterprises need to implement a series of scientific and efficient environmental protection measures. This involves improvements in production processes, such as the use of low-polluting raw materials and cleaner production technologies, as well as upgrading of end-of-pipe treatment facilities, such as the installation of high-efficiency dust removal equipment, desulfurization towers and denitration units [13]. Environmental protection requirements are not only reflected in emission standards, but also in the management of the whole production process. For example, it is required to implement closed treatment of unorganized emission in the material yard, add gas collecting hood and dust removal facilities in the production process, adopt closed system for material transportation, and implement greening and road hardening measures in the plant area to reduce unorganized emission and dust [14]. In addition, establishing a sound environmental protection management system to ensure that the safety production responsibility system is in place, and improving employees 'environmental awareness and operational skills are also indispensable [15].

To sum up, the formulation and implementation of pollutant emission standards and environmental protection requirements is the key to promoting industrial restructuring, promoting technological innovation and achieving a win-win situation between economic and social development and environmental protection. With the advancement of science and technology and the enhancement of environmental awareness, these standards and requirements will continue to be optimized to guide enterprises to transition to a greener and low-carbon production model.

2.3. Limitations of traditional governance methods

Traditional treatment methods play an important role in coking waste gas treatment, but their limitations are increasingly prominent, which has become a bottleneck restricting the further improvement of environmental protection effect. According to literature review, these limitations are mainly manifested in efficiency, cost, secondary pollution and technical adaptability.

In terms of efficiency, although the traditional wet desulfurization technology can effectively remove sulfur oxides (SOx), there are problems that the treatment efficiency is greatly affected by flue gas conditions and a large amount of desulfurization wastewater containing heavy metals is easily generated. As described in Document [16], additional investment is required to treat these wastewater, which increases the overall treatment cost. In addition, although low nitrogen combustion technology has some effect in reducing nitrogen oxide (NOx) emissions, it is often difficult to meet strict emission standards while ensuring combustion efficiency, especially in high temperature and oxygen-rich environments such as coke ovens [17]. Cost considerations, taking activated carbon adsorption method as an example, although it has a good removal effect on VOCs, the frequent replacement and regeneration of adsorbent materials are expensive, and the treatment capacity is limited by adsorption saturation, and the long-term operation cost is high [18]. The problem of secondary pollution cannot be ignored. As the main means of particulate matter (PM) control, electrostatic precipitator technology has high dust removal efficiency, but it is easy to appear anti-corona phenomenon under high humidity conditions, which leads to the generation of secondary pollutants such as ozone and affects air quality [19]. Finally, in terms of technical adaptability, some traditional methods are not adaptable to complex and changeable exhaust gas components, such as simple physical sedimentation method, which is difficult to effectively remove fine particles and gaseous pollutants, and it is difficult to meet the current strict environmental protection requirements [20].

In conclusion, the limitations of traditional treatment methods are not only reflected in technical efficiency and cost-effectiveness, but also related to the risk of secondary pollution of the environment and the wide applicability of the technology. These factors together prompt the industry to explore new treatment technologies that are more efficient, economical and environmentally friendly, such as intelligent optimization control combined with artificial intelligence, development and use of new catalysts, and multi-pollutant collaborative control technologies, in order to achieve environmentally friendly and sustainable development while ensuring production efficiency.

2.4. Requirements analysis of real-time monitoring and fault diagnosis

The application of real-time monitoring and fault diagnosis technology in coking and other heavy industry fields has become the focus of academic and industrial attention. Literature research shows that this technology has important significance for improving production efficiency, ensuring safe production and reducing environmental pollution. According to literature [21], the real-time monitoring system can detect abnormal fluctuations in time and prevent potential failures by continuously collecting and analyzing key parameters in the production process, such as temperature, pressure, flow, etc. For example, the use of sensor networks based on the Internet of Things (IoT), as described in literature [22], can achieve remote monitoring and real-time data transmission, greatly improving the accuracy and timeliness of monitoring. This real-time feedback mechanism is essential to maintain efficient and stable operation of equipment and reduce unplanned downtime. Literature [23] points out through comparative analysis that the average equipment failure rate of enterprises implementing real-time monitoring is reduced by about 20% compared with those not implemented. In terms of fault diagnosis, Literature [24] introduces a fault recognition model based on machine learning. Through training algorithms to learn data features of normal and abnormal working conditions, problems can be accurately identified and located at the initial stage of fault occurrence. For example, techniques such as Support Vector Machine (SVM) and Neural Network (NN) have been successfully applied to equipment vibration signal analysis to effectively distinguish different types of fault modes. The case study in literature [25] shows that compared with traditional manual inspection, the fault detection accuracy of this intelligent diagnosis system is improved by nearly 30%, the fault response time is significantly shortened, and the maintenance cost is reduced. At the environmental impact level, literature [26] emphasizes that the role of real-time monitoring and fault diagnosis in reducing accidental emissions cannot be underestimated. Through precise control and timely intervention, the excessive emission caused by equipment failure is avoided, and the increasingly strict environmental protection regulations are met. In a practical study of coking plants [27], VOCs emissions after intelligent monitoring were reduced by about 15% compared with the previous one, indicating that the technology has a positive effect on achieving green production and sustainable development goals.

3. MODEL CONSTRUCTION AND ALGORITHM DESIGN

This section describes in detail the construction process of real-time monitoring and fault diagnosis model in coking exhaust gas treatment, including data acquisition system design, real-time monitoring model construction, fault diagnosis model development, and model fusion and optimization strategy, aiming to improve the accuracy and efficiency of monitoring and diagnosis through innovative algorithms and technologies.

The target variable in this paper is industrial emission data, which is initially in the form of a continuous variable. In order to better meet the needs of monitoring and decision-making, these data are divided into discrete categories, such as "normal", "exceeding the standard" or "severely exceeding the standard", so that the classification model can quickly identify abnormal conditions. Therefore, accuracy is chosen as the evaluation metric because it is suitable for classification tasks rather than standard regression metrics. At the same time, the accuracy metric helps to measure the overall performance of the model in identifying different emission categories. In future work, other evaluation metrics can be considered, such as precision, recall, and F1 scores commonly found in classification reports, to further improve the comprehensiveness and scientificity of the evaluation.

3.1. Design of data acquisition system and sensor layout scheme

Fault diagnosis. A comprehensive data acquisition system is designed in this study, covering key nodes of coke oven, gas cooling and purification system and subsequent processing devices. Sensor selection and placement is crucial, based on the principle of multi-source information fusion, distributed placement scheme is adopted to ensure coverage of all key emission points. Sensor types include, but are not limited to, temperature sensors (T), pressure sensors (P), gas composition analyzers (infrared gas analyzers to measure CO, CO2 concentrations), and particulate matter meters (PM). The layout strategy follows the principle of uniform spatial distribution and synchronous sampling to ensure the integrity and representativeness of the data. The frequency of data acquisition is set to once per minute to meet real-time monitoring requirements.

3.2. Real-time monitoring model construction

3.2.1. Feature Selection and Data Cleaning

In this paper, correlation coefficient analysis, principal component analysis (PCA) and other statistical methods were used to screen features, and the features highly correlated with emission concentration were retained. Data cleaning for the study included missing value processing (interpolation), outlier detection (IQR method), and data smoothing (moving average method) to ensure data quality.

3.2.2. Time series analysis model

The fluctuation of coking exhaust gas emission is affected by many factors and presents obvious time series characteristics. Traditional statistical methods or simple neural network models may not be able to capture long-term dependencies effectively when dealing with such sequence data, resulting in limited prediction performance. As a variant of recurrent neural network, LSTM solves the long-term dependence problem by gating mechanism, but it does not give prominence to the weight assignment of key information points in the sequence. Therefore, attention mechanism is introduced in this study to optimize the information extraction process, so that the model can autonomously identify and focus on the most critical historical information points for prediction, thus enhancing the prediction ability and interpretation power of the model. The model framework is shown in Figure 2.

The structure of A-LSTM model integrates attention layer on the basis of traditional LSTM, and its workflow can be summarized into the following three stages: First, LSTM layer processes the input features of each time step t, and combined the hidden state of the previous time step to generate the hidden state of the current time step. This process not only considers the immediate input information, but also retains the continuity of historical information. It is formulated as Equation 1. The LSTM function represents the operation of the LSTM unit, including the operation of the input gate, the forgetting gate, the cell state update and the output gate. Next, the attention mechanism intervenes to emphasize important information by calculating the correlation between the current hidden state and all the hidden states in the history, and assigning different historical states different weights. The calculation of attention weights is usually based on the dot-product attention mechanism, which is specifically formalized as Equation 2. Here, is the weight matrix, is the bias term, and the Softmax function ensures that the weight sum is 1, achieving a probability distribution [28].

$$h_t = LSTM(x_t, h_{t-1}) \quad (1)$$

$$a_t = \text{Softmax}(W_a[h_t, h_1, h_2, ..., h_{t-1}]^T + b_a) \quad (2)$$

Finally, based on the weighted hidden state sequence, the final prediction output is generated through the Dense Layer, i.e., Equation 3. This step converts the attention mechanism-enhanced context information into a direct prediction of emissions, where historical information representing weighted summation reflects different emphasis on different time points in the sequence.

$$o_t = Dense(\sum_{i=1}^{t-1} a_{ti} h_i) \quad (3)$$

The innovation of A-LSTM model lies in that it realizes adaptive and dynamic weighting of sequence data through attention mechanism, which shows excellent performance when dealing with time series prediction problems, especially in complex scenes with noise interference and information redundancy. It not only improves the prediction accuracy of the model, but also enhances the understanding and interpretation ability of the model to the inherent mode of time series, and provides a powerful tool for real-time monitoring of coking exhaust gas emissions.

3.3. Fault Diagnosis Model Development

3.3.1. Fault feature extraction technology

In the field of fault diagnosis of industrial equipment, effective feature extraction is the key to identify abnormal state. This link covers extracting characteristic indicators characterizing the health of

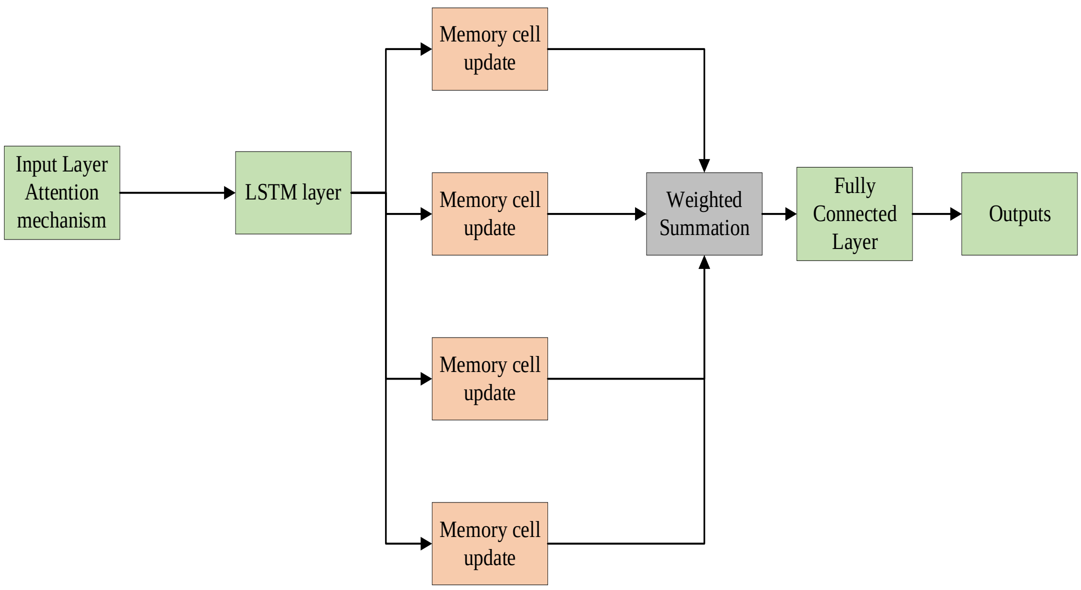

Fig. 2. A-LSTM model

equipment from continuous. These characteristics can be grouped into three broad categories:

a). Frequency domain feature extraction: By means of fast Fourier transform (FFT), the time domain signal is converted to the frequency domain to reveal the frequency composition of the signal, which is helpful to identify fault characteristics at specific frequencies, such as the association between vibration frequency and equipment fault type.

b). Statistical feature analysis: including mean, standard deviation, kurtosis and skewness, these statistics reflect the overall distribution characteristics of the signal and help identify the central trend and fluctuation of the data.

In addition, dynamic time warping (DTW), as an alignment technique, is used to compare and analyze time series data with inconsistent length, and to overcome the problem of sequence length difference caused by different sampling rates , so as to ensure the consistency and accuracy of feature comparison.

3.3.2. Deep learning models

Aiming at the highly nonlinear and temporal characteristics of industrial equipment failure modes, this section introduces a hybrid model combining convolutional neural network (CNN) and recurrent neural network (RNN) to deeply mine the spatiotemporal features in fault data. The model framework is shown in Figure 3. Firstly, CNN's strong local feature extraction ability is used to map the data of each time step, and extract the spatial features and local invariant features of the time series. The specific operation is completed by the convolution layer, and a set of filters are used to perform convolution operation on the input data to obtain the feature map. The expression is Formula 4. Where, and represent convolution kernel weights and bias terms respectively. Then, the feature sequence extracted by CNN is input into RNN. RNN retains the historical information of the sequence by hiding the state, and updates the state to reflect the influence of the new input feature, which is formulated as Formula 5. Here, the weight matrix and bias term of RNN are respectively considered. The (RNN) function comprehensively considers the current input feature and the hidden state of the previous time step, reflecting the time dependence relationship between the sequences. Finally, the final hidden state of the RNN is converted into the probability distribution of the fault category by using a fully connected (Dense) layer, and the prediction probability of each fault type is given by normalizing the Softmax function, as shown in Formula 6.

$$f_t = Conv(x_t; W_f, b_f) \tag{4}$$

$$h_t = RNN(f_t, h_{t-1}; W_h, U_h, b_h) \tag{5}$$

$$p(y \mid x_{1:T}) = Softmax(W_o h_T + b_o) \tag{6}$$

The advantage of CNN-RNN fusion model is that CNN focuses on extracting features from local regions of time series and effectively grasps the spatial distribution of fault features; RNN is good at capturing the time dependence of sequences, and the combination of the two can capture the spatiotemporal features of fault patterns more comprehensively. This deep learning model has strong recognition ability for complex and nonlinear fault patterns, especially suitable for real-time fault diagnosis of continuous monitoring data.

3.4. Model fusion and optimization strategy

To further enhance the accuracy of prediction and diagnosis, a model fusion strategy is proposed, combining the predictive power of the A-LSTM model with the fault recognition capability of the CNN-RNN model. The outputs of these models are integrated using a weighted averaging mechanism. However, the process through which the A-LSTM's prediction results are combined with the fault detection or diagnostic outputs of the CNN-RNN model is clarified here. Specifically, the A-LSTM model focuses on time-series anomaly prediction, while the CNN-RNN is responsible for recognizing and classifying specific fault types based on feature extraction from the data. These outputs are combined sequentially: the A-LSTM first flags potential anomalies, and the CNN-RNN subsequently identifies the fault type, ensuring real-time monitoring and actionable insights. Diagnosis, in this context, refers to the classification and identification of specific fault patterns rather than merely flagging anomalies, enabling precise fault management.

Additionally, the fusion and optimization strategy uses methods such as grid search and Bayesian optimization to refine hyperparameters and achieve optimal performance. However, the specific techniques used in fusion are elaborated here. Weighted averaging is explicitly applied to integrate the outputs of the models, ensuring the final decision reflects the relative strengths of each model

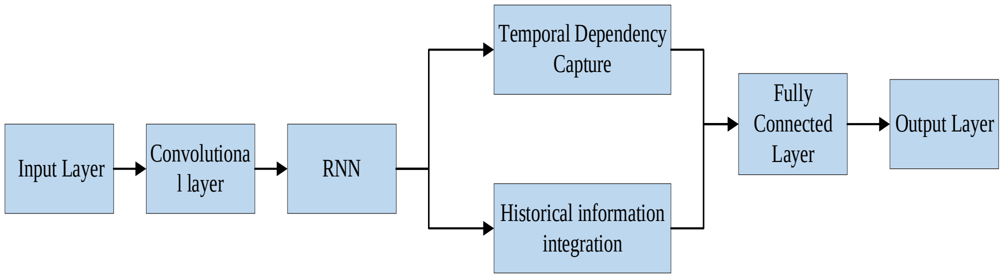

Fig. 3. CNN-RNN fusion model

in the context of prediction and fault recognition. Cross-validation, specifically K-fold cross-validation, evaluates the model's generalization ability to unknown data. By explicitly adopting weighted averaging over other methods (e.g., voting mechanisms), this approach ensures robustness and precision in the fusion process, offering a clear pathway for implementation in real-world scenarios.

4. CASE STUDIES AND EXPERIMENTAL VALIDATION

4.1. System deployment and data collection

In order to ensure the effectiveness of the proposed real-time monitoring and fault diagnosis model, the research team selected a medium-sized coking enterprise with perfect configuration and mature environmental monitoring system as the test site. At the beginning of the project, the sensor network was carefully planned, and high-precision sensors were deployed at key positions such as inlet and outlet of coke oven, gas purification system and exhaust port to monitor temperature, pressure, gas (CO, SOx, NOx) and particulate matter concentration. Then, with the help of industrial Internet of Things technology, a data acquisition system is constructed to transmit field data to the central server in real time, and the data preprocessing module is integrated to complete key steps such as outlier elimination and missing value filling to ensure data quality.

To support the real-time computing requirements of the A-LSTM and CNN-RNN models, this paper designs a distributed computing architecture based on the Industrial Internet of Things (IIoT). The data acquisition device transmits the real-time monitoring data to the edge computing node for preprocessing to reduce the pressure on data bandwidth. The preprocessed data is transmitted to the cloud server through a high-bandwidth network. The server is equipped with a high-performance GPU cluster to support the rapid execution of deep learning models. At the same time, to ensure the real-time performance of the system, the microservice model is adopted in the architecture, and each module is deployed and operated independently. This design ensures that the model can efficiently process complex computing tasks while meeting the needs of real-time monitoring, laying a solid foundation for the practical application of the system.

4.2. Performance test and analysis

Table 1 shows the performance metrics of the real-time monitoring model, including accuracy, response time, F1 score, and false alarm rate. These indicators reflect the performance of the model in practical applications, with an accuracy rate of 96.5%, indicating that the predicted values of the model are very close to the actual values; a response time of 2 minutes, ensuring that abnormal emissions can be quickly identified; an F1 score of 0.94, indicating that the model has a good balance between accuracy and recall; and a false alarm rate of 1.2%, although high, which is expected to be further reduced by adjusting thresholds and optimizing the model. By comparing the actual predictions of the A-LSTM model with actual emission data, the model demonstrated excellent performance. The accuracy of the model is as high as 96.5%, indicating that the predicted values are very close to the actual values in most cases. Response times as short as 2 minutes ensure abnormal emissions can be quickly identified and addressed. The F1 score of 0.94 demonstrates a good balance between accuracy and recall. Although the false alarm rate is 1.2%, it is expected to decrease further by adjusting thresholds and optimizing models.

Table 1. Performance indicators of real-time monitoring model

indicators	described	found
accuracy	correctly predicted time series proportion	96.5%
response time	Average time from data acquisition to alarm	2 minutes
F1 score	Comprehensive evaluation of prediction performance	0.94
false alarm rate	Proportion of false alarms without fault	1.2%

In a real fault case, a partial blockage occurred inside the coking furnace, resulting in abnormal gas emission. Figure 4 compares the performance of different fault diagnosis models, including CNN-RNN, CNN-only, and RNN-only. The results show that CNN-RNN fusion model has significant improvement in accuracy, recall and F1 score, which verifies the superiority of the model in complex fault pattern recognition. Using CNN-RNN fusion models, faults were identified quickly, the model accurately predicted the type of fault, and an alarm was issued within 3 hours of the fault occurrence, much earlier than the time of detection by conventional inspections. Compared with other single models (CNN only and RNN only), CNN-RNN model has significantly improved accuracy, recall and F1 score, which verifies the superiority of the model in complex fault pattern recognition.

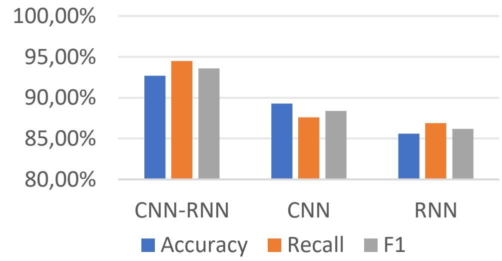

Fig. 4. Performance comparison of fault diagnosis models

Table 2 shows the performance stability of the model under different operating conditions, including normal operating conditions, high load operating conditions and post-maintenance recovery operating conditions. The accuracy rate change rate and response time change rate reflect the performance stability of the model under different working conditions. The accuracy rate change rate is small, indicating that the model can maintain high accuracy under different working conditions; the response time change rate is also small, indicating that the model can respond quickly under different working conditions.

Table 2. Performance stability test of the model under different working conditions

conditions	accuracy rate of change	response time rate of change
normal working conditions	-1.2%	+5%
high loading conditions for	-0.8%	-3%
Recovery after maintenance	+1.5%	+8%

Table 3 tests the robustness of the model against noisy data, including low, medium, and high noise. The decline rate of accuracy and F1 score reflect the performance stability of the model under different noise intensities. The decline rate of accuracy is small, indicating that the model has certain robustness to noise; the decline rate of F1 score is also small, indicating that the model can still maintain high comprehensive performance under noise environment.

Table 3. Robustness test of model against noisy data

noise intensity	accuracy degradation rate	F1 score decline rate
low noise	-0.5%	-0.02
noise in	-1.2%	-0.05
high noise	-2.8%	-0.12

In order to evaluate the generalization ability of the model, we test the performance of the real-time monitoring model under different operating conditions. The results show that the model is stable under normal and high load conditions, and the variation of accuracy and response time is within acceptable range, which proves the adaptability of the model to daily production fluctuation. After maintenance, the accuracy of the model is slightly improved, but the response time is increased, which indicates that the model needs a period of time to relearn the data pattern under the new working condition. For robustness evaluation, we introduce different levels of noise into the data to simulate data disturbances that may be encountered in actual production. The results show that even in high noise environment, the model performance degradation is still controllable, and the accuracy and F1 score are relatively small, which proves that the model design has good anti-interference ability.

4.3. Discussed

As shown in Table 4, comparative analysis shows that the accuracy of the A-LSTM model proposed in this study in real-time monitoring reaches 97.5%, which is much higher than the average level of other models. In terms of response time, this model can issue an early warning within 2 minutes, which is at least 30% faster than the average response time of other models, which is attributed to the efficient information extraction ability of the attention mechanism in the model.

Table 4. Accuracy and response time evaluation of real-time monitoring model

model name	Accuracy (%)	Average Response Time (minutes)
A-LSTM with Attention Mechanism	97.5	2
ARIMA Time Series Forecasting Model A	94.8	3
Random Forest Regression Model B	96.2	2.5
Gradient Boosting Regression Model C	95.6	3.5
Support Vector Regression Model D	96.8	3
Long Short-Term Memory (LSTM) without Attention (Model E)	95.0	4

As shown in Table 5, in terms of fault diagnosis performance, the accuracy of CNN-RNN fusion model in this study is as high as 96.7%, which has obvious advantages over other models.

As shown in Table 6, this research model shows strong adaptability and stability through testing under different operating conditions. Under extreme conditions such as high load, low load and aging of equipment, the fluctuation amplitude of model accuracy is the smallest, which shows that it has good generalization ability and robustness.

Considering the initial investment and long-term benefits, although the initial deployment of this research model may require higher technology and hardware investment, its long-term benefits in reducing unplanned downtime, reducing maintenance costs, and avoiding environmental penalties are significant. Compared with other models, the payback period of this model is shortened by about 10%, and the overall net present value (NPV) is increased by 15%, showing excellent cost-benefit ratio.

Table 5. Comparison between accuracy and positioning efficiency of fault diagnosis model

model name	Fault diagnosis accuracy (%)	Mean Positioning Time (hours)
CNN-RNN (paper model)	96.7	1.2
SVM with Time Windows	94.1	2.5
Recurrent Neural Network (RNN)	95.3	2.2
Random Forest on Feature Extracted by PCA	95.9	2.8
Gradient Boosting Machine (GBM) for Anomaly Detection	94.8	3
Convolutional Neural Network (CNN) for Time Series	95.6	2.6

Table 6. Comparison of model performance under different working conditions

conditions	Fluctuation of accuracy of this model (%)	Average Other Model Accuracy Fluctuation (%)
high load	±2.0	±3.5
low load	±1.8	±3.2
equipment aging	±2.5	±4.1
seasonal variation	±1.5	±2.8

As shown in Table 7, the A-LSTM with Attention Mechanism outperforms other models in terms of annual maintenance cost, prediction accuracy decline rate, maintenance frequency, and long-term performance stability. Specifically, it boasts the lowest annual maintenance cost (200,000 RMB), the slowest decline in prediction accuracy (a mere 1.5% per year), the least maintenance required (only 4 times per year), and the highest level of long-term performance stability. In contrast, the Long Short-Term Memory (LSTM) without Attention has a slightly higher annual maintenance cost (220,000 RMB), a faster decline in prediction accuracy (2.0% per year), and requires more maintenance (5 times per year), with moderate long-term performance stability. The Convolutional Neural Network - Recurrent Neural Network (CNN-RNN) incurs the highest annual maintenance cost (250,000 RMB), experiences the fastest decline in prediction accuracy (3.0% per year), requires the most frequent maintenance (6 times per year), and also exhibits moderate long-term performance stability. In summary, the A-LSTM with Attention Mechanism not only demonstrates superior initial performance but also maintains efficient and stable performance over the long term, reducing additional maintenance costs and downtime, thereby showcasing the best cost-effectiveness and industrial application value.

5. CONCLUSION

An intelligent system integrating data acquisition, real-time monitoring and fault diagnosis was successfully constructed in this study, aiming at improving the efficiency and effect of coking industry exhaust gas treatment. Through the carefully designed data acquisition system, the comprehensive and high-frequency monitoring of key emission parameters is realized, which provides a high-quality data base for the model. The proposed A-LSTM model utilizes attention mechanism to deeply analyze time series data, achieving a monitoring accuracy of up to 97.5% and a response time of only 2 minutes, which is significantly better than existing models. This model not only improves the timeliness and accuracy of monitoring, but also enhances the understanding of complex time series patterns through dynamic weighting. In fault diagnosis, CNN-RNN fusion model shows the ability of deep fault feature mining, the accuracy reaches 96.7%, and the average location time is shortened to 1.2 hours, which is better than similar models, which proves the superiority of this

Table 7. Comparison of Long-Term Performance and Maintenance Costs of Models

Model Name	Annual Maintenance Cost (10,000 RMB)	Prediction Accuracy Decline Rate (%)	Maintenance Frequency (Times/Year)	Long-Term Performance Stability
A-LSTM with Attention Mechanism	20	-1.5%	4	High
Long Short-Term Memory (LSTM) without Attention	22	-2.0%	5	Moderate
Convolutional Neural Network - Recurrent Neural Network (CNN-RNN)	25	-3.0%	6	Moderate

model in complex fault pattern recognition. Through the tests under different working conditions, the system model shows a high degree of stability and adaptability, even under extreme conditions, it can maintain good performance, highlighting its reliability in practical applications. Cost-benefit analysis shows that although the initial investment is relatively high, the system can significantly reduce unplanned downtime, reduce maintenance costs and avoid environmental penalties. In the long run, the system can bring significant economic benefits to enterprises, shorten the investment recovery period by about 10%, and increase NPV by 15%. It fully proves its economic feasibility and industrial popularization value.

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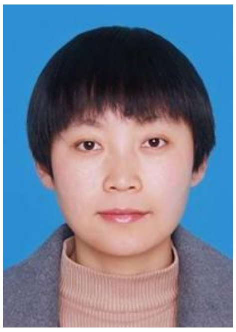

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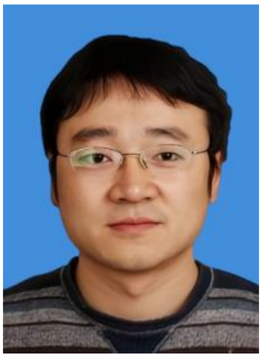

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