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Real-Time Monitoring and Intelligent Analysis Platform for Carbon Emission in Smart Power Plants

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Abstract: As global climate change intensifies, the power industry—a major source of carbon emissions—plays a pivotal role in achieving carbon peaking and neutrality goals through its low-carbon transition. Traditional power plants' carbon management systems can no longer meet the demands of high-precision, real-time monitoring. Smart power plants now offer innovative solutions for carbon emission tracking and intelligent analysis by integrating IoT, big data, and AI technologies. Current research predominantly focuses on optimizing individual processes, lacking systematic exploration of comprehensive dynamic monitoring and intelligent decision-making across the entire workflow. To address this gap, we propose a smart carbon emission monitoring and analysis platform for power plants that integrates IoT sensing, multimodal data analytics, and AI-driven decision-making. The platform establishes a multi-source sensor network to collect emissions data throughout the fuel combustion, auxiliary equipment operation, and waste treatment processes. Combining carbon emission factor analysis with machine learning models enables real-time emission calculations and utilizes long short-term memory networks to predict future emission trends.

Keywords: Smart power plant; Real-time carbon emission monitoring; Intelligent analysis platform; Internet of Things perception

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1. Introduction

With the increasingly severe global climate change, carbon emission management has become a core issue for countries to achieve the Sustainable Development Goals. As one of the main sources of carbon emissions, the low-carbon transformation of the power industry plays a decisive role in achieving the goals of carbon peaking and carbon neutrality. In the context of carbon neutrality, the extensive carbon emission management model of traditional power plants has become inadequate for meeting the demands of high-precision and dynamic monitoring. As a crucial direction in intelligent control of power engineering, smart power plants integrate technologies such as the Internet of Things (IoT), big data, and artificial intelligence, providing a new technical pathway for real-time monitoring and intelligent analysis of carbon emissions. Existing studies focus on the optimization of a single link or the construction of static models, and lack of systematic exploration of dynamic monitoring and intelligent decision-making of the whole process. As a result, problems such as lagging carbon emission data collection and a single analysis dimension are still prevalent [1].

2. Correlation theory

2.1. Carbon emission monitoring theory

Carbon emission monitoring theory is the core foundation of smart power plant carbon emission real-time monitoring and intelligent analysis platform construction. Its core is to achieve accurate collection, processing, and analysis of carbon emission data through scientific monitoring methods and advanced technical means. The basic principle of carbon emission monitoring is based on the calculation of carbon emission factors in the energy consumption process, combined with real-time data collection technology, to build a multi-dimensional monitoring system. As a key area of carbon emission, the low-carbon development of the power industry needs systematic monitoring from three key links: power generation side, power grid side, and electricity consumption side. For example, the power generation side needs to calculate carbon emissions through fuel consumption, power generation efficiency, and other parameters; while the grid side needs to pay attention to the loss and indirect carbon emissions in the transmission and distribution process; while the monitoring of the electricity side needs to combine the terminal load changes and user behavior characteristics to form a complete monitoring chain.

2.2. Smart power plant theory

Smart power plant is an intelligent energy management system built on modern information technology, automatic control technology, and big data analysis capability. Its core is to realize dynamic optimization and precise regulation of the power generation process through an integrated platform. By real-time collection of equipment operation data, environmental parameters, and energy consumption information, combined with a prediction model and intelligent algorithm, the system forms a closed-loop management architecture covering the whole production chain. Its core features are manifested in three dimensions: digital perception, networked transmission, and intelligent decision-making. At the device level, sensor networks are deployed to achieve comprehensive physical space perception. Industrial Internet technology is utilized to construct a neural network for data interaction. Ultimately, through digital twin and bionic system architectures, the power generation process is virtualized and dynamically optimized.

The deep integration of smart power plants and carbon emission monitoring is essential to incorporate carbon emission indicators into the production optimization objective function through technical means. For example, in the optimization of generator set operation strategy, the output of distributed energy can be coordinated through two layers of game theory. The inner layer manages demand side response through a price elasticity coefficient model, and the outer layer establishes a multi-energy collaborative optimization framework based on renewable energy uncertainty analysis, so as to minimize carbon emissions while ensuring power supply reliability.

3. Platform architecture design

3.1. Data acquisition and transmission module design

In the platform architecture design, the data acquisition and transmission module serves as the foundational support layer of the system. Its design objectives are to achieve efficient collection, real-time transmission, and quality assurance for multi-source heterogeneous carbon emission-related data. The data acquisition phase adopts a distributed sensing architecture, deploying high-precision sensor networks and industrial equipment interfaces to establish a monitoring system that covers the entire production process of power plants. In the combustion system, temperature, pressure, flow sensors, and CEMS (continuous emission monitoring system) are deployed to collect core parameters such as fuel consumption and flue gas composition concentration in real time. Key equipment such as steam turbine and boiler is equipped with vibration and displacement monitoring devices, and the operation status data of the equipment is obtained through the SCADA system interface. In the flue gas treatment process, in addition to the conventional pollutant monitoring, carbon isotope analyzers are added to realize online identification of fuel types and provide a data basis for carbon emission source analysis. All sensors are manufactured to industrial protection standards, support 4-20mA, RS-485, and other standard communication protocols, and are equipped with an edge computing gateway for local data aggregation.

The unified data parsing middleware is developed in the protocol adaptation layer to support the standardized conversion of various industrial protocols such as Modbus, OPC UA, and Profibus, and build a service-oriented API interface to realize seamless docking with the superior system [2,3]. In view of the timing characteristics of data flow, the timestamp alignment and order guarantee algorithm is adopted to ensure that the synchronization error of multi-source data is controlled within 50 ms.

3.2. Data analysis and processing module design

As the core technical component of the platform, this module is responsible for the analysis, modeling, and intelligent analysis of carbon emission data. Its design focuses on real-time, high precision, and scalability. In the data preprocessing stage, the system first cleans and standardizes the collected raw data, removes invalid data through a missing value interpolation algorithm and an outlier detection model (such as an isolated forest algorithm), and then uses a multi-dimensional normalization method to unify the dimensions of heterogeneous parameters such as temperature, pressure, and fuel consumption (**Table 1**) [4]. The feature engineering module constructs the time series features through sliding window technology and extracts the physical correlation between key variables combined with domain knowledge to form a feature matrix containing historical emission intensity, equipment load rate, meteorological conditions, and other dimensions, laying a foundation for subsequent modeling.

Table 1. Data preprocessing record table (data_preprocessing_log)

Field name	Type	Restrain	Description note
preprocess_id	BIGINT AUTO_PK	PRIMARY	Pre-treatment batch ID
raw_data_id_range	VARCHAR(50)	NOT NULL	Original data ID range (e.g., 100001-100500)
missing_rate	DECIMAL(5,2)	NOT NULL	Original data missing rate (%)
outlier_count	INT	NOT NULL	Number of anomalies (detected by isolated forest algorithm)
normalization_type	ENUM	NOT NULL	Normalization methods (MinMax/Z-Score/Log, etc.)
process_duration_ms	INT		Preprocessing time (ms)
timestamp	TIMESTAMP(3)	NOT NULL	Processing completion timestamp

4. Experimental and result analysis

4.1. Experimental method and step

This study verifies and evaluates the functions and performance of the smart power plant carbon emission real-time monitoring and intelligent analysis platform through a systematic experimental process. The experimental design adopts a modular architecture, consisting of four phases: hardware deployment, system integration, data acquisition, and analysis validation. The hardware deployment utilizes a hierarchical architecture, featuring front-end installations of industrial-grade IoT sensor networks. These include the CEMS, fuel flow meters, and unit status collectors. Sensor data undergoes real-time preprocessing through 5G-MEC edge computing nodes before being transmitted to the cloud. The server cluster adopts a hybrid cloud architecture, with core computing modules deployed in private clouds to ensure data security. Data analysis services achieve high-concurrency processing through elastic scaling on public clouds. The experimental environment configuration complies with IEC 61499 industrial communication standards, maintaining network latency below 200 ms. Data transmission employs a dual-protocol redundancy mechanism using both MQTT 3.1.1 and OPC UA protocols [5].

The system integration phase focuses on verifying inter-module collaboration capabilities. The data acquisition layer utilizes Python-developed drivers to integrate multi-source heterogeneous devices, establishing sensor data dictionaries and standardized conversion protocols. This ensures compatibility for critical parameters, including SO_2, NO_x, CO_2 concentrations, and fuel consumption metrics. The data processing layer uses Apache Kafka to build a real-time data flow pipeline and combines Flink to realize sliding time window calculation. A 10-second window period is set for emission rate calculation. The analysis layer is deployed with a TensorFlow-based LSTM-GRU hybrid neural network model to predict carbon emission trends, and a random forest algorithm is integrated to identify abnormal emissions.

4.2. Experimental results and analysis

Based on the actual operation data of a smart power plant, this experiment builds a carbon emission monitoring platform including multi-source sensor input, a real-time data processing module, and an intelligent analysis algorithm. This paper compares the performance of three methods in carbon emission monitoring: the traditional fixed coefficient method, the improved random forest algorithm, and the deep learning LSTM model. The experimental data were sourced from the 2022 operational records of a coal-fired power plant, encompassing 12 real-time parameters, including boiler load, fuel consumption, and flue gas composition, comprising 1.2 million valid samples. Through cross-validation and rolling window testing, we conducted a systematic evaluation of the monitoring accuracy, response time, and anomaly detection capabilities of various methodologies.

In the real-time index test, the single calculation response time of the fixed coefficient method is stable at 23 ms, the average delay of the random forest algorithm is 48 ms, and the LSTM model reaches 85 ms with GPU acceleration. Although the computing overhead of the deep learning model is high, the response time can be compressed to 62 ms through lightweight processing of the model (such as the introduction of knowledge distillation technology), which meets the real-time requirements of 500 ms for the power plant SCADA system. Experimental data show that the LSTM model can still maintain a real-time processing rate of more than 95% at the data throughput of 3000 points/second [6–10].

5. Conclusion

The smart power plant carbon emission real-time monitoring and intelligent analysis platform developed in this study has achieved remarkable results in both technical implementation and engineering applications. By integrating multi-source heterogeneous data acquisition systems, dynamic carbon emission accounting models, and intelligent decision support modules, the platform enables high-precision dynamic tracking and forward-looking analysis of carbon emissions throughout the entire power generation process. The research results show that the sensor network and edge computing architecture based on the Internet of Things can effectively improve the real-time performance and reliability of data collection, which lays a foundation for dynamic accounting of carbon emissions. The machine learning driven emission factor correction model performs well in the pilot of coal-fired units, and its prediction error is 18.7% lower than the traditional static accounting method, which significantly improves the accuracy of carbon emission data [10]. The multi-dimensional visual interface and abnormal emission early warning system developed by the platform have successfully reduced the response time of operation and maintenance personnel to minutes, effectively preventing the risk of sudden carbon emission exceeding the standard caused by equipment failure or process deviation.

Disclosure statement

The authors declare no conflict of interest.

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