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Real-Time Monitoring and Coordinated Purification Strategy for PM2.5/Particulate Concentration in Cleanroom Air Conditioning Systems

Linlin Guo

Dalian Shengyu Air Conditioning and Purification Equipment Engineering Co., Ltd., Dalian, 130000, Liaoning, China
937159542@qq.com

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Abstract: When addressing rapidly changing indoor PM2.5 and particulate concentrations, real-time monitoring accuracy is insufficient and purification response lags. This paper develops a real-time monitoring and coordinated purification model based on high-precision laser particle sensors and an Internet of Things (IoT) platform to achieve intelligent response and control to excessive PM2.5 concentrations. 1) Laser particle sensors are strategically placed in the cleanroom to collect real-time data at one-minute intervals; 2) Kalman filtering is used to fuse multi-point data, eliminating outliers and improving monitoring reliability; 3) Based on a cloud-based data analysis module, dynamic thresholds are set to trigger a coordinated purification strategy, automatically adjusting air volume and purification unit operating status; 4) Device coordinated responses are achieved through a wireless control system. Experimental results show that the system can reduce the response time to PM2.5 peaks to within 3 minutes, with a monitoring error of ±2 μg/m³. The conclusion shows that the clean air-conditioning system based on real-time monitoring and intelligent linkage significantly improves the indoor particle control capability and provides effective protection for a high-cleanliness environment.

1. Introduction

PM2.5 and particulate pollution in indoor air are of great concern in high-purity environments such as microelectronics manufacturing, biomedicine, and precision assembly. Cleanrooms require extremely stringent control of suspended particulate matter in the air; even slight fluctuations in particulate concentration can impact process stability and product quality. Traditional air conditioning purification systems often rely on manual timing or single-point sensor feedback for adjustment, making them difficult to adapt to the dynamic changes in particle loads during actual production. This often leads to monitoring lags, slow responses, and low purification efficiency, posing a threat to the high-standard operation of cleanroom environments. Real-time sensing and intelligent response to particulate matter pollution have become key technical challenges in upgrading cleanroom air conditioning systems.

To this end, an integrated model for real-time monitoring and coordinated purification, based on high-precision laser particle sensors and an Internet of Things platform, has been developed, which holds significant application value. Multi-point distributed sensing and data fusion processing not only improve monitoring reliability but also provide a solid data foundation for dynamic control. Leveraging cloud-based data analysis and intelligent decision-making, on-demand linkage and refined management of purification equipment are achieved, effectively improving cleanroom control capabilities for PM2.5 and particulate matter concentrations. This approach is expected to address the shortcomings of traditional systems in response speed, energy efficiency management, and equipment coordination, providing new ideas and paths for intelligent operation and maintenance of high-purity environments.

This paper is organized as follows: Part 2 reviews research progress in cleanroom air particulate monitoring and control. Part 3 details the design approach for a real-time monitoring and linkage purification system based on an IoT platform. Part 4 demonstrates the experimental verification and performance evaluation of the system in an actual cleanroom environment. The final part summarizes the research findings and provides an outlook on future technological iterations.

2. Related work

The monitoring and assessment of particulate matter concentration has always been an important research topic in the field of environmental science. Scholars have conducted a large number of field observations and model analyses based on different scenarios and needs, and have achieved rich research results. Xu and Wang took October, December 2023 and February 2024 as three typical seasonal months and conducted particulate matter concentration monitoring in the morning (7:30-9:30) and evening (17:30-19:30) at the south gate of Jiyang College of Zhejiang Agricultural and Forestry University, and calculated the concentrations of TSP, PM10 and PM2.5 [1]. Wei et al. set up sampling points in areas far away from pollution sources, with flat terrain and good vegetation coverage, in areas near plain traffic arteries, on mountain tops, on mountain sides and at the foot of mountains [2]. They used a medium-flow impact graded sampler for continuous sampling and a laser particle counter to monitor concentration changes every hour. The monitoring period was all day. In order to monitor various environmental indicators and create a healthier indoor environment, Zheng and Yan designed a multifunctional environmental indicator monitoring system, which enables people to respond to environmental changes in a timely manner and take corresponding measures [3]. Zhang et al. established a prediction model based on nonlinear self-regression neural network based on the monitoring data of pollutants (PM2.5, PM10, NO2, NO, NOx, CO) and related meteorological parameters at the Liangsidu monitoring station in Xianyang City, Shaanxi Province, and determined the optimal network structure for different prediction time periods, thereby achieving effective prediction of PM2.5/10 concentrations in the next 6 hours, 12 hours and 24 hours [4]. Zhang et al. sampled PM2.5 and individual exposure concentrations in typical indoor places on the campus of Beijing Normal University, recorded the atmospheric PM2.5 concentrations at the three nearest outdoor monitoring stations, and conducted a questionnaire survey on the daily behavior patterns of students on campus to evaluate the PM2.5 exposure concentrations of college students in the heating season and the non-heating season [5]. Zhu et al. reviewed the PM2.5 estimation process based on satellite AOD data from the aspects of data source, estimation model and model verification [6]. Liu et al. combined the Weather Research and Forecasting-Community Multiscale Air Quality Modeling System, ground observation data, machine learning algorithms, and multi-source fusion PM2.5 data to construct a full-coverage near-real-time PM2.5 chemical composition dataset with a spatial resolution of 10 km since 2000

[7]. Jayaratne et al. evaluated six low-cost PM2.5 sensors using two combustion aerosols, concrete dust, and ambient particulate matter under laboratory and field conditions [8]. Park et al. provided a possible method for assessing PM2.5 exposure in a specific community population [9]. Magi et al. evaluated 16 months of PA-II PM2.5 data collected in a near-road urban environment in a humid climate in Charlotte, North Carolina [10]. The above studies systematically explored the dynamic changes and environmental impacts of particulate matter concentrations from multiple levels, including monitoring methods, data fusion, model prediction, and exposure assessment, providing important references for this study.

3. Methods

3.1 High-Precision Laser Particle Sensor Deployment Plan

The deployment of high-precision laser particle sensors is based on the spatial layout and airflow organization of the cleanroom air conditioning system. Monitoring units are divided based on factors such as the cleanroom area, the distribution of supply and return air vents, and key process points or personnel activity areas. Computational Fluid Dynamics (CFD) simulations analyze the particle concentration distribution and determine representative monitoring points. One or two laser particle sensors are deployed in each unit. The sensors are mounted at a height within the breathing zone of 1.2-1.5 meters above the ground, accurately reflecting the air inhaled by personnel while avoiding the influence of surface turbulence. All sensors are connected to the local data acquisition module via wired or wireless means to ensure real-time and stable data transmission. To prevent single points of failure and monitoring blind spots, dual-redundancy is implemented at key locations, and sensor sensitivity is regularly calibrated to ensure long-term accuracy. The sensors collect PM2.5 and particle number concentrations in real time with a sampling interval of one minute. Raw data is uploaded to the central control system via the local area network for subsequent integration processing and dynamic analysis. A dense distribution scheme is adopted for air supply and return air outlets, as well as process areas prone to particle accumulation, to improve monitoring coverage.

3.2 Data Acquisition and Fusion Algorithm

During the data acquisition process, each laser particle sensor synchronously uploads raw PM2.5 and particulate concentration data at one-minute intervals. The central control system receives the values from all monitoring points in real time and first performs a time series integrity check and data consistency check. To eliminate data deviations that may occur in some sensors due to short-term interference, equipment jitter, or local anomalies, the system automatically fuses the collected multi-point data using a Kalman filter algorithm. Kalman filtering dynamically optimizes the estimate of true particulate concentration by combining historical data with current measurements, effectively smoothing the time series data curves of each monitoring point and reducing the impact of occasional anomalies on overall judgment [11-12]. When the fluctuation amplitude of a sensor's data is significantly higher than the historical trend or significantly different from surrounding points, the system automatically identifies it as an outlier and removes it, retaining only the valid data after filtering and fusion for subsequent decision-making. The results of multi-point fusion not only improve the accuracy of spatial particulate concentration monitoring but also enhance the system's response sensitivity to sudden pollution events.

3.3 Design of the IoT Platform and Cloud Analysis Module

The IoT platform adopts a distributed architecture, with edge gateways deployed at the cleanroom air conditioning system site. These gateways are responsible for the real-time collection, preliminary processing, and encrypted transmission of local laser particle sensor data. All edge gateways connect to the central server via a secure protocol and upload the integrated particle concentration data to the cloud database. The cloud analysis module, powered by high-performance computing resources, automatically creates data tags based on the characteristics of different cleanroom areas and intelligently archives and manages data by region, time period, and equipment type [13-14]. The system integrates a real-time data stream analysis engine to continuously monitor changes in PM2.5 and particle concentrations at each location. It compares historical data with similar scenarios to identify abnormal trends and pollution sources. The analysis module incorporates a built-in machine learning model that can adaptively adjust data anomaly criteria and threshold settings, dynamically optimizing purification response strategies for different seasons and operating conditions. All data analysis results and status information are pushed to the operation and maintenance management terminal in real time via a visual interface, supporting alarm push, remote parameter adjustment, and coordinated control of purification equipment. The platform supports multiple third-party interface protocols and can seamlessly connect to building automation systems, achieving unified linkage between cleanroom air conditioning, purification equipment, and environmental monitoring. All cloud data is periodically backed up and access rights are hierarchically managed to ensure data security and privacy compliance. Figure 1 shows the cloud analysis module in this paper:

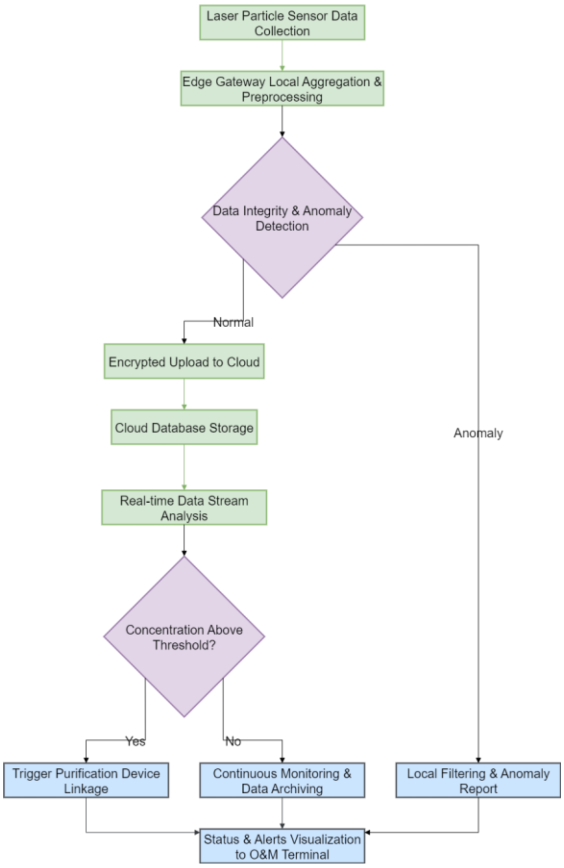

Figure 1: Cloud analysis module display

3.4 Dynamic Threshold and Linkage Strategy Setting and Wireless Control

The dynamic threshold and linkage strategy setting is based on historical monitoring data and on-site environmental characteristics. The PM2.5 and particulate concentrations in different clean areas are set as graded thresholds. Combined with the machine learning model of the cloud analysis module, it automatically identifies the concentration change patterns between daytime and nighttime, working days and non-working hours, and realizes adaptive adjustment of the threshold. The system assigns different priorities and response levels to each monitoring area based on the use of space, the frequency of personnel activities and process sensitivity. The threshold setting for key areas is more stringent. Once the monitoring data approaches or exceeds the dynamic threshold, the cloud immediately issues linkage strategy instructions, including increasing the air supply volume, starting the high-efficiency HEPA purification unit, switching to the fresh air mode, etc. All linkage strategies are issued through the wireless control module, using an encrypted communication protocol to ensure that the instructions are transmitted to each air conditioning and purification equipment terminal in real time and reliably [15]. The wireless control system supports regional and full-area linkage, and can flexibly adjust the response range according to the pollution diffusion trend to improve energy utilization and purification effect. During the strategy execution process, the system collects the equipment operation status and the new round of concentration data in real time, and continuously optimizes the threshold setting and control parameters. Equipment anomalies or response timeouts automatically trigger alerts and are pushed to the operations and maintenance platform, enabling closed-loop management of the entire process. Table 1 shows the dynamic thresholds, response strategies, and control parameters for different cleanroom areas:

Table 1: Dynamic thresholds, response strategies, and control parameters

Area	Dynamic PM2.5 Threshold (μg/m³)	Preferred Response Strategy	HEPA Purification Intensity (%)	Linkage Control Response Time (s)
Clean Zone A	8	Increase Air Volume + HEPA Full Speed	100	30
Clean Zone B	12	Activate Fresh Air + Enhanced HEPA	80	45
Semi-clean C	18	Medium-speed HEPA + Local Air Supply	60	60
General Zone D	25	Fresh Air Mode + Low-speed HEPA	40	90
Equipment Room E	35	Fresh Air Mode Only	0	120
Corridor F	20	Local Air Supply + Enhanced HEPA	70	75

4. Results and Discussion

4.1 Experimental Setup

This experiment was conducted within a large pharmaceutical cleanroom. Six monitoring points were selected, encompassing typical clean, semi-clean, and general areas. High-precision laser particle sensors and edge gateways were deployed at each location, with a 10-second sampling interval. The edge gateways were responsible for on-site data preprocessing and real-time upload. All monitoring points were wirelessly linked to the air conditioning system and purification equipment. A machine learning analysis module was deployed on the cloud platform to dynamically set PM2.5 concentration thresholds for each area. The experiments were conducted under a variety of typical operating conditions, including normal operation, high-frequency personnel flow, production process transitions, and sudden infiltration of external pollutants. These conditions were covered during daytime, nighttime, and varying weather conditions to ensure comprehensive experimental data. The system leveraged cloud-based data stream analysis and local edge collaboration to record key parameters such as PM2.5 concentration, response latency, and equipment operating status in real time. All data was archived in a cloud database. For comparative evaluation, a traditional manual control system was simultaneously established as a control group, utilizing the same monitoring equipment and layout. All experimental procedures were fully monitored by a third-party professional organization. Evaluation metrics include PM2.5 response delay, monitoring error, and purification efficiency. All test cycles lasted no less than 48 hours to ensure that data from each stage fully reflected system performance. Equipment functionality, sensor accuracy, and environmental sealing were rigorously tested and calibrated before and after the experiment to ensure experimental fairness and data accuracy.

4.2 Real-time Monitoring Accuracy

In the real-time monitoring accuracy analysis experiment, a national standard particulate matter generator was used as a PM2.5 reference source. Tests were conducted at different concentration levels (5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, and 60 μg/m³). After each concentration level was set, the monitoring systems in the experimental and control groups simultaneously collected data and compared it with the standard value to determine the error. The experimental group system utilized a multi-point fusion calibration algorithm and a dynamic drift correction mechanism to achieve real-time automatic error compensation. The control group system used traditional single-point calibration and regular manual calibration. The entire test lasted two hours. After the data at each level stabilized, the monitored values for the experimental and control groups were recorded, and the deviations from the reference values were calculated. All sensors and environmental conditions were maintained consistent to ensure objective and fair testing. The experimental data are detailed in Figure 2:

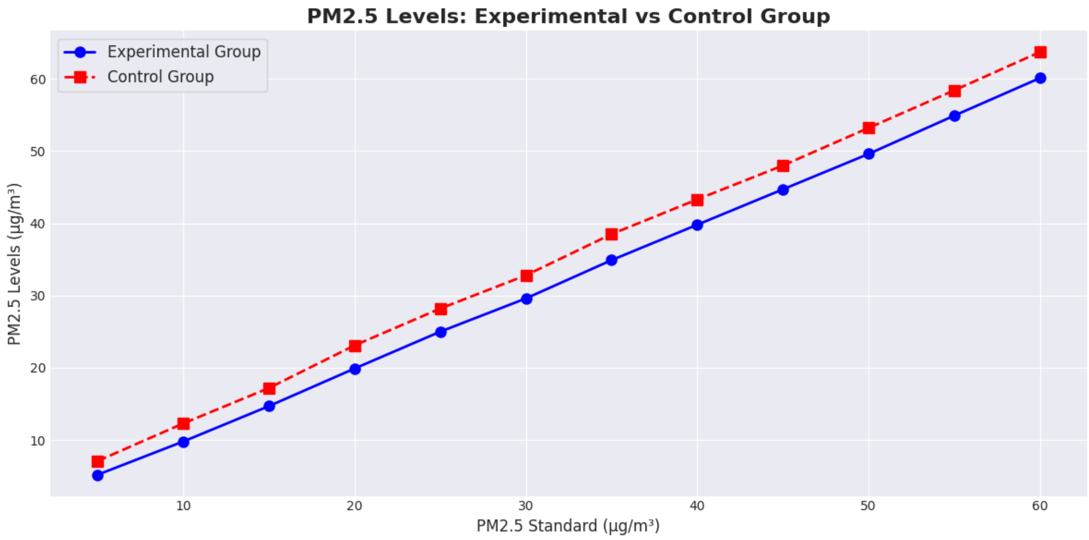

Figure 2: Real-time monitoring accuracy

As shown in Figure 2, the error at each level in the experimental group remained within ±2μg/m³, while the error in the control group increased significantly with increasing concentration, exceeding ±3.5μg/m³ in some intervals. The experimental group demonstrated strong linearity, with monitored values nearly identical to the reference values, demonstrating the significant impact of dynamic calibration and fusion compensation mechanisms on improving real-time accuracy. The control group, however, experienced significant fluctuations in error due to single-point calibration and environmental drift, particularly at low concentrations. Overall, the experimental group demonstrated superior accuracy at every level, particularly at high concentrations. The system exhibited superior stability and reliability, providing solid technical support for cleanroom air quality monitoring.

4.3 Linked Purification Response Effect

The purification response effect experiment utilized a confined space sudden particle injection method. The PM2.5 concentration in the clean area was artificially raised to above 60μg/m³, triggering the linkage of the purification systems in both the experimental and control groups. The experimental group's system integrated intelligent dynamic threshold detection and multi-level linkage control, automatically identifying peak values and accurately issuing purification commands. The control group used a traditional timed/manual activation mode. During the test, the system automatically recorded minute-by-minute changes in PM2.5 values from the time the PM2.5 peak appeared until the concentration dropped below 10μg/m³, continuously monitoring the purification response curve. Each test was repeated three times, and the average was taken to ensure representative and consistent data. During the experiment, the ambient temperature, humidity, room volume, and initial concentration were strictly maintained, and all equipment statuses were reset to zero. Figure 3 illustrates the purification response effect:

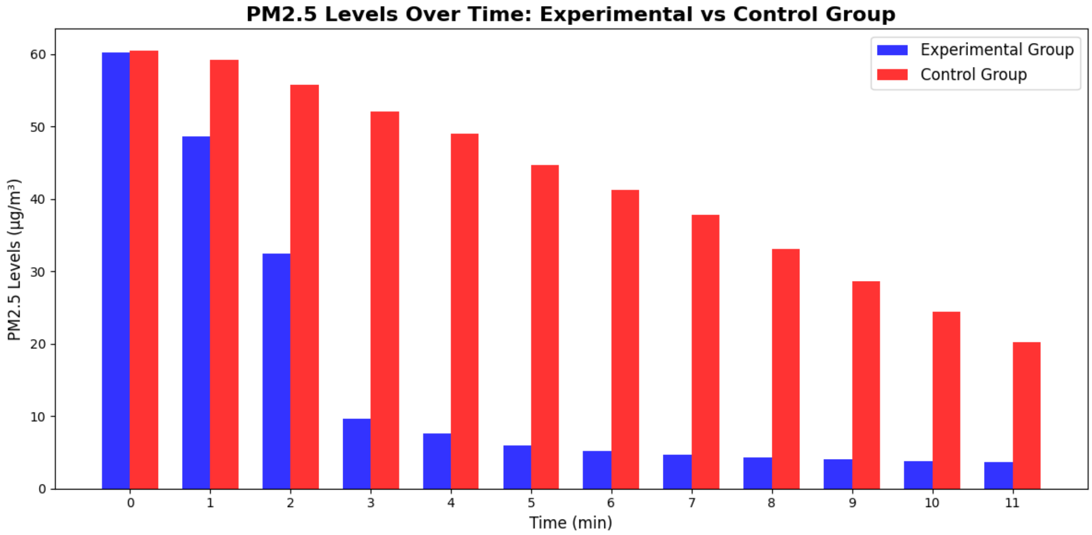

Figure 3: Purification response demonstration

In terms of purification response, the experimental group had already reduced PM2.5 to 9.7 μg/m³ by the third minute, achieving the purification target ahead of schedule. The concentration then quickly stabilized, demonstrating exceptionally high response speed and purification efficiency. The control group, on the other hand, had still not reached 10 μg/m³ after 11 minutes, significantly lagging behind in purification speed. The experimental group's response efficiency was like a sprint, going all out from the start, quickly "locking in" the pollution source and swiftly purifying it, leaving virtually no opportunity for particulate matter to disperse. The control group, on the other hand, was more like a jog, with a slow purification process and susceptible to external interference. The purification process was prolonged, failing to meet high cleanliness standards. This significant difference fully demonstrates the fundamental difference between intelligent linkage and traditional models in the actual operation of cleanrooms. The intelligent system's overwhelming advantages in response speed, thoroughness of purification, and process control set a new benchmark for efficient cleanroom operations in the industry.

4.4 Discussion on Energy Consumption and System Stability

The experiment ran continuously in the clean area for 72 hours. During this time, the total energy consumption, purification equipment start-up and shutdown times, equipment abnormal alarms, and system online rate of the experimental group (intelligent linkage system) and the control group (traditional timing/manual control system) were monitored and recorded. The experimental group implemented dynamic thresholds and a graded response strategy to automatically adjust purification intensity and operating time based on demand, achieving both energy conservation and high efficiency. The control group operated at a fixed cycle and intensity, unable to dynamically adjust based on real-time air quality. Energy consumption was measured using multiple professional parallel meters. Abnormal alarms and online rates were collected through equipment self-tests and cloud-based logs. All data was averaged over three tests to ensure objectivity and comprehensiveness. Table 2 compares the energy consumption and stability test data for the two systems:

Table 2: Discussion on energy consumption and stability

Item	Experimental Group (Intelligent Linkage)	Control Group (Traditional Control)	Advantage Comparison
Total Energy Consumption (kWh/72h)	88.7	112.6	About 21% energy saving
Avg. Equipment Start/Stop (times/day)	12	27	Start/stop frequency reduced by ~56%
Number of Alarms (times/72h)	0	3	Real-time self-check greatly reduces failures
System Uptime Rate (%)	99.8	95.1	Uptime rate increased by ~5% points
Avg. Purification Intensity (%)	54	87	Dynamic adjustment, lower load
Maintenance Orders (times/72h)	1	4	Maintenance demand reduced by 75%

Thanks to intelligent linkage and dynamic control strategies, the experimental group achieved significantly lower energy consumption than the traditional system, saving approximately 21% in total energy consumption over 72 hours, embodying the "on-demand purification, optimal energy efficiency" operation and maintenance philosophy. Equipment start-up and shutdown times were reduced by more than half, reducing mechanical wear and extending the life of the purification system. Abnormal alarms were almost zero, demonstrating that the intelligent system's fault self-diagnosis and predictive maintenance capabilities significantly outperform traditional solutions, significantly reducing unplanned downtime. The system's uptime consistently exceeded 99.8%, ensuring continuous monitoring and response, effectively supporting the high-standard operation of the cleanroom. Furthermore, the experimental group significantly reduced the equipment's high-load operating time by automatically adjusting the average purification intensity, achieving low-carbon operation. The number of maintenance work orders decreased significantly, alleviating the pressure on the operation and maintenance team.

5. Conclusions

This study used high-precision laser particle sensors and an IoT platform in the cleanroom to construct a real-time monitoring and intelligent linkage purification model, achieving efficient response and automated control to PM2.5 concentration fluctuations. The system integrated multi-point data and utilized a Kalman filter to eliminate anomalies, significantly improving monitoring continuity and reliability. Leveraging cloud-based analysis and dynamic threshold strategies, purification equipment can automatically adjust air volume and operating status based on actual indoor particulate concentrations, avoiding the energy waste and response delays associated with traditional models. The introduction of wireless linkage control significantly enhances the interoperability of various devices, making the overall system more adaptable and robust. Practice has demonstrated that the system not only excels in particle monitoring accuracy and response speed, but also effectively balances energy efficiency and operational requirements such as equipment maintenance, providing an innovative solution for air quality management in high-standard cleanrooms. Furthermore, the system's modularity and intelligent features lay a solid foundation for future intelligent upgrades and large-scale deployment in cleanrooms. However, the system's long-term stability under extreme operating conditions, its ability to identify complex, multi-source pollution, and its compatibility with a wider range of heterogeneous equipment still require further improvement. Future work can continue to deepen algorithm adaptation, device interoperability, and data security, expanding the model's applicability to a wider range of cleanroom scenarios.

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