# Research on Precise Monitoring and Prevention of Environmental Pollution Based on Environmental Big Data Analysis

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**ABSTRACT** Environmental big data analysis has become an important approach for achieving intelligent environmental governance, while reliable wireless communication and electromagnetic signal transmission provide the essential infrastructure for distributed sensing and real-time data acquisition in modern monitoring systems. This study established a VOC-based online monitoring cloud platform to analyze gas distribution characteristics within a chemical park. Five monitoring stations were deployed to continuously collect real-time VOC concentration data, enabling the evaluation of localized pollution patterns and emission characteristics. Based on the acquired VOC datasets, environmental information was uploaded to the cloud platform through wireless communication networks and analyzed using the USEPA Positive Matrix Factorization (PMF) model to identify and localize pollution sources with high precision. The results demonstrate that the proposed framework effectively distinguishes multiple VOC emission sources, including alkane leakage, preparation process emissions, olefin synthesis, urban transmission, and storage tank emissions, thereby providing accurate source apportionment and spatial localization for environmental management. By integrating environmental big data analytics with cloud-based monitoring architecture and electromagnetic information transmission technologies, the proposed approach enhances the efficiency and reliability of real-time pollution surveillance and offers a practical reference for intelligent environmental monitoring and industrial emission prevention.

**INDEX TERMS** environmental big data, volatile organic compounds (VOCs), precise monitoring, electromagnetic information transmission, wireless sensor network

## I. INTRODUCTION

WITH the rapid expansion of large-scale industrial cities, fighting the ecological battle by upgrading traditional manufacturing clusters into green production zones is a necessary part of future urban development. Building a green ecological environment requires the implementation of advanced water recycling and energy efficient weaving technologies to harmonize intensive industrialization with sustainable city planning. In the field of atmospheric environmental protection monitoring, with the continuous deterioration of urban air quality, air pollution has become a topic of close concern to the public, and people's need to improve the monitoring of atmospheric air quality is becoming more and more urgent [1], [2]. In recent years, with the issuance of the Outline of Action for the Promotion of Big Data, artificial intelligence and big data have gradually risen to a high level of national strategy, and mobile Internet, cloud computing, big data, Internet of Things, artificial intelligence and other cutting-edge technologies have been deeply integrated with the atmospheric environmental protection field, it has become a major trend to build a set of energy saving and environmental protection monitoring systems based on environmental protection big data as technical support, while the foundational data for this specific case study were collected during a intensive monitoring campaign in 2019, the integration of these datasets with 2024–2025 analytical frameworks demonstrates how historical baseline data can be leveraged to train modern predictive models for the city's environmental protection work and regional ecological environment function guarantees [3]–[5].

In the field of atmospheric environmental protection monitoring, in recent years, the construction of chemical parks in China's industrial cities has shown a rapid growth trend. With the rapid development of the economy and the further advancement of urbanization, deep-processing chemical enterprises are gathering in industrial parks, and industrial parks have rapidly become the main carrier of the chemical industry [6], [7]. At the same time, the problem of air emission pollution caused by chemical enterprises is becoming more and more obvious. Air pollution in chemical parks is dominated by the emission of volatile organic compounds (VOCs), which are characterized by a wide variety of gases, complex and variable composition, and high volume fraction. With the implementation of the most stringent new environmental protection law, many VOCs emitting enterprises will face greater pressure on emissions, forcing major chemical parks to strengthen the monitoring of VOCs gas, thus strengthening the online VOCs gas monitoring system and precise identification of pollution sources is an important solution to achieve effective management of VOCs gas emissions in industrial parks, and is one of the most important tasks in air environment monitoring and control [8]–[10]. Based on this, this study built an environmental pollution monitoring system based on environmental big data analysis, which consists of Infrastructure as a Service (IaaS), Platform as a Service (PaaS) and Software as a Service (SaaS), and then built an online VOCs gas monitoring cloud platform based on this monitoring system. This study chose a chemical park as the object of study, set up five monitoring points and used VOCs online monitoring equipment to collect VOCs gas concentrations and analyzed the gas distribution state of each monitoring point. Further, based on the collected VOCs gas data, the information is imported into a cloud-based monitoring platform where the USEPA PMF model identifies emission sources from industrial activities. This big data analysis enables the precise localization of VOCs pollution within industrial parks, providing a robust theoretical basis for managing the unique air quality challenges posed by advanced fabric treatment facilities.

## II. MATERIALS AND METHODS

### A. BUILDING AN ENVIRONMENTAL POLLUTION MONITORING SYSTEM BASED ON ENVIRONMENTAL BIG DATA ANALYSIS

This study firstly built an environmental pollution monitoring system based on environmental big data analysis, with a system structure consisting of Infrastructure as a Service (IaaS), Platform as a Service (PaaS) and Software as a Service (SaaS). The underlying architecture is IaaS, which provides a cloud computing infrastructure for environmental pollution monitoring systems through virtualization technology [11]. The infrastructure in this system architecture comprises a comprehensive array of hardware integrated into the IaaS layer. This includes low-level data collection terminals (inputs) such as indoor environmental monitoring sensors, VOCs online monitoring devices, amtax analyzers, COD analyzers, pH meters, flow-meters, turbidity analyzers, and intelligent cameras. Crucially, the architecture also integrates industrial actuators, such as solenoid valves, which function as output control terminals to execute automated mitigation strategies (e.g., closing emission valves) when pollution thresholds are exceeded. The data from the collection terminals is uploaded to the cloud service platform of the monitoring system through LoRa base stations and NB-IoT modules after summary processing. IaaS provides the same technology and functionality as data center without having to physically maintain or manage it. IaaS includes multiple databases such as pollution source databases, environmental quality databases, and environmental metadatabases.

The middle architecture layer is PaaS, which consists of a POE switch and a cloud platform for environmental pollution monitoring based on environmental big data analysis, where the POE switch consists of Modbus communication protocol, CorePro agent module, and is supported by LTe technology. This architectural layer focuses on providing cloud components for certain software and provides a framework for developers to create custom applications based on it [12]. SaaS is the most commonly used option for enterprises in various environmental protection industries. SaaS uses the Internet to provide mobile apps and computer software applications for environmental pollution monitoring and pollution source identification. This layer incorporates automated data validation filters to identify and flag outliers caused by sensor electronic noise or signal jitter, ensuring that only verified atmospheric data is used for the PMF source apportionment model [13]. Through the construction of the system, the platform finally realizes real-time environmental monitoring, environmental anomaly notification, and intelligent pollution source identification. Furthermore, the integration of actuators within the IaaS layer supports active "environmental control recommendations", enabling the SaaS layer to trigger solenoid valves for the immediate containment of accidental leakages or the redirection of non-compliant wastewater streams based on real-time sensor feedback [14], [15].

### B. GAS COLLECTION AND POLLUTION SOURCE IDENTIFICATION ANALYSIS OF VOCS ATMOSPHERIC

#### 1) Gas Collection Location and Time

This study selected a chemical park in Hebei Province, with a total area of about 35.4 km$^2$ and 34 enterprises (as shown in Figure 1, A1–F5), which mainly produces oil, natural gas, industrial syngas, new thin film materials and other chemical deep processing products. To evaluate the impact of external pollutants, the park's boundaries were defined relative to the surrounding urban infrastructure: the southwest and southern perimeters of the park are immediately adjacent to a major municipal residential and commercial district (urban area). Five monitoring points were strategically distributed to capture both internal process emissions and cross-boundary "urban transmission" flux entering from the southwest. The gases emission during daily operation included $H_2$, $CH_4$, $C_2H_2$, $C_2H_4$, $C_2H_6$, CO and other VOCs. In this study, five monitoring points (as shown in Figure 1) were set up to monitor VOCs gas, thus achieving full coverage of VOCs gas monitoring in the park. Among them, the monitoring points are 3.5 m away from the bottom surface and the height of the gas emission outlet is more than 20 m, and the monitoring period is from March 15 to April 15, 2019.

2) VOCs Gas Collection, Testing and Precise Identification of Pollution Sources

In this study, an independent VOCs online monitoring system (Shanghai Siyuan Co., Ltd., TROM-600S) was installed at five monitoring points to collect VOCs gas data, and a spectral analyzer and flame ionization detector were used to detect 43 VOCs gases. The test equipment was responsive and data reliable. The test gained a total of 7883 valid data items and an efficiency of 89.3%. The identification of VOCs gas pollution source has adopted the positive matrix factor analysis (PMF), which is a mature quantitative method for analyzing sources of air pollution, and it is commonly used to estimate the relative contributions of various types of pollution sources to the pollutants in the atmosphere. The matrix is decomposed according to the matrix form $X = GF + E$ [16], where $G$ is the $n \times p$ source contribution matrix, $p$ is the number of major pollution sources, $F$ is the $p \times m$ source profile matrix, and $E$ is the residual matrix. This study introduced positive matrix factor analysis technology into a cloud platform based on environmental big data, and finally obtained the minimum value of the objective function $Q$ by not counting iterations $G$ and $F$. The function $Q$ is defined as follows [17]:

$$Q = \sum_{i=1}^{n} \sum_{j=1}^{m} \left(E_{ij}/S_{ij}\right)^2 . \tag{1}$$

where $S_{ij}$ is the uncertainty valuation of the concentration $X_{ij}$ of the $j$th component in the $i$th sample and $E_{ij}$ is the residual.

## III. RESULTS

### A. CONSTRUCTION OF AN ONLINE MONITORING CLOUD PLATFORM BASED ON VOCS GAS IN THE ENVIRONMENT

Under the framework of environmental pollution monitoring system based on environmental big data analysis, this study designed and developed a cloud platform for online monitoring of VOCs gas in the environment, focusing on online monitoring of VOCs pollutant gas data and identification of pollution sources in the chemical park, and presenting the data collected and analyzed through a data interface or an environmental management screen (the platform architecture is shown in Figure 2). As shown in Figure 2, the platform first connected the VOCs online monitoring system to the external network through a WIFI wireless network card. In order to achieve real-time online collection of raw data from monitoring devices, this study adopted a combination of dual network cards to ensure continuous data integrity and redundancy. The primary network card manages local data acquisition from the TROM-600S system, while the secondary card is dedicated to the encrypted cloud uplink. This physical separation prevents local processing delays from interfering with data transmission. The second step involves deploying online monitoring devices equipped with industrial-grade USB wireless network cards featuring high-gain antennas to overcome the electromagnetic interference common in chemical parks; The third step is to link the data collection system to the cloud service platform, by accessing the host name of each collection terminal device to obtain a shareable data file for data collection, and then upload the data to the VOCs gas online monitoring cloud platform through a network connected by industrial-grade WIFI routers utilizing the IEEE 802.11ax protocol for enhanced signal penetration and collision avoidance in metal-dense environments. To further guarantee data integrity against signal fluctuations, the system utilizes an “edge-store-and-forward” mechanism: data is cached locally on the monitoring terminal and only cleared once a successful handshake and MD5 checksum verification are confirmed by the cloud platform. This dual-layer architecture ensures that even during temporary wireless interference or power instability, no 1-hour average data points are lost [18].

### B. VOCS MONITORING DATA COLLECTION

The data collection of VOCs monitoring is done by file sharing after uploading the data collection terminal to the data collection system. 43 types of VOCs gases were collected from the five monitoring sites in this study, including alkanes (17 types), olefins (10 types), acetylenes (1 type), aromatic hydrocarbons (11 types) and halogenated hydrocarbons (4 types). As well as the VOCs concentration characteristics and monitoring conditions are respectively shown in Tables 1 and 2. From Table 2, we can see that the mean values of the total VOCs volume fractions of the monitoring points are as follows: Point 4 ($109.54 \times 10^{-9}$) > Point 2 ($88.47 \times 10^{-9}$) > Point 1 ($86.68 \times 10^{-9}$) > Point 3 ($32.14 \times 10^{-9}$) > Point 5 ($29.68 \times 10^{-9}$). The standard deviation of each monitoring point is large, and the dispersion of the data is large, indicating that the volumetric fraction of VOCs at each test point fluctuates greatly with the monitoring time. In addition, the average temperature of the monitoring points during the monitoring period was 12.5–14.8 °C, the relative humidity was 72.3%–79.8%, and the average wind speed was 1.8–3.1 m/s.

TABLE 1. VOCs Gas Composition Monitoring Results


**FIGURE 1.** Schematic Diagram of the Layout of the Selected Chemical Park and VOCs Monitoring Sites for the Study

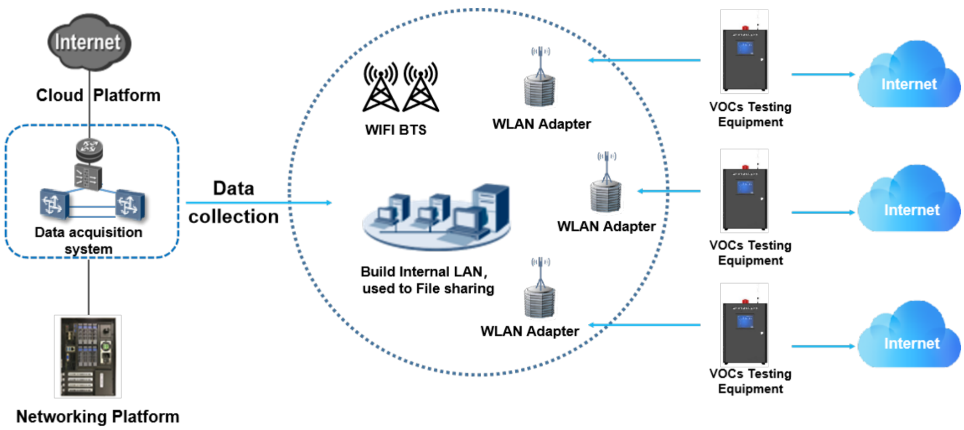


**FIGURE 2.** Network Topology of an Online Monitoring Cloud Platform Based on VOCs Gas in the Environment

**TABLE 1** . VOCs Gas Composition Monitoring Results

| VOCs Gas | Mean$\pm$SD $\times 10^{-9}$ | VOCs Gas | Mean$\pm$SD $\times 10^{-9}$ | VOCs Gas | Mean$\pm$SD $\times 10^{-9}$ |
|---|---|---|---|---|---|
| ethane | 8.35$\pm$7.83 | 3-methylhexane | 0.24$\pm$0.36 | ethylbenzene | 0.84$\pm$0.55 |
| propane | 7.02$\pm$13.45 | 2,3,4-trimethylpentane | 0.23$\pm$0.18 | n-propylbenzene | 0.12$\pm$0.09 |
| n-butane | 5.47$\pm$10.24 | ethylene | 8.25$\pm$10.49 | Isopropyl benzene | 0.08$\pm$0.04 |
| isopentane | 3.04$\pm$1.69 | propylene | 5.26$\pm$8.94 | 1,3,5-trimethylbenzene | 0.45$\pm$0.31 |
| pentane | 0.86$\pm$0.68 | 1-butylene | 0.98$\pm$1.56 | N-xylene | 1.22$\pm$0.88 |
| isobutane | 10.23$\pm$22.14 | 1-pentene | 0.27$\pm$1.03 | M-xylene | 0.55$\pm$0.41 |
| n-hexane | 1.26$\pm$0.85 | O-2-pentene | 0.58$\pm$0.41 | styrene | 0.31$\pm$0.19 |
| n-heptane | 0.42$\pm$0.27 | isoprene | 0.73$\pm$0.25 | 1,2,3-trimethylbenzene | 0.22$\pm$0.15 |
| n-octane | 0.44$\pm$0.49 | P-2-butylene | 0.55$\pm$0.22 | 1,2,4-trimethylbenzene | 0.68$\pm$0.42 |
| methyl cyclohexane | 0.18$\pm$0.29 | O-2-butylene | 0.47$\pm$0.34 | chloromethane | 1.15$\pm$0.76 |
| cyclopentane | 0.52$\pm$0.67 | 1,3-butadiene | 0.58$\pm$1.08 | trichloroethylene | 0.09$\pm$0.05 |
| 2,3-dimethylbutane | 0.64$\pm$0.32 | P-2-pentene | 0.77$\pm$0.24 | 1,2-dichloroethane | 0.14$\pm$0.11 |
| n-decane | 0.21$\pm$0.34 | benzene | 2.04$\pm$1.56 | tetrachloroethylene | 0.06$\pm$0.03 |
| 2,2,4-trimethylpentane | 0.09$\pm$0.33 | toluene | 1.34$\pm$0.57 | acetylene | 3.06$\pm$4.57 |

According to the test results in Tables 1 and 2, the volume fractions and percentages of VOCs were obtained by statistically integrating the VOC gas types at the five monitoring sites (as shown in Figure 3 and Figure 4). From Figure 4(a)

**TABLE 2.** Total VOCs Concentration Characteristics and Monitoring Conditions at Each Monitoring Point

| Monitoring sites | Mean±SD $\times 10^{-9}$ | Maximum $\times 10^{-9}$ | Wind speed (m/s) | Relative humidity (%) | Temperature (°C) |
|---|---|---|---|---|---|
| 1 | 86.68±66.75 | 774.526 | 1.87 | 79.44 | 12.65 |
| 2 | 88.47±76.32 | 798.543 | 2.45 | 77.56 | 13.24 |
| 3 | 32.14±18.25 | 287.421 | 1.92 | 65.48 | 14.76 |
| 4 | 109.54±89.57 | 998.478 | 2.87 | 72.54 | 14.59 |
| 5 | 29.68±14.64 | 156.218 | 3.05 | 66.87 | 13.65 |

to (f), it can be seen that alkanes and olefins account for a large proportion of the VOCs at all monitoring points, while acetylenes and halogenated hydrocarbons account for a lower proportion. At monitoring point 1, olefins had the largest volume fraction (41.9 $\times 10^{-9}$, 49.76%), followed by alkanes (23.3 $\times 10^{-9}$, 30.05%), aromatics (8.9 $\times 10^{-9}$, 10.57%), and alkynes (4.8 $\times 10^{-9}$, 5.7%), and halogenated hydrocarbons had the smallest volume fraction (3.3 $\times 10^{-9}$, 3.92%), while the volume fraction of alkanes is the largest in monitoring point 2, 3, 4 and 5 monitoring sites. By statistically analyzing the top 5 gas types in terms of average VOCs concentration, it can be found that the high concentration gases in the 5 monitoring points have a high similarity, and the top 5 gas types in the 5 monitoring points are ethane, propane, ethylene, toluene and n-butane. In addition, the proportion of isobutane, acetylene and other gases is also high, so it is tentatively assumed that these gases are the main sources of VOCs in this park.

### C. PRECISE IDENTIFICATION OF VOCS GAS SOURCES IN CHEMICAL INDUSTRY PARKS

Based on the collected VOCs gas data, the data is imported into an environment-based VOCs gas online monitoring cloud platform, using the platform's big data analysis capabilities, and by importing positive matrix factor analysis methods, using the USEPA PMF model to identify the sources of various types of VOCs gas collected from all monitoring points. After several iterations of factor data, it finally identified five factors as VOCs gas sources: alkane leakage, preparation process emissions, olefin synthesis, urban transmission, and storage tank emissions [19], [20]. The analysis results of the cloud platform showed that in factor 1, the contribution of alkanes such as propane, n-butane, and isobutane is more than 95%, which is significantly higher than that of other gases, so this factor was recognized as an alkane leak; in factor 2, the highest contribution of chlorobenzene, benzene, toluene, propane, and ethane are common gases in the preparation and synthesis process, so they were recognized as emissions from the preparation process; in factor 3, the contribution of ethylene, propylene, and butene exceeded 90%, so they were recognized as olefin synthesis. Factor 4 contained more than 85% of the gas characteristic of vehicle emissions (including isopentane, n-pentane, acetylene, etc.), the concentration gradient of these species increases significantly at the park's southern boundary. Given that these tracers originate from the urban district situated directly to the southwest and south of the industrial zone, this factor was recognized as urban area transmission; Factor 5 contained aromatic hydrocarbons such as toluene and xylene, as well as n-octane, n-ketane, n-acetylene, and n-acetylene, which are more than 92%. The onsite assessment confirmed that a large amount of these substances stored in the park, and therefore they were identified as storage tank emissions [21], [22].

Figure 5 showed the statistical results of the percentage contribution of the gas sources at each monitoring site. From Figure 5, it can be seen that there are significant differences in the emission sources of the various monitoring points. At monitoring point 1, located southeast of the campus, the percentages of storage tank leaks and olefin synthesis were 28.60% and 29.80%, followed by urban transmission (18.90%) and preparation process emissions (16.20%). This may be due to the fact that enterprises A1 to A5 at monitoring point 1 are large petroleum secondary enterprises that mainly produce propylene, ethylene and other chemical products. Olefin synthesis was the largest contributor at 55.40% in monitoring point 2, followed by alkane leakage, storage tank emissions, and preparation process emissions respectively at 15.80%, 13.50%, and 9.90%. Storage tank emissions and olefin synthesis make the largest contribution at monitoring point 3, with a total of over 50%, followed by olefin synthesis and alkane leakage, which respectively accounts for 21.80% and 16.50%. Similar to point 2, the urban area has the smallest share of transmission, mainly due to the distance of monitoring points 2 and 3 from urban areas. The contribution of alkane leakage from monitoring point 4 is as high as 85.40%, while the contribution of the other four gas sources ranges from 2.20 to 5.80% respectively, which may be related to the large alkane producer at monitoring point 4; Monitoring point 5, located at the southwestern-most edge of the study area (see Figure 1), is the primary interface between the industrial park and the adjacent urban area. Consequently, it shows the highest urban transmission contribution (56.30%), serving as the entry point for vehicular-derived VOCs into the park's atmosphere. This spatial correlation between Point 5's position and the high contribution of Factor 4 allows for the precise localization of external versus internal pollution sources, preparation process emissions and alkane leakage, respectively accounts for 22.20%, 14.20% and 3.80%.

### D. PRECISE IDENTIFICATION OF VOCS GAS SOURCES

Using the built big data analysis function based on the VOCs gas online monitoring cloud platform in the environment, comprehensive wind direction probability distribution, and further identify the VOCs emission source of each monitor-

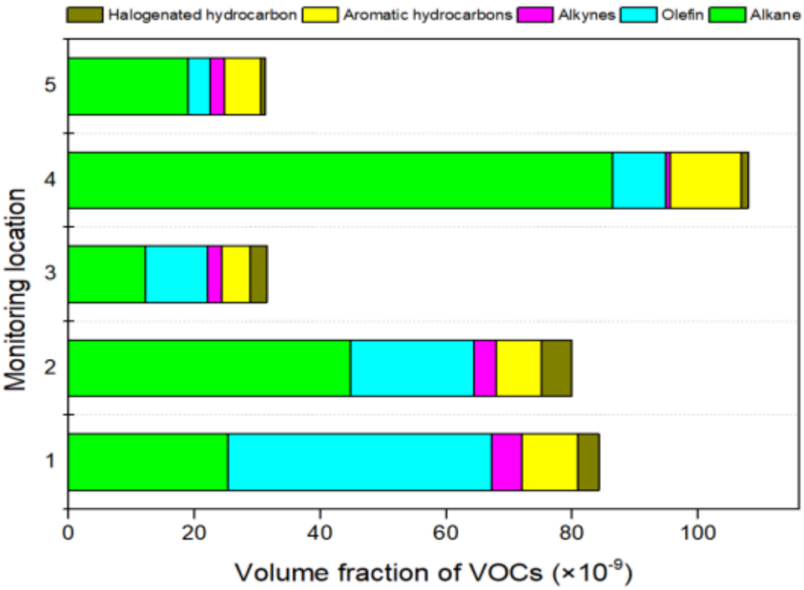


**FIGURE 3.** Volume Fractions of Major VOCs at Five Monitoring Sites in the Chemical Park

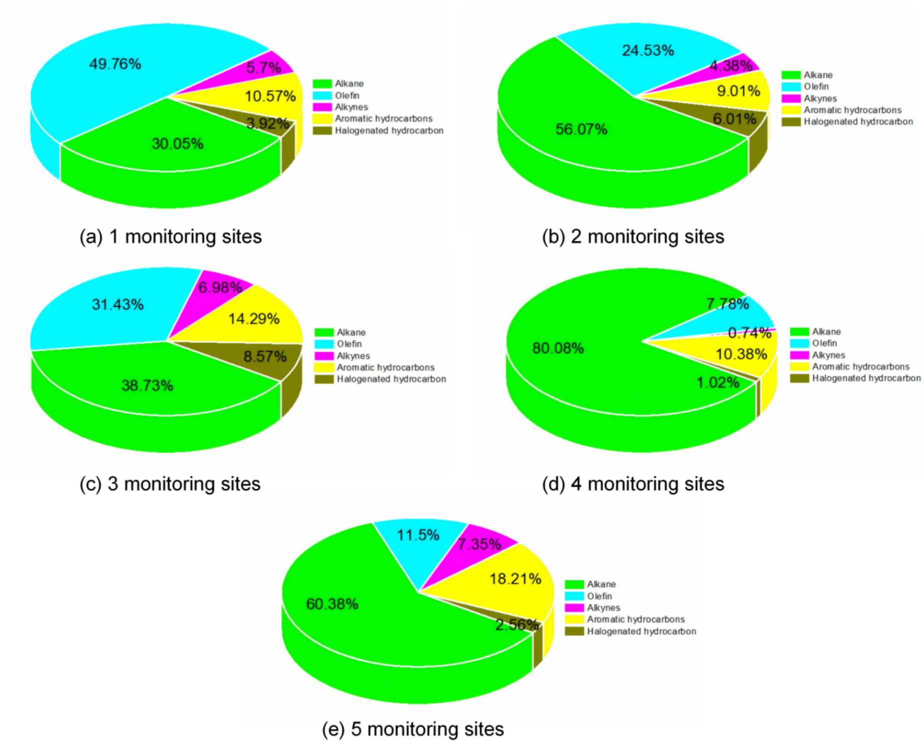


**FIGURE 4.** Volume Percentages of Major VOCs at Five Monitoring Sites in the Chemical Park

ing point. the results showed that the leakage of alkanes mainly originated from the northwest direction of point 1, the southwest and southeast directions of points 2–4, conversely, the high urban transmission signature at point 5 confirms that vehicular VOCs are transported into the park from the southwest, whereas points 2 and 3, situated deeper within the park interior, show significantly lower urban influence due to the distance from these boundaries; as for the emission sources of the preparation process, combined with the emission characteristics of the enterprises in the park, enterprises A2 and A4 in the northwest direction of point 1, and enterprises C4 and D4 in the southeast direction of point 4 are the main sources of preparation process emission sources; while 6 enterprises located in B4–C4 and C5–E5 are the main sources of VOCs storage tank leakage; finally, comprehensive analysis of the emission

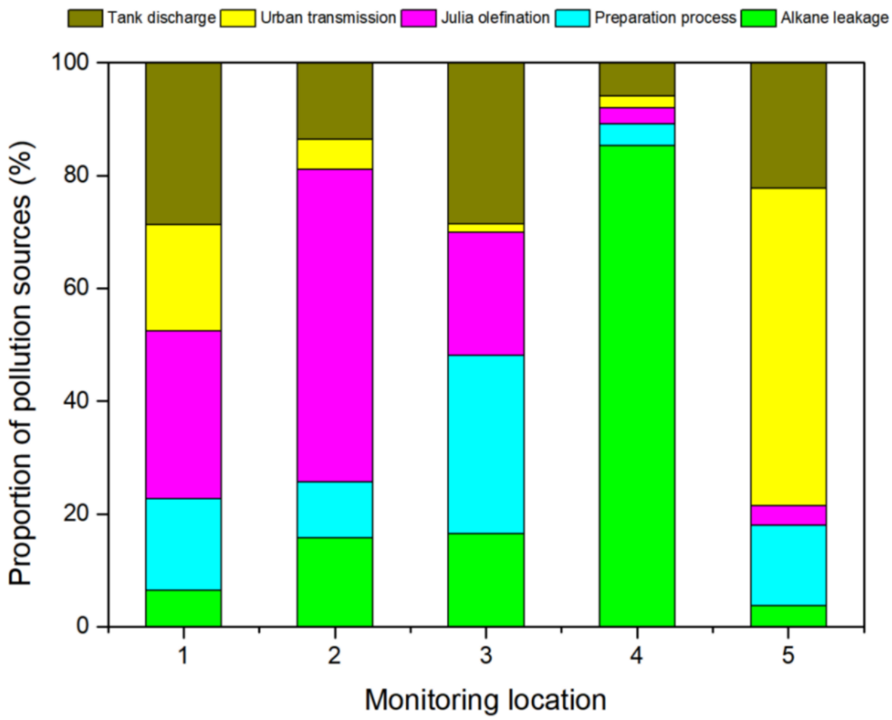


**FIGURE 5.** Percentage of Identified Pollution Sources at Each Monitoring Site

characteristics of each enterprise showed that enterprises C3 and D3 in the southwest direction of point 3, enterprises D5 and E6 in the north of point 4 are the main sources of VOCs storage tank leakage, and enterprises E3 and F2 in the northeast of point 5 are the main VOCs emission sources of olefin synthesis sources in the park.

## IV. CONCLUSION

This study built an online monitoring cloud platform to track VOCs pollutant data and identify emission sources within industrial parks, specifically targeting the volatile organic compounds released. By integrating real-time collection and analysis, the platform realizes precise identification of VOCs gas pollution sources originating, ensuring rigorous environmental compliance within the manufacturing sector. The test results showed that among the five monitoring points, alkanes accounted for the largest proportion (up to 86.4 $\times 10^{-9}$), followed by olefins and aromatic hydrocarbons, acetylenes and halogenated hydrocarbons accounted for the lowest proportion.

The results of the analysis of the difference of VOCs gas concentration characteristics showed that the volume fraction of olefins was the largest in monitoring point 1, and the volume fraction of alkanes was the largest in monitoring points 2, 3, 4 and 5.

The results of VOCs gas source analysis in the chemical park showed that alkane leakage, emissions from the preparation process, olefin synthesis, urban transmission, and storage tank emissions were the sources of VOCs in the study park, and the largest sources at monitoring points 1–5 were olefin synthesis, olefin synthesis, emissions from the preparation process, alkane leakage, and urban transmission.

## AUTHOR CONTRIBUTIONS

Yuanping Zhang designed, collected and analyzed the data, and drafted the manuscript. Yuanping Zhang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Yuanping Zhang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

## CONFLICTS OF INTEREST

The author declares no conflict of interest.

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