

Design of online monitoring system for heavy metal mercury in industrial wastewater based on ZigBee wireless network

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ABSTRACT

Aiming at the problems of long monitoring time, low reliability of monitoring results and insufficient data collection in traditional methods, an online monitoring system for heavy metal mercury in industrial wastewater based on ZigBee wireless network was designed. According to the overall architecture of the monitoring system, the hardware modules are divided into network coordinator structure, data management and maintenance module, distributed monitoring node module and coordinator node, etc., according to the connection between each module to achieve effective heavy metal mercury pollution in industrial wastewater monitor. Based on the hardware design, the source of heavy metal mercury pollution in industrial wastewater is located, and the BP neural network is used to monitor the total discharge of heavy metal mercury pollutants in industrial wastewater. The monitoring results are displayed on the main monitoring interface to facilitate visual inspection of pollution changes. The simulation experiment results show that the system designed in this paper has obvious advantages in the monitoring time, the accuracy of the monitoring results, and the method of collecting pollution data, indicating that the system has higher application value.

Keywords: ZigBee wireless network; Industrial wastewater; Heavy metal mercury; Monitoring system; Network coordinator

1. Introduction

With the rapid development of industrial production capacity, the discharge of industrial sewage is increasing. When the sewage that cannot meet the discharge standard is discharged into other water bodies, it will cause huge pollution to the surface and groundwater, especially the heavy metal mercury pollution, which has a greater degree of pollution to the water body. Therefore, it is particularly important to monitor the sewage in real time and accurately [1,2]. At present, industrial wastewater monitoring methods are still mainly in the manual measurement stage, which is inefficient, difficult to collect data, and lack of effectiveness in wastewater monitoring, which brings a lot of inconvenience to subsequent wastewater treatment [3,4]. Although some companies and manufacturers have

adopted wired sewage monitoring systems, due to the large number and scattered distribution of sewage sources, it is difficult to achieve the desired effect in terms of cost and system reliability by using wired monitoring methods.

In the above context, related researchers have conducted a lot of research on water pollution monitoring methods and have achieved considerable research results. Kolumban-Antal et al. [5] designed a portable air pollution measurement system to ensure user privacy and data authenticity. The data is collected from sensor modules, which can be carried manually or installed on the vehicle, and the vehicle sensor network may cover a larger area. The system uses group signatures and a secure storage structure similar to blockchain to ensure the authenticity and non-repudiation of the collected data. A regular key exchange protocol based on elliptic curve cryptography is used to

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securely guide the session key, and then use a secure tunnel to export sensor data to a remote server [6]. By using a blockchain-like structure on the data server, can prevent tampering after updating. Experimental results show that the system can not only determine the calculation requirements of the program, but also measure the air quality indicators in nearby areas, but the monitoring efficiency of the system is not high, and pollution data cannot be obtained in real-time. Mishra et al. [7] proposed a real-time monitoring method of urban traffic congestion and emissions based on Google maps in order to control the instantaneous pollution increase and reduce vehicle emissions. Calculating the pollution parameters of real-time mobile sources, it is concluded that the impact of traffic congestion on vehicle emissions is also different in two different spatial regions. This method concludes that vehicle emission variability is more likely to occur when congestion fluctuates. On this basis, a calculation method for pollutant discharge in a short time and space is proposed. Experimental results show that this method can obtain real-time changing pollution data, but the accuracy of the monitoring results is not high. Xue [8] proposed a multi-parameter water quality monitoring method based on a random forest classification algorithm. By analyzing the water quality of urban heavily polluted rivers, the single-parameter water quality fluctuation probability and the multi-parameter dynamic correlation coefficient were combined to obtain the heavy pollution. The probabilistic composite matrix of river water quality indicators is processed for dimensionality reduction [9]. The membership function of the fluctuation of water quality indexes is obtained, and the weak correlation features among water quality indexes are removed by the obtained membership function, and the strong correlation features of water quality indexes are obtained, which are input into the random forest classifier to complete the multi-parameter detection of river water quality. Experimental results show that this method takes a short time to complete the detection, but the amount of data collection is small, which cannot meet the needs of environmental monitoring.

In view of the difficulty of data collection and the lack of real-time performance in the current industrial wastewater monitoring, a ZigBee wireless network-based industrial wastewater heavy metal mercury online monitoring system was researched and designed. The system is based on ZigBee wireless communication technology, and through the effective connection between various hardware modules, it realizes the automatic collection and long-distance transmission of industrial wastewater heavy metal mercury pollution data. The experimental results show that the system has fast transmission rate, strong real-time performance and high stability, and can effectively monitor the heavy metal mercury pollution of industrial wastewater online [10].

2. Design of online monitoring system for heavy metal mercury in industrial wastewater based on ZigBee wireless network

2.1. Overall architecture design of the monitoring system

The ZigBee wireless sensor network is the core of the online monitoring system for heavy metal mercury in

industrial wastewater. It has the characteristics of flexible and convenient networking, fast transmission speed, strong compatibility, and low cost. The monitoring system is based on ZigBee wireless communication technology and is composed of data collection terminals distributed at various sewage monitoring points, and a data collection terminal is placed at each monitoring point. The data acquisition terminal is composed of various ZigBee modules [11]. The data acquisition terminal is mainly responsible for the real-time collection of sewage information. After the sewage information collected by each monitoring point is processed by single chip microcomputer, the ZigBee module is packaged into a communication protocol package, which is transmitted to the coordinator node through TCP/IP protocol, and finally uploaded to the monitoring center to realize on-line monitoring.

The main idea of system design is to use ZigBee wireless modules to form a wireless transmission network, so that data can be transmitted in this network quickly and in real-time [12]. The system is mainly composed of three parts: network coordinator, data management and maintenance module, and distributed monitoring node module. The overall system architecture is shown in Fig. 1.

In Fig. 1, the network coordinator, data management and maintenance module and distributed monitoring node module together form a ZigBee wireless sensor network, which is responsible for data collection and transmission, and finally sends the data to the monitoring center, so that the monitoring personnel can obtain the information of heavy metal mercury in industrial wastewater in time, which is convenient for the next step of treatment [13]. In this system, the entire monitoring area is divided into multiple lines, and each line is equipped with a ZigBee wireless module. Each monitoring station uploads data to the data management and maintenance module. This design ensures real-time data upload on the one hand. On the other hand, it is convenient for management personnel to carry out related processing, which greatly improves efficiency [14]. At the same time, in order to comprehensively detect the heavy metal mercury pollution parameters of industrial wastewater in different regions, it is necessary to arrange many sensors with different functions to detect changes in environmental parameters in each region [15]. The main control computer controls the execution equipment to realize internal automatic adjustment. For practical needs, to enhance the flexibility and versatility of the system, the monitoring system decided to adopt a tree topology structure.

2.2. System hardware module design

2.2.1. Network coordinator structure

The network coordinator node is the main module composed of the CC2430 chip, which is specifically composed of antenna, debugging interface, power supply module, keyboard, display and RS232/RS485 serial bus interface [16]. The structure of the network coordinator node is shown in Fig. 2.

In order to ensure the long-term reliable operation of the system, the network coordinator adopts the AC power supply mode. The realization of the monitoring function is mainly realized by the upper host. In addition, various

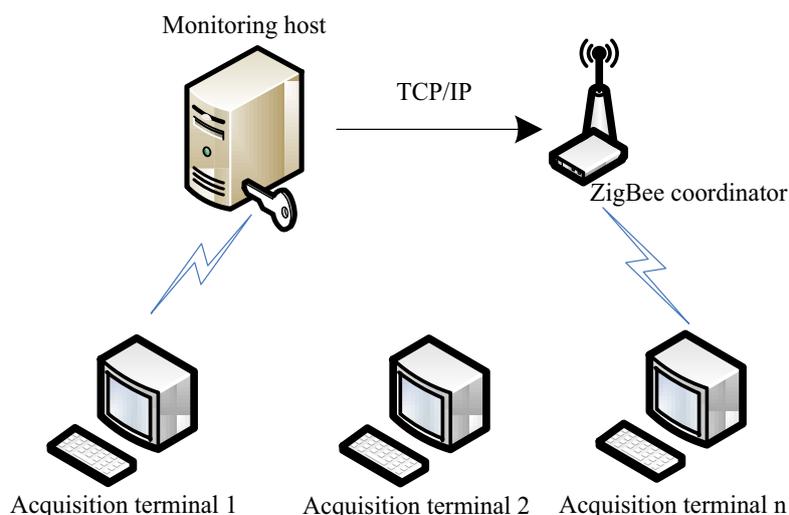


Fig. 1. The overall architecture design of the monitoring system.

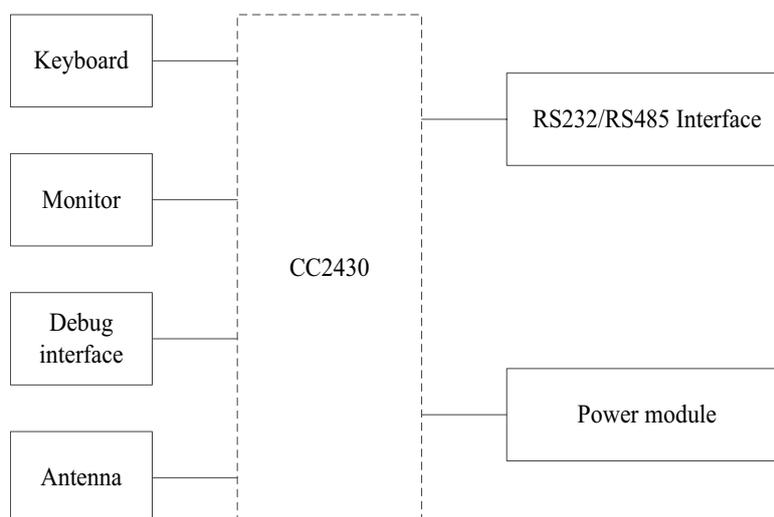


Fig. 2. Network coordinator structure diagram.

functions can be set and viewed through the keyboard display configured by the network coordinator. The network coordinator serves as the main hub for information exchange between the monitoring host and other nodes. On the one hand, it is connected to the upper monitoring host through the RS232 or RS485 serial bus, and on the other hand, it exchanges data with routing nodes or sensor nodes through wireless means [17]. During the working process of the system, the network coordinator receives the environmental parameters detected by the sensors and then sends them to the host, sends the control commands issued by the host to the routing node, and detects and displays the network status in real time.

2.2.2. Data management and maintenance module

Data management and maintenance is an important part of the online monitoring of heavy metal mercury in industrial wastewater. The internal data query, addition,

modification, update and deletion of the system are closely related to the monitoring. Data maintenance is the basic maintenance operation of the database, including the addition, deletion, and modification of industrial wastewater heavy metal mercury pollution data. In addition, it also includes the dynamic operation of pollution data, including the entry of detailed information about pollution incidents, the addition, deletion, and modification of monitoring data during the development process, and related data query and processing operations [18]. The hardware structure diagram of the data management and maintenance module is shown in Fig. 3.

2.2.3. Distributed monitoring node module

The distributed monitoring node module is the main module of the entire monitoring system, and all the collection of pollution characteristic information comes from this part. It is responsible for the collection and storage of heavy

metal mercury pollution information in industrial wastewater, and then transmits the data to the upper-level node [19]. The hardware structure of each monitoring node is shown in Fig. 4:

As shown in Fig. 4, the distributed monitoring node module includes the following parts: the core processor is used to process pollution data in the upper data management and maintenance module; the power module provides energy supply for all monitoring nodes; the JTAG debugging interface provides online debugging functions for system software design; the communication module in the cluster is responsible for the communication between the acquisition node and the transmission node; the communication module outside the cluster is responsible for the data transmission between the transmission node and the server. The task of monitoring information on the heavy metal mercury pollution of industrial wastewater is completed through the collaborative work between various distributed monitoring nodes [20].

2.2.4. Coordinator node circuit design

The network coordinator node is responsible for the establishment and management of the monitoring system,

maintaining the normal operation of the monitoring network, and assigning network addresses to newly added nodes [21]. Its core is the ZigBee wireless communication module with CC2530 as the processor. The circuit of the coordinator node is shown in Fig. 5.

The heavy metal mercury in industrial wastewater is a kind of pollution source which seriously damages the ecological environment and threatens human health. It does not have a fixed way and way of discharge, suddenly occurs and comes fiercely, and discharges a large number of toxic and harmful pollutants in a short period of time. As a result, it causes great pollution to the environment, not only causes huge economic losses, but also poses a great threat to the health and life safety of the surrounding residents. Its harm restricts the ecological balance and economic and social development. Therefore, it is necessary to establish a scientific and effective monitoring system, so as to minimize the loss in a short time when a heavy metal mercury pollution accident occurs [22,23]. Under the coordination of the hardware modules of the monitoring system, the effective monitoring of heavy metal mercury pollution in industrial wastewater is realized. In order to further improve the monitoring performance of the system, the system software functions are designed on the basis of hardware design.

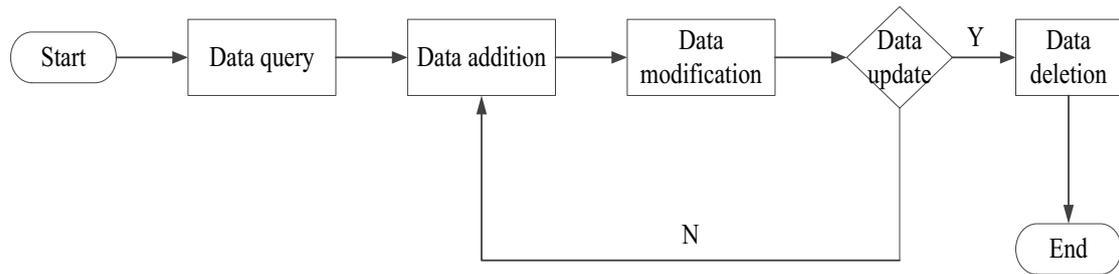


Fig. 3. Data management and maintenance module structure diagram.

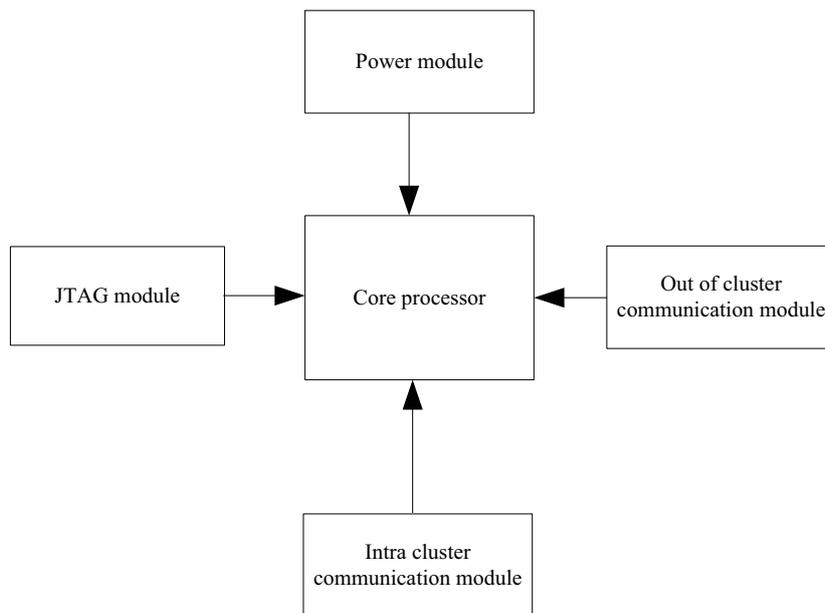


Fig. 4. Hardware structure diagram of distributed monitoring node module.

2.3. Monitoring system software design

2.3.1. Location of heavy metal mercury pollution sources in industrial wastewater

In the vicinity of the pollution source, the change rate of concentration is often greater than the set value. Due to the influence of water flow, the concentration in the downstream of the river will be higher. Compared with the concentration in the upstream, it will be found that the concentration will decrease quickly. Therefore, there will be dramatic concentration changes, and the change can form the maximum value [24], which can be calculated by Eq. (1):

$$P_{\max} = \frac{U_A(X) \times U_B(Y)}{C_n} \times T \times 100\% \tag{1}$$

where C_n represents the leakage quality of pollutants, the unit is g; $U_A(X)$ represents the size of the unit pollutant measured in the water, the unit is mg/L; T represents the movement time of the pollutant, the unit is s; $U_B(Y)$ represents the distance that the pollutant diffuses and flows, using m to count.

When the standard listed in Eq. (2) is reached, it can be determined that the source of water pollution is in nearby waters:

$$S = D(k_1, k_2)^2 \times P_{\max} \tag{2}$$

where D represents the water pollution flow field unit; k_1 represents the amount of pollutants produced; k_2 represents the amount of pollutants discharged.

2.3.2. Monitoring the discharge of heavy metal mercury pollutants in industrial wastewater

According to the location results of heavy metal mercury pollution sources in industrial wastewater, the BP neural network is used to monitor the total discharge of heavy metal mercury pollutants in industrial wastewater. First, take the wavelet function as the transfer function of the hidden layer of the BP neural network. The signal propagates forward and the error propagates back. The relationship between the layers of the BP neural network is shown in Fig. 6:

Thus, Eq. (3) is obtained:

$$F_i = V_n^M W_i - \left(\sqrt{\sum_{i=1}^n P(V_i)} \right) \tag{3}$$

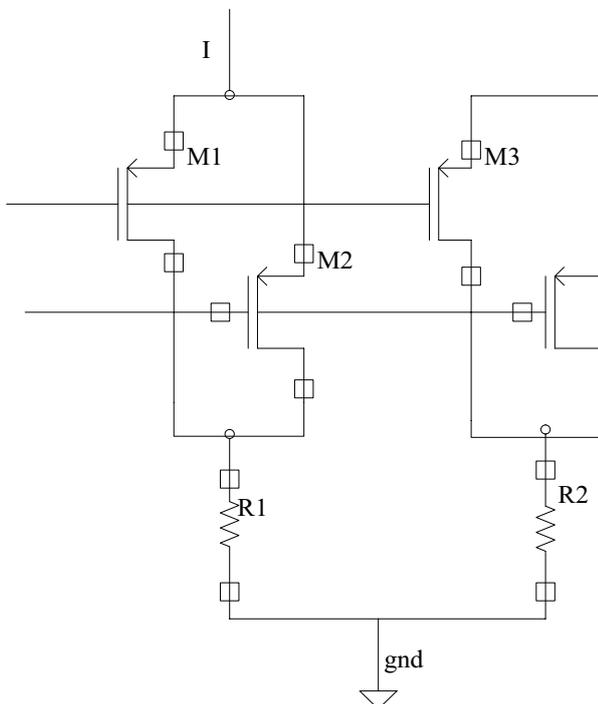


Fig. 5. Coordinator node circuit diagram.

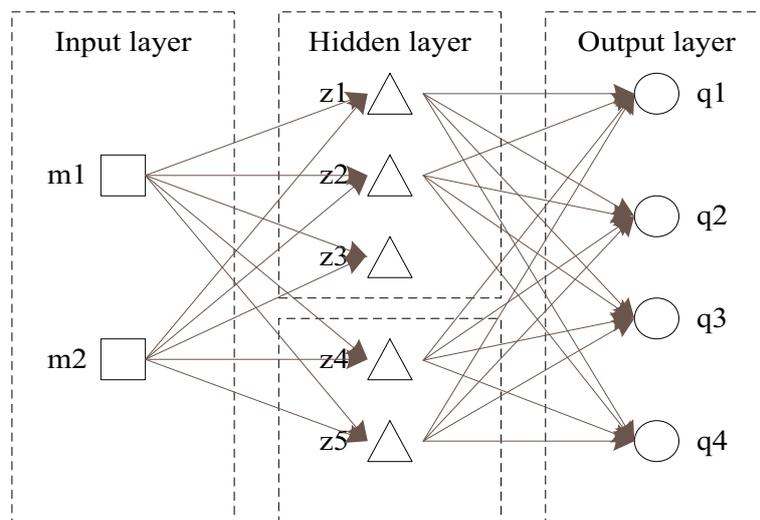


Fig. 6. Relationship between layers of BP neural network.

where W_i represents the original parameters of the BP neural network; V_i represents the predicted value of the BP neural network; V_n^M represents the weight value of the BP neural network.

Set $x(n)$ as the original input signal, the hidden layer result is:

$$F(i, j) = \left(\prod_{i=1}^n J_{i-1} \right) x(n) + \sum_{i=1}^n \varepsilon \eta_j \times \delta_{ij} \quad (4)$$

where J_i represents the output value of the i -th node of the hidden layer; η_j represents the wavelet basis function; ε represents the connection weight value of the input layer and the hidden layer; δ_{ij} represents the translation parameter of the wavelet basis function.

The result of the output layer of the wavelet basis network is:

$$K(x, y) = \left(-\frac{F(i, j)}{\sigma^2} \right) \times v_i + k_i k_m \quad (5)$$

where σ^2 represents the weight from the hidden layer to the output layer; v_i represents the number of nodes in the i -th hidden layer; k_i and k_m represent the number of hidden layer and output layer nodes, respectively.

The wavelet basis BP neural network weight correction method can modify the weight value and the coefficient of the wavelet basis function in the network, so that the monitoring result of the wavelet basis function is closer to the expected value [25]. In the correction process of wavelet-based BP neural network, the monitoring error is:

$$E_i = \begin{cases} 1, D_i \leq V_{i1} \\ 0, D_i \geq V_{i2} \end{cases} \quad (6)$$

where V_{i1} represents the expected result; V_{i2} represents the monitoring result of the wavelet base BP neural network.

In this system, heavy metal mercury pollution in industrial wastewater can be monitored around the clock to ensure the surrounding environment and personal safety. The monitoring process of BP neural network is shown in Fig. 7.

2.3.3. Function analysis of monitoring system software

The main functions realized by the monitoring software are:

- Receive pollution data transmitted by each network coordinator, perform comprehensive data analysis and processing according to preset values, and send control commands to the controller to control the operation of monitoring equipment.
- Store the heavy metal mercury pollution data in the database regularly.
- The operating status of the monitoring equipment is

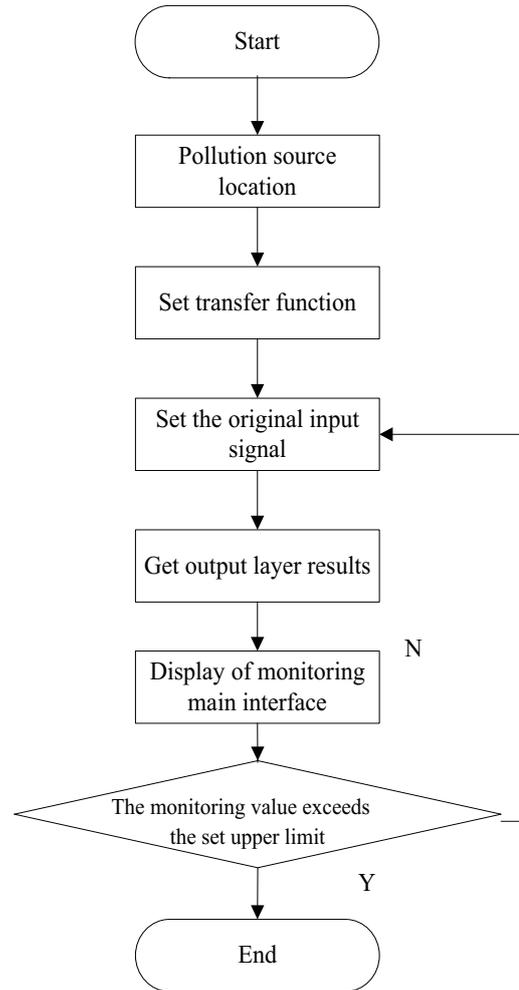


Fig. 7. Monitoring system software design process.

displayed through the control panel interface to realize the switch between manual and automatic control status of the equipment.

- The main control interface displays the heavy metal mercury data of each monitoring point in real time. In order to facilitate the visual inspection of pollution changes, when the monitoring value exceeds the set upper limit, a red alarm will be displayed, and when the monitoring value exceeds the set lower limit, a blue alarm will be displayed, when the monitored value is within the set limit, the display window is green.

The main control interface also dynamically displays the operating status of the monitoring equipment, and the equipment operation is controlled automatically or manually through the equipment control panel. In order to facilitate the operation, the main interface is provided with shortcut keys to quickly enter other function windows. The main monitoring interface is shown in Fig. 8.

The real-time monitoring interface displays the current changing law of each monitoring point in real time, and makes corresponding settings through the monitoring interface.



Acquisition equipment: data acquisition instrument
Equipment number: 20190509013333

Historical data

	Report time: 19:34:07, August 7, 2019	0.006mg/L
	Report time: 8:12:35, September 11, 2019	1.023mg/L
	Report time: October 23, 2019 00:12:27	1.358mg/L
	Report time: November 23, 2019 15:01:36	0.029mg/L
	Report time: December 25, 2019 17:09:48	15.279mg/L
	Report time: January 30, 2019 5:47:59	74.096mg/L

Fig. 8. Monitoring main interface.

In summary, on the basis of the hardware modules of the system, the overall design of the online monitoring system for heavy metal mercury in industrial waste water based on the ZigBee wireless network is realized through the location and discharge monitoring of heavy metal mercury pollution sources in industrial waste water.

3. Experimental research

In order to verify the effectiveness of the online monitoring system of heavy metal mercury in industrial wastewater based on ZigBee wireless network, MATLAB software is used for simulation experiment, and the simulation results of the system designed in this paper are compared with the real-time monitoring method of urban traffic congestion and emission based on Google map in Method [7] and the multi parameter detection method of water quality based on random forest classification algorithm in Method [8].

3.1. Experiment preparation

In order to verify the effectiveness of the system designed in this paper, a script is used to compare different methods under the same test environment. The test environment is shown in Table 1.

In order to test the practicability of the system, an area that has been polluted by heavy metal mercury in industrial wastewater for a long time was selected as the experimental area, and the environmental data of the area was collected and transmitted to the host computer display interface in real time. When the positioning information conveyed by the positioning module deviates from the designated path, the upper computer will automatically alarm and adjust the position in real time. The environmental data receiving interface of the host computer records the position and the set position in real time at different monitoring points. After testing, the monitoring system is operating in good condition and can save the data collection period. Under this condition, the heavy metal

Table 1
Test environment

Classification	Project	Parameter
Hardware environment	Server	5 units, each with 24 cores
	RAM	8 GB
	Hard disk	1 T
	Operating system	Linux CentOS
Software environment	Server platform	Tomcat
	Database	Mysql
	Software platform	Java web project, Hadoop distributed system

mercury pollution in the experimental area within 24 d is obtained, as shown in Fig. 9.

In the system performance test, in order to ensure database consistency, data insertion is set to single-threaded execution. In order to test the performance of the system designed in this paper in all aspects, the accuracy of monitoring results, monitoring time and data collection volume are selected as experimental indicators for comparative testing.

3.2. Experimental results

3.2.1. Comparison of monitoring accuracy

Taking the accuracy of the monitoring results as the experimental index, the monitoring effects of different methods are compared, and the results are shown in Fig. 10.

Analyzing Fig. 10, it can be seen that within a period of time since the experiment, the accuracy of the monitoring results of the system designed in this paper is basically lower than that of the traditional method. In the experiment, it is always higher than the traditional method, and the highest accuracy rate of its monitoring results has reached more than 80%. According to the above analysis, the accuracy of

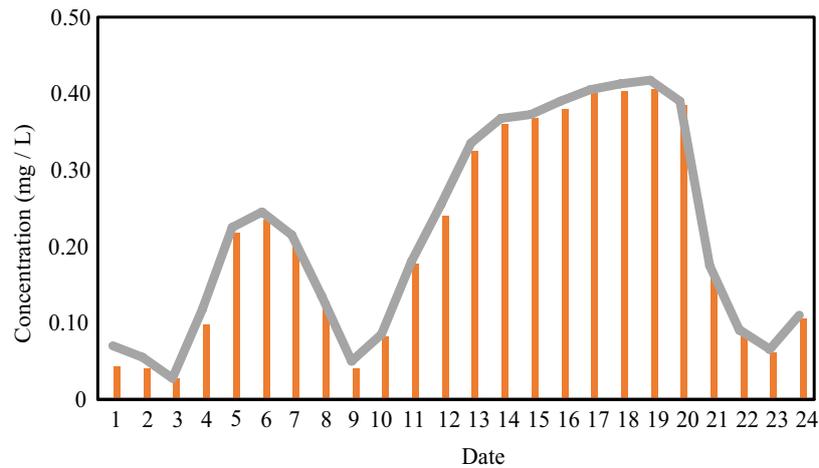


Fig. 9. Heavy metal mercury pollution in the experimental area within 24 d.

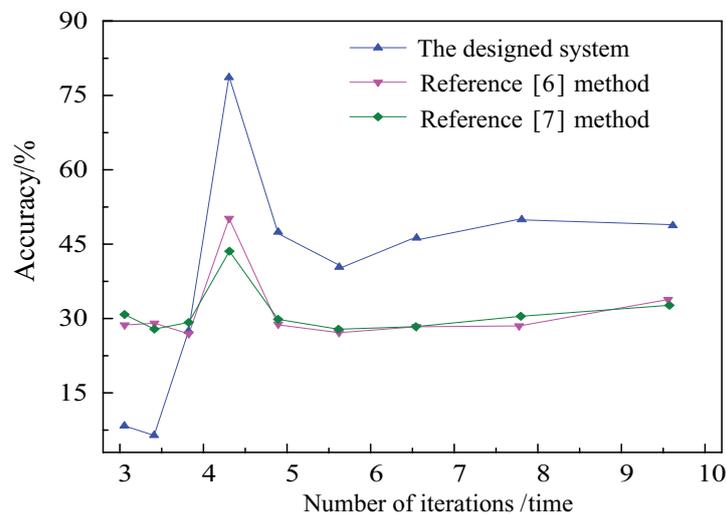


Fig. 10. Comparison of accuracy of monitoring results.

the monitoring results of the system designed in this paper is higher, indicating that the monitoring results obtained by the system are more reliable, and can provide a more accurate data basis for the monitoring work of environmental monitoring departments.

3.2.2. Comparison of monitoring time

Taking the monitoring time as the experimental indicator, the monitoring effects of different methods are compared, and the results are shown in Fig. 11.

Analyzing Fig. 11, it can be seen that the monitoring time of the system designed in this paper is always lower than that of the traditional method, and its monitoring time is always less than 1.5s, and the maximum value of the monitoring time of the method in [7] reaches 2.4s, the method in [8]. The highest value of the monitoring time reached 4.4s. Through data comparison, it can be known that the monitoring efficiency of the system designed in this paper is higher. This is because in this design system,

the whole monitoring area is divided into multiple lines, each line is set with a ZigBee wireless module, and each monitoring machine uploads the data to the data management and maintenance module, which is convenient for the management personnel to carry out relevant processing and greatly improves the efficiency.

3.2.3. Data collection volume

Taking the amount of data collected as an experimental indicator, the monitoring effects of different methods are compared, and the results are shown in Table 2.

The data in Table 2 shows that the maximum data collection volume of the system designed in this paper is 853MB, which is significantly higher than the traditional method, indicating that this method can obtain more data in the monitoring of metal mercury pollution in industrial wastewater and provide more information for pollution analysis and treatment. A more comprehensive data basis is conducive to obtaining more comprehensive monitoring results.

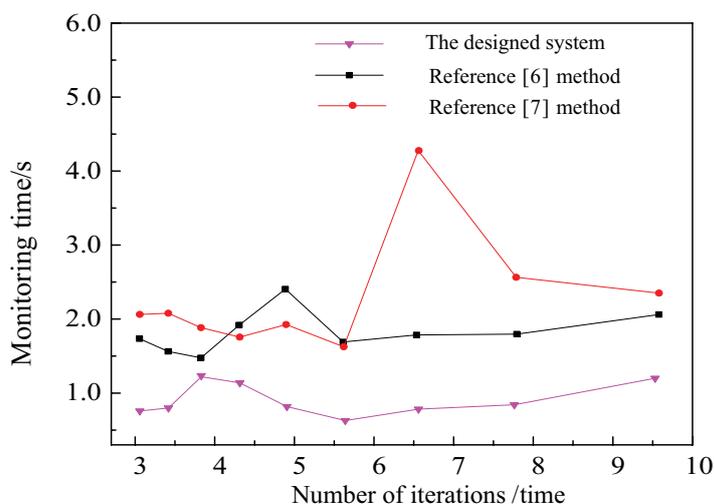


Fig. 11. Comparison of monitoring time.

Table 2
Comparison of data collection

Number of experiments/time	Data collection volume/MB		
	This paper design system	Method [7]	Method [8]
10	853	527	472
20	849	510	463
30	820	493	436
40	792	473	412
50	781	460	396
60	766	447	385
70	743	428	374
80	711	416	321
90	690	382	307
100	689	350	299

4. Conclusion

Organic pollution in the water environment is very bad, which is not only related to the health of residents and human living standards, but also related to the sustainable development of the coastal economy. Therefore, there is a higher demand for the current situation of environmental pollution monitoring, and it is necessary to implement macro, rapid, accurate, and economic monitoring of water pollution. In this context, related scholars have proposed a large number of monitoring methods, but the traditional methods generally have the problems of low monitoring efficiency and low monitoring accuracy. For this reason, an online monitoring system for heavy metal mercury in industrial wastewater based on ZigBee wireless network is designed. Through simulation experiment analysis, it can be seen that the system realizes the long-distance, automatic monitoring and transmission of sewage information, effectively solves the problems of real-time and reliability of sewage monitoring, and has high promotion and application value.

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