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Research on an Online Monitoring System for Efficient and Accurate Monitoring of Mine Water

LEI BO[1], YANG LIU[1], ZIHANG ZHANG[1], DONGXU ZHU[1], AND YIYING WANG[2]

[1]School of Mechanical Electronic and Information Engineering, China University of Mining and Technology (Beijing), Beijing 100083, China
[2]School of Mechanical and Equipment Engineering, Hebei University of Engineering, Handan, Hebei 056038, China

Corresponding author: Yang Liu (yangliuy@yeah.net)

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ABSTRACT Our goal is to solve the complexity of laying down wiring for traditional monitoring systems for mine water, while taking into account the poor timeliness of sampling and continuous monitoring, based on the processing and reuse of mine water. In this article, we focus on the theory of multi-sensor networks to estimate mine water quality, quantity monitoring equipment, and mine water Internet of Things (hereafter denoted ''IoT'') communication systems. We designed a mine water IoT monitoring system for the wireless monitoring of water quantity and quality, developed an experimental platform for the wireless monitoring of mine water. This platform has the advantages of simple wiring and strong expandability. Finally, we tested and analyzed the system operation effects. To solve the problem of partial data abnormalities caused by problems of sensing equipment, we propose a data abnormality detection method based on an isolated forest that combines the characteristics of the sufficient timeliness of mine water monitoring data, and we offer experimental verification and analysis. The experimental results show that the system can realize the real-time wireless monitoring of mine water quality and quantity information with stable and fast data transmission capability. Furthermore, the system can quickly discover, analyze, and process abnormal data, has sufficient timeliness while guaranteeing the validity of the data output from the monitoring platform.

INDEX TERMS Mine water, sensor networks, communication, wireless monitoring, isolated forests, anomaly monitoring, Internet of Things.

I. INTRODUCTION

Mine water is underground gushing water produced during the mineral mining process. Influenced by human activities such as underground coal mining, mine water is highly susceptible to pollution, and if discharged directly without treatment, it inevitably pollutes the environment and wastes resources. Hence, in the production of coal, it is of strong practical significance to ensure the coordination of production and environmental conservation to monitor and treat mine water for reuse to achieve environmental and economic benefits [1]. Traditional monitoring technology is relatively independent of each testing node, the water quality data it obtains cannot be managed quickly and centrally (''data silos''), and the testing data used by dispatching systems are lagging. Due to the harsh production environment underground, it is difficult to achieve rapid unified and centralized management of monitoring data as well as to provide timely data support for the dispatching system [2]. In particular, traditional mine water treatment systems use wired cable communications, and as mining operations move deeper underground, the communications and mine water treatment equipment required involves expansion and upgrading. This increases the cost of a full-scale mine water monitoring system and limits its effectiveness. Furthermore, due to the lack of fast and accurate real-time monitoring, the reuse of mine water starts at a relatively late stage in the treatment process. This stage is usually the last clear water tank with stable water quality (much higher than the water quality required at the point of use). This means that the treatment and reuse processes are independent and hence mine water reuse currently has a poor recycling rate. In fact, the water quality requirements in coal production are not the strictest in terms of meeting direct discharge standards but rather, they are undergoing progressive shift. This trend is similar to that of the mine water treatment process, where the quality of

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the mine water improves as the treatment process progresses in a stepwise manner. This means that the mine water in the treatment process can meet the needs of some water usage scenarios [3]. If the nodal water quality and the water demand at the point of use can be detected in time and the corresponding water pathway can be set up, rapid deployment can achieve the in situ reuse of mine water underground. This will largely increase the reuse rate of mine water and reduce energy consumption for water treatment. Therefore, the establishment of comprehensive, real-time and effective mine water quality and quantity monitoring technology is the key to achieving efficient utilization and comprehensive management of mine water.

Benefiting from the development of IoT technology, it is possible to obtain data directly from devices for centralized processing and distribution to other locations where data are required [4]. IoT technology connects various sensing devices and control devices with monitoring systems and mobile terminals and thus providing a reasonable solution for data sharing and unified management of various equipment supply chains. This can help achieve a variety of functions, such as real-time online monitoring and remote control, as well as intelligent optimization [5]. China is in the initial stage of smart mine construction, in which IoT plays an important role [6]. In addition, keeping communications open and fast is important in online real-time monitoring. Existing wireless mine communication technologies mainly involve leaky communication such as ZigBee, and Wi-Fi [7], which are applied to mine monitoring [8], transportation scheduling [9], and signal contact [10]. However, this leads to problems such as complicated installation requirements and high-power consumption [11]. Hence the application of these existing methods is not ideal in areas with relatively harsh environments and low data transmission rate requirements due to factors such as communication distance, power consumption, and the number of access points [12]. LoRa communication technology is a long-range wireless communication technology that uses a direct-sequence spread spectrum [13] and it has started to flourish in recent years. It possesses strong anti-interference and high reception sensitivity [14]. It is an ideal technology for long-range, low-power, large-scale network communication. It has been applied in scenarios requiring stringent real time and accuracy [15] properties, such as highly reliable sensor networks [16]. Based on the stable and efficient sensor networks built using this technology, ensuring that data acquired by the sensors truly reflect the actual changes of detected objects and ensuring data validity are key issues for an effective online monitoring system. In this context, for anomaly detection, there are three basic methods, namely, supervised, semisupervised, and unsupervised [17]. Supervised and semisupervised methods need to obtain a large number of training sets with labels, which in turn requires considerable labeling time and training time [18]. However, the anomaly data detection of sensor networks for online monitoring systems has the characteristics of timely data processing and result outputs [19]. Therefore, anomaly monitoring of mine water quality data should not use learning algorithms that require a large amount of learning time. Thus it should be accomplished by unsupervised learning algorithms.

Turning to previous work in this context, [20] presents the design a data acquisition system with a MySQL Web database based on a Web interface. [21] designed an IoT-based renewable energy monitoring system while [22] proposed a low-cost real-time IoT without cables for monitoring photovoltaic systems. [23] describes an online generator temperature monitoring system built by a sensor network based on open-source hardware and software. However, these studies were aimed at surface communications and did not consider the requirements of underground coal production. Here it is worth mentioning that [6] points out that the integration of IoT with the coal industry is key to to enhancing the intelligence of China's coal mines. In addition, [13] developed a management and emergency rescue system for mine employees based on LoRa technology and validated the system's safety and dependability. [24] analyzed the role and application scenarios of LoRa for communication in the complex environment of underground mines, where underground data communication has sufficient timeliness and accuracy in addition to supporting audio/video mega data streams. [25] researched the framework and application of IoT in coal mines for precise early warning of catastrophic power events. In [26], an IoT monitoring system for mining truck tires was designed to monitor tire temperature, pressure and provide early warning, and positioning, with the management of opencast mining truck tires as the target. [27] designed an IoT system based on ZigBee transmission and tested web browsers to device IP access. [28] established an underground coal mine dynamic information platform based on the IoT for safety monitoring in coal mines, and [29] studied the basic framework of the IoT in the context of underground ambient air quality monitoring systems. [30] studied the IoT system for mine water flood monitoring with the objective of mine water washout disaster early warning, acquiring water quality and water pressure data of each aquifer. The current research on IoT in coal mines is thus mainly focused on solving the safety problems of personnel during production, monitoring with one of the main goals being to produce early warning of various catastrophic power events in mines. There is relatively less research on IoT technology for the efficient use of mine water treatment that takes into account the high construction cost of underground water treatment systems. Thus, it is a relevant research goal to study the construction of mine water IoT platforms by simulating the actual production process to design an experimental platform for system testing and optimization.

The key for improvement is obtaining water quality and quantity data quickly and accurately from the monitored tanks for comparison with water quality at the point of use and to provide data support for the blending system. With these objectives in mind, we carried out the work reported below: The Section.II analyzes the requirements of the online monitoring system combined with the IoT, solved the problem of direct access to sensor equipment data utilization, and completed the collaborative structure design of online monitoring. The Section.III builds a simulation experimental platform of a mine water online monitoring system,and completes experimental tests on the simulation experimental platform. The Section.IV proposes an isolated forest anomaly detection algorithm to identify anomalous data, which based on mine water quality and quantity. The Section.V provides an experimental validation of the proposed algorithm The Section. VI is a summary of the research and future outlook

II. DESIGN OF AN IOT-BASED ONLINE MONITORING SYSTEM FOR MINE WATER

In this paper, we take the Narim River mine, located in the Inner Mongolia Autonomous Region, China, as the object of study. We have based our study on the comprehensive utilization system of mine water and the graded stratification theory of water quality for mine water utilization [31]. Guided by this work, we improved the water use pathway of mine water and designed a mine water simulation and monitoring platform based on the improved pathway. The treatment and reuse process of mine water is shown in Fig.1. From the figure, we can see that the original mine water treatment consists of a full process treatment followed by a partial reuse method. It has the drawbacks of being a simple process and single reuse, and its reuse rate is only 36.5%. The mine water treatment process is improved according to the water balance of the mine area with the objective of efficiently using water resources. The improved process adds a coagulation and sedimentation device and a mechanical filtration device underground so that the water from the clear water tank meets the standard for in situ reuse. In the surface section, an intermediate pond is added between the high-efficiency cyclone and the high-density sedimentation tank, and the water from the V-filter enters the high-level pond so that the effluent is graded and utilized. This improvement can increase the reuse rate of mine water to over 80%.

Due to the differences in the sensors [32] and the nonuniform standards of equipment suppliers [33], it is difficult to form a standardized sharing of sensing information [34]. In this study, we first address the problem of centralizing and standardizing the processing of data from multiple sensor devices, i.e., online data collection and unified management. The devices communicate with the data center on the surface via an underground communication network. In some industrial IoT application scenarios, reliance on gateway coordination nodes to form sensor networks can enable sensing and sensing of different devices [35]. Therefore, we propose an online monitoring system for mine water based on an industrial IoT system. The system comprises three parts: a perceptual layer, a communication network layer, and an application layer [36]. The overall framework for the monitoring system is shown in Fig.2.

The perceptual layer in is defined as a sensor network built by networking multiple detection units. The function of this is to network devices and interconnect people, devices, and communication systems. In the communication system, each device in the sensing layer has a unique node identifier and an independent communication address after joining the network. Furthermore, it can establish stable communication with the adaptor node. Each detection unit is made up of sensors to detect water quality and quantity information.

The communication network layer is composed of an adaptation layer and a communication network that allows for remote communication between the equipment on the work surface and the control center. Here, each node is a communication base station supports the detection unit's communication protocol which establishes a stable wireless connection with several sensors via TCP (transmission control protocol) communication. It also forwards data upwards to the data service center and downwards to the equipment for propagating application layer operation instructions. Underground wireless communication base stations, communication cables, signal repeaters, and network switches comprise the communication network. Wireless communication base stations must adapt to the radio propagation environment in the special underground space. Communication cables connect multiple underground base stations to the data service center server while signal repeaters are signal enhancement devices used to avoid signal weakness in long-distance transmission. Finally, network switches are suitable for connecting devices with multiple protocol communication to the communication network in a network. For example, using a network switch, wireless base stations with two communication protocols, Wi-Fi and LoRa, can be standardized in the communication system, and sensor devices with different communication protocols can be managed in a unified manner.

The data service center and the mine water application make up the application layer. The mine water application enables online monitoring of mine water and includes applications such as sensor equipment data monitoring and data processing, while the data service center shares the sensing layer's basic data. The Mysql database is a widely used relational database with low cost, high security, fast running speed, open source programs and support for at least 20 cross-platform developments. It stores various data on mine water in different tables, provides fast access and enables flexibile shared data operations for various applications. The data service center cleans and distributes the data uploaded by the sensory layer and sends it to relevant applications, such as visual monitoring on large-screens, computation centers for data processing, and remote servers for off-site operations. In addition, the acquisition commands sent by the mine water application to the sensory layer equipment must be sent through the data service center.

The wireless collection system consists of quantity and quality sensors, multiplex signal collectors, and wireless communication nodes to achieve on-site water quality and quantity information collection. The IoT communication system consists of communication base stations with industrial routers and local communication servers to provide a

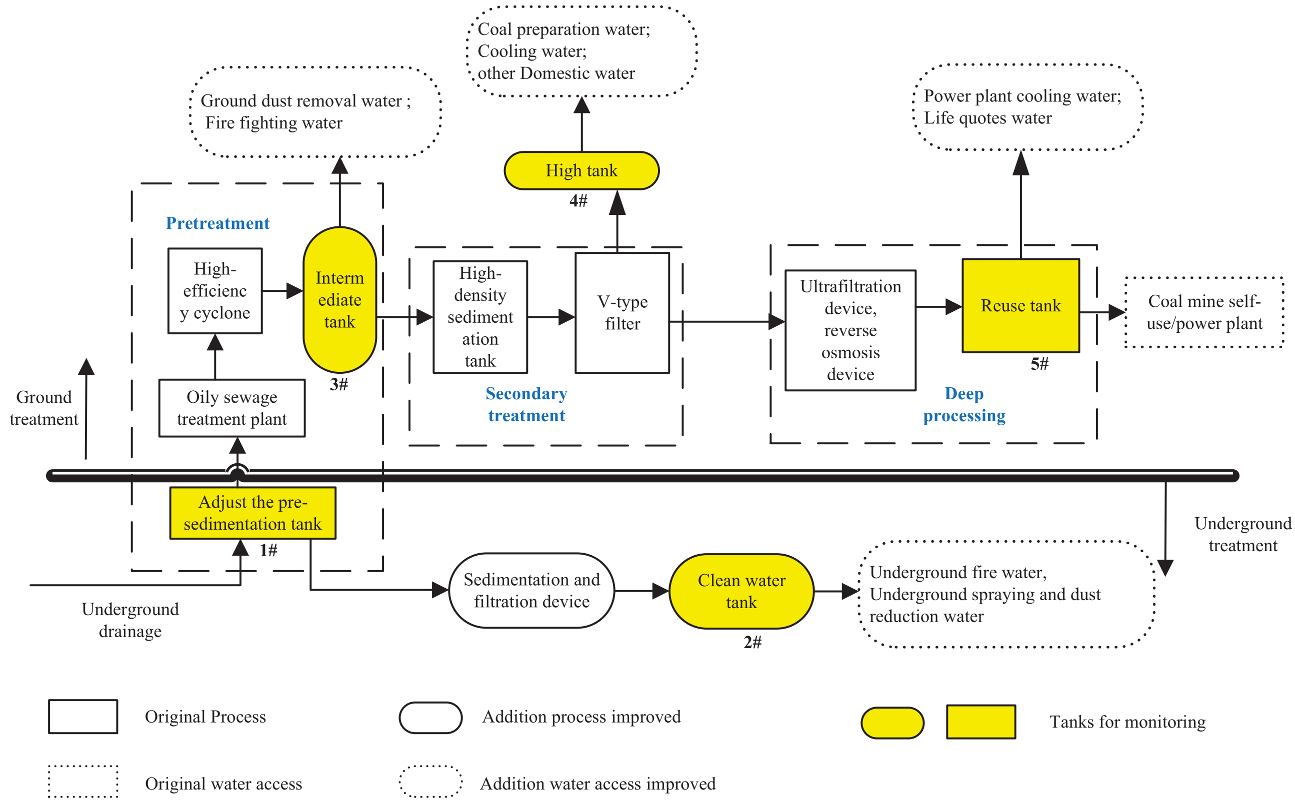

FIGURE 1. Mine water treatment processes and efficient uses pathway diagram.

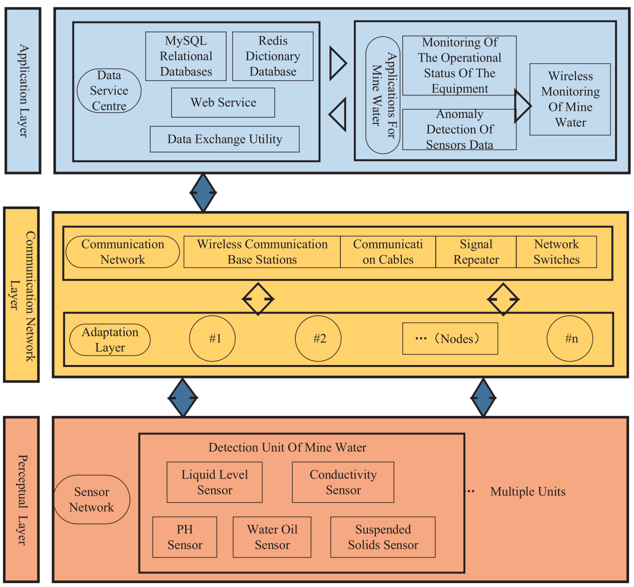

FIGURE 2. The framework for an online mine water monitoring system based on IoT.

communication guarantee for information interaction. The online monitoring terminal contains a monitoring platform for the dispatch center, which can provide remote monitoring and monitoring of other mobile devices and servers for data cleaning. The server cleans, stores, backs up, and distributes data for use by monitoring hosts, users, and other mobile terminals.

A. DESIGN OF PERCEPTUAL LAYER: ACQUISITION SYSTEM

Data acquisition is the basis of the online mine water monitoring system. With the help of gateway coordination nodes, wireless routers realize IoT sensing and interactive communication. This reduces the complexity of hardware design while improving the scalability of the system [37].

Based on the relevant requirements of China for water quality at each water point, we use the following quality indicators to characterize water quality: (1) suspended solids (hereafter called "SS"), which detect solids suspended in water, including inorganic and organic substances insoluble in water, mud, sand, clay, and microorganisms. The amount of SS in water is one of the indicators of the degree of water pollution; (2) hydrogen ion concentration (hereafter called "pH"), which detects and characterizes the acidity and alkalinity strength of mine water; (3) conductivity (hereafter called "Cond"), which characterizes the electrical Cond of mine water; and (4) water oil (hereafter called "Oil"), which is lighter than water and floats on the water surface, is insoluble in water and reduces dissolved oxygen in the water when it enters the water body. It characterizes the amount of dissolved oxygen in the mine water and the degree of deterioration. In addition, the volume of water is characterized as the liquid level (hereafter called the "Level"), which detects the level

FIGURE 3. Quantity and quality sensors.

FIGURE 4. Multichannel signal collector.

of water and characterizes the volume of water in the mine water.

Therefore, the quantity and quality sensors selected in this paper consist of pH, SS, Level, Oil, and Cond, as shown in Fig.3.

The sensor output signals are current and voltage signals after temperature compensation and linear calibration. The multiplex signal collector is shown in Fig.4 and it collects the sensor signals according to the communication commands issued by the IoT.

$$V_S = \alpha \frac{i_c}{I_e} * L_d \tag{1}$$

α is the calibration error.

V_s indicates the actual value of the tested water quality object.

I_c denotes the sensor output current.

I_e indicates the rated current range of the sensor; and

L_d denotes the water quality parameter corresponding to the full range of the sensor.

After this, the collected data are integrated, compressed, packaged, and sent to the target communication server. In the acquisition work, the sensor is connected to and powered by the collector, as shown in Fig.5.

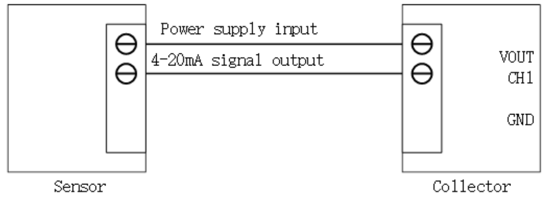

FIGURE 5. Connection between the collector and the sensor.

B. DESIGN OF COMMUNICATION NETWORK LAYER: WIRELESS COMMUNICATION MODULE

The communication base station and wireless nodes establish a star network wireless collection system. We note that a star network has strong fault resistance [38], as shown in Fig.6. Wireless communication nodes of multiple signal collectors and multiple sensors or multiple equipment relays form a wired star network, and wireless communication nodes and communication base stations form a wireless star network. The monitoring platform by the dispatch center through the communication base station sends collection instructions to wireless communication nodes. Water quality information or equipment status information is reported and collected by the node, forming a stable and fast IoT sensing and transmission network.

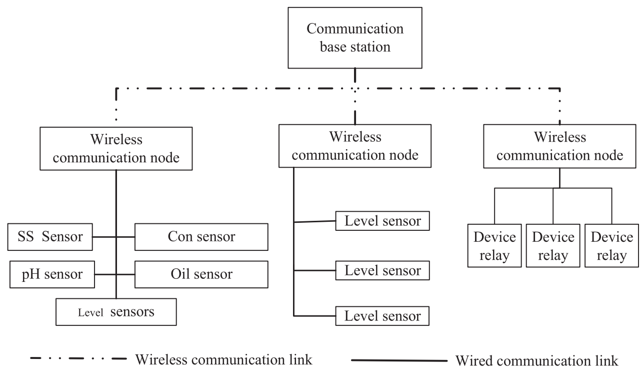

FIGURE 6. Connection between the collector and the sensor.

The communication protocol between the communication network devices uses the Modbus TCP protocol, which is widely used in field automatic control systems and has become the de facto communication standard for industrial devices [39]. Taking the LoRa private communication protocol networking acquisition communication as an example, the wireless acquisition process is shown in Fig.7. After the system is powered on, the LoRa concentrator first initializes the device communication base station (gateway concentrator) and then polls the LoRa nodes under the LoRa star network at regular intervals according to the number of terminal nodes and information. The concentrator then receives the synchronized data, and the nodes are passively polled; after the set conditions are reached, the nodes report the data.

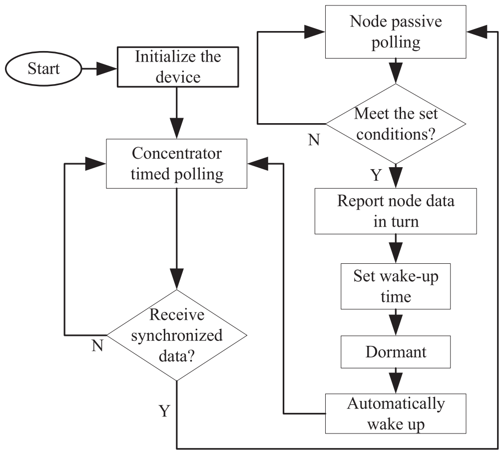

FIGURE 7. Work process of LoRa wireless acquisition system.

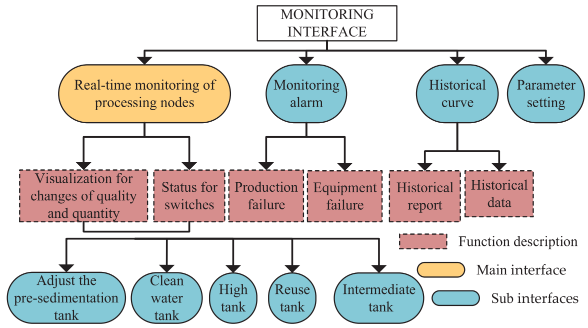

FIGURE 8. Work process of LoRa wireless acquisition system.

C. DESIGN OF APPLICATION LAYER: ONLINE MONITORING PLATFORM

Based on the mine water treatment process, an online monitoring platform for mine water was built to visualize quantitative and qualitative changes, scheduling information, equipment status, and other information in the process of mine water treatment.

The online monitoring platform takes the actual coal mine water treatment process as the theoretical basis and the scientifically selected treatment nodes of Fig.1 as monitoring nodes to realize the visualization and monitoring of the water treatment process. The online monitoring platform should satisfy the following four design principles.

Dynamism: the monitoring system interface should be dynamic, with a real-time dynamic simulation of water quantity, water destination, pump switching status, and real-time changes in water quality in the water treatment process.

Diversity: the monitoring system should realize the dynamic simulation display of multiple data, be able to monitor multiple subsystems, and have functions to help producers make decisions, such as fault alarms.

Interactivity: a monitoring system should support human-computer interaction, with the ability to take over some or all of the operating privileges.

Commonality: the monitoring system should be designed to enable coordination under the premise of meeting the above three functions. In addition, to give the mine water monitoring information a more intuitive display, the system interface was divided into a main interface and eight secondary interfaces. The main interface dynamically displays the mine water treatment process, the real-time data changes of important monitoring indicators (level, oil, Cond, SS, pH), and information such as the status of the opening and closing valves. The eight secondary interfaces consist of five monitoring tank interfaces and three data analysis interfaces. They can monitor each tank and display historical curves, historical reports, and threshold alarms.

III. IMPLEMENTATION AND TESTING OF THE ONLINE MONITORING SYSTEM FOR MINE WATER

A. HARDWARE DESIGN OF ONLINE MONITORING SYSTEM

This section describes building an online monitoring system with LoRa as the networking protocol. An underground clear tank (DBT) and the surface intermediate tank (OAT) were designed as monitoring nodes as also nine water points, and water volume monitoring nodes. They are transmitted to the analog data collector with LoRa node function through RS485/232 communication. The IoT gateway is a star-shaped network environment monitoring transmission system established by the LoRa concentrator and nodes. The hardware system is shown in Fig.9. It is divided into five parts. From the perspective of spatial layout, it is locally divided into three parts: (1) LoRa node: connected with on-site sensing equipment and the IoT to realize the online detection of water quality and quantity information; (2) IoT gateway: the LoRa concentrator and node establish a star-shaped network environment monitoring transmission system, which is connected to the Internet through the IoT router; (3) Local monitoring platform: includes a communication server and local monitoring host for local data cleaning, storage, and backup as well as system operation configuration monitoring. It is then remotely divided into two parts: (4) Data servers and databases: data storage and backup for big data operations and providing data and channel support for remote services; (5) Remotely monitoring the host: the remote monitoring water treatment system can be logged into via mobile phones, laptops, computers, and other devices.

It consists of a communication system, power supply system, an exhaust system, etc. In the communication system, the multichannel signal collector (HUADIAN AUTOMATION AI-12) collects the analog signal output from the sensors and connects to the LoRa node via RS485. The LoRa node (usr-LG206-L-C) and the LoRa concentrator (USR-LG220-L) form a star-shaped sensing network, and the LoRa concentrator is wired to a WiFi router. The LoRa concentrator is wired to a WiFi router, providing a channel for data interaction between other networks and the sensing network. Fig.10 shows some of the communication devices of the online monitoring platform, where two LoRa nodes are shown in the

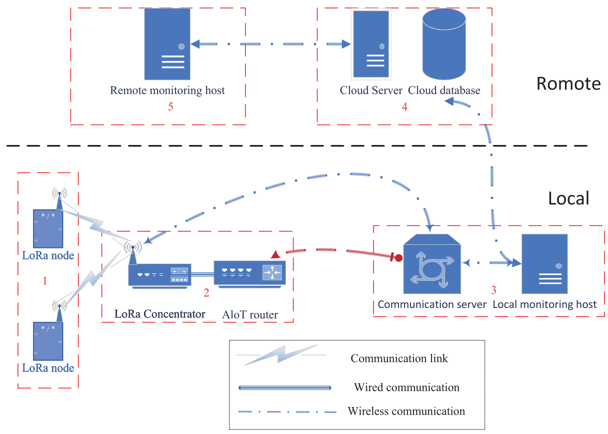

FIGURE 9. Hardware composition of the online monitoring system.

FIGURE 10. Online monitoring system hardware (behind the experimental platform).

FIGURE 11. Physical diagram of a power adapter.

upper right corner and a multiplexed signal collector is shown in the lower left corner.

In addition, the power supply system has three power adapters with different output voltages. The 24 V power adapter supplies power to the Multichannel Signal Collector.

FIGURE 12. Physical diagram of the distribution box.

The 12 V power adapter supplies power to the Lora nodes. The 5 V power adapter powers the status indicators. As for the relay protection in the low-voltage distribution network and power system, the various voltage levels are separated and their operating status is monitored using smart meters. The installation equipment for the power supply system is shown in Fig.11 and Fig.12.

Specific information on the models, functions and communication protocols of the abovementioned devices can be found in Table1.

B. SOFTWARE DESIGN OF THE ONLINE MONITORING SYSTEM

The program flowchart for functional realization of the IoT communication system is shown in Fig.13. The dispatch center server issues data collection instructions through the established connection with the wireless acquisition system and the IoT gateway. The acquisition system responds to acquisition instructions to upload data. There are two types of water quality and quantity data in addition to other data: monitoring objects and system status information. The returned data are stored in the local database after data cleaning. The local database provides online monitoring data support for the dispatch center. Local databases are simultaneously used for cloud database backups, while cloud server computing centers are used for big data calculations and provide online monitoring data support for remote and mobile devices.

C. EXPERIMENTAL PLATFORM CONSTRUCTION AND TESTING

According to the mine water reuse method in the actual mining area, we built a mine water online monitoring experiment platform, and the physical map is shown in Fig.14. We then tested the mine water online monitoring system. The reuse, high-level, intermediate, pre-sedimentation, and clean tanks were selected in the mine water treatment process as the online monitoring objects; information on Cond, SS, pH, and the level were monitored; and the monitoring time

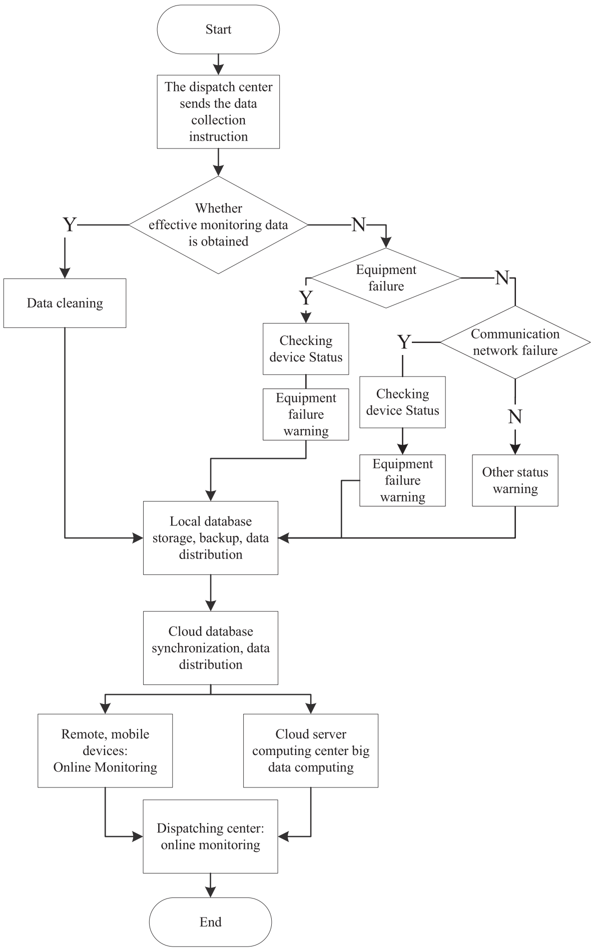

FIGURE 13. Program flowchart.

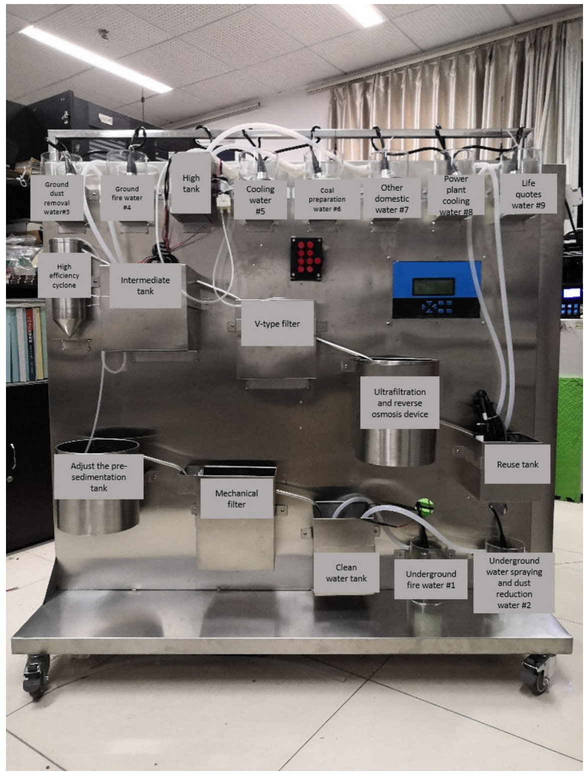

FIGURE 14. Physical map of the mine water online monitoring experimental platform.

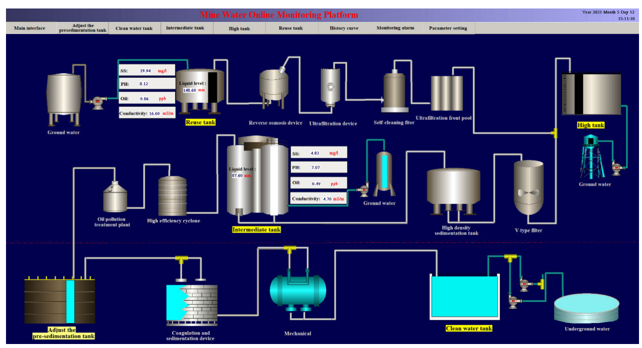

FIGURE 15. Mine water monitoring platform.

was 1 hour. Pure water was added before the experiment, high-concentration mine water was added after the experiment, and changes in the interface of the mine water online monitoring platform were observed.

Table1 contains the equipment list for the online mine water monitoring experimental platform, with information about the equipment discussed in this study.

The test results in Table2 show that the online monitoring system could reflect changes in the quantity and quality of mine water in real time. The real-time data display section in Fig.15 shows the real-time data of multiplexed and intermediate tanks.

The local dispatch center monitoring platform provides a real-time display of mine water quantity and quality data information. The communication server cleans, stores, and backs up local data. It also carries out unified data management; and transmits data to the remote cloud server for analysis, computing work, and remote auxiliary work. Table2 represents the server's unified and standardized storage of various data after cleaning. As shown in Fig.16, the server data are real-time monitoring data, visualized in the monitoring platform in Fig.15. (Mysql database, viewed by Navicat15). The timestamp (15:11:18) in the top right corner of the monitoring screen indicates that the data currently displayed are the latest data available from the data center (marked section in Table2). Table2 shows a steady update frequency of 1 s/time for the data center data (some of the 2 s intervals are where there are fluctuations in detection; anomalies in fluctuations are examined later). These results show that the monitoring system continuously monitored the mine water with sufficient timeliness.

Fig.16 shows the real-time change graph of the detection platform at a specific time. It is representative of abnormal fluctuation scenarios taken from the monitoring interface/history curve interface. In particular, it shows the variation in the intermediate tank level using two sets of

TABLE 1. Equipment list for the online mine water monitoring experimental platform.

Function	Equipment	Model/Related parameters
Sensor Network	Level Sensor	HDL300.Testing unit: mm; scope of test: 0–1000 mm; resolution: 0.1 mm; operating voltage: DC12V;Output: Analog current signal
	Cond Sensor	JZ-DD.Testing unit:(mS/m); scope of test: 0–200 (mS/m); resolution: 0.2 (mS/m); operating voltage:DC5/12/24V ;Output: Analog current signal
	pH Sensor	JZ-PH.Testing unit:pH; cope of test: 0–14 pH; resolution: 0.01 pH; operating voltage: DC12V;Output: Analog current signal
	Oil Sensor	JZ-Oil.Testing unit:(mg/L); scope of test:0.5–4000 (mg/L); resolution:0.1 (mg/L); operating voltage:DC5–12V ;Output: Analog current signal
	SS Sensor	JZ-SS.Testing unit:PPb; scope of test:0–500 PPb; resolution: 0.1 PPb; operating voltage: DC5–12V ;Output: Analog current signal
	Signal Collector	HUADIAN AUTOMATION AI-12. Input: 12-way analog current signal,4–20 mA ;Output:RS485 communication bus and standard MODBUS-RTU protocol; Testing unit:mA;operating voltage: DC9–30V
Communication Network	LoRa Concentrator	USR-LG220-L.Input:LoRa; Output:Wired WAN Port(RJ-45 interface)/WiFi wireless LAN; Communication protocols:TCP; Frequency band:398–525MHz; transmit power:≦ 20 dBm
	LoRa Node	USR-LG206-L-C.Input:RS232/485;Output:LoRa;Communication protocols:TCP ;Working frequency:398–525 MHz; transmission distance:2500m; baud rate:1200–115,200bps
	IoT Router	AX3600.Input&Output:Wired WAN Port(RJ-45 interface)/WiFi wireless LAN; Communication protocols:TCP; Unlimited rate: 2976 $Mbps$; RAM: 512 MB
Data Service	Compute Service	Baidu Cloud Compute C3.CPU: 8 Core;Memory: 16G;Processor frequency: 2.4 GHz;Network bandwidth: 1.5 Gbps
	Cloud Database	Baidu Cloud Database(Mysql). 2 Core/ 4G
Power Supply System	24V power adapter	LPV-100-24.INPUT: 100-240V,2.2A/OUTPUT: +24V, 4.2A
	12V power adapter	LPV-60-12.INPUT: 100-240V, 0.8A /OUTPUT: +12V, 5.0A
	5V power adapter	LPV-35-5.INPUT:100-240V, 1.1A/OUTPUT: +5V, 5.0A
	circuit breaker	CHNT NXBLE-32 air switch.Product parameters: 230V, 50Hz, 6000A
	miniature breakers	Schneider IDPNa C 16A.miniature circuit breakers,Product parameters: 230V, 50Hz, 30mA
	Status indicator	Specification: AD56-16DS;Voltage: AC/DC 6.3V
	Cable	Product model: RV 1;Outer diameter: 2.5mm;Voltage: 300/500V; Current: 7.5A
Other Auxiliaries	radiator	QVKS Power distribution box FK6622.230;Product parameters: 220V, 50Hz, 0.12A
	Multi-Function Digital Meter	D52-2066.Monitor the following information on the platform: current(0-100A), voltage(AC,40.0V-300.0V),Active power(0-30000W),Frequency(45Hz-65Hz),Electric energy(0-99999Kwh),Power factor(0-1)

mm = millimetres,V = volt, mS = millisiemens,m = meter,pH = potential of hydrogen, mg = milligram ,L = litre, PPb= part per billion,mA= milliampere,DC = Direct Current,dBm = decibel relative to one milliwatt,bps = bits per second,Mbps = megabits per second.MB = MByte,Hz=Hertz,W=watt,Kwh=kilowatt hour

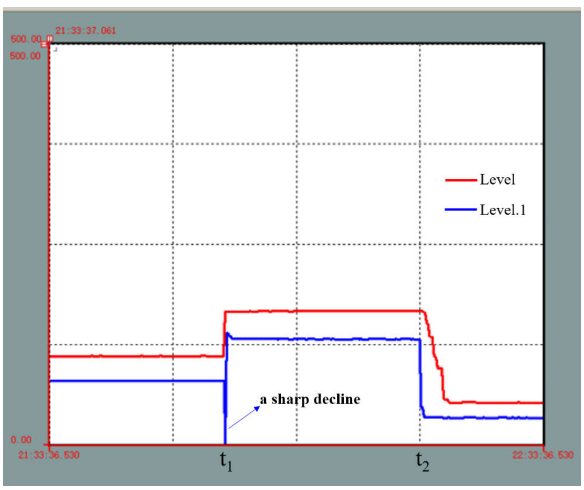

FIGURE 16. Background monitoring data for a certain period.

data collected by the level sensor. The two obtained variation curves are represented by Level and Level 1. At time t_1, the intermediate tank was supplied with water from outside, the level, and the values of Level and Level 1 increased, but Level 1 had a short and obvious decrease. At time t_2, the intermediate tank was supplied with water from outside and the values of Level and Level 1 decreased. While Level had a slowly decreasing trend, Level 1 had a sharp decreasing trend. This is due to the difference in sensor accuracy that led to the difference in the speed of change. In the actual measurement process, the data directly detected by the sensor could abruptly change at unspecified times, and these abrupt changes do not reflect objective changes in the monitored object but rather due to the detection principle and accuracy of the sensing. To obtain accurate changes in various quantitative and qualitative data, it is necessary to eliminate invalid data.

IV. ABNORMAL DETECTION OF MINE WATER QUANTITY AND QUALITY DATA

A. ABNORMAL DATA FROM THE MINE WATER MONITORING SYSTEM

Due to the high accuracy and timeliness of sensor detection, changes in the external environment can affect the accuracy of the detection data. For example, the level sensor detects the liquid level by detecting hydraulic pressure. A pump turning on induces sudden hydraulic pressure changes which then causes sudden changes in the system monitoring signal.

TABLE 2. Accumulated server data.

Time	Con	Con.1	pH	pH.1	SS	SS.1	Oil	Oil.1	Level	Level.1
15:10:54	14.77	2.43	8.16	7.50	22.84	4.28	0.66	0.41	148.40	83.40
15:10:55	15.52	4.05	7.16	7.54	25.58	0.36	0.53	0.39	138.80	90.06
15:10:56	17.62	1.69	8.41	6.92	32.56	0.34	0.54	0.32	107.44	84.70
15:10:57	12.08	0.26	6.76	7.54	21.98	3.06	0.97	0.36	148.10	115.90
15:10:59	14.73	1.68	7.87	7.79	13.79	2.90	0.89	0.33	141.00	93.90
15:11:00	13.34	1.62	8.27	7.04	24.34	2.20	0.73	0.49	109.40	116.56
15:11:02	14.84	1.04	7.66	7.20	16.16	2.29	0.65	0.31	110.94	97.25
15:11:03	16.40	0.86	8.19	6.20	38.62	4.41	0.52	0.40	131.60	106.60
15:11:04	16.48	2.18	8.31	7.48	37.06	2.46	0.51	0.45	111.94	114.06
15:11:05	10.56	1.67	5.84	8.09	15.27	0.63	0.89	0.33	106.30	94.80
15:11:06	10.66	1.66	8.67	7.20	25.52	3.93	0.91	0.43	108.94	101.70
15:11:08	11.94	1.97	6.07	7.18	38.80	0.69	0.95	0.33	104.94	85.60
15:11:09	11.04	2.16	7.21	7.31	32.40	1.93	0.62	0.49	134.20	94.44
15:11:10	18.50	3.39	6.01	6.84	26.62	0.43	0.68	0.31	134.80	118.40
15:11:12	12.52	4.90	6.02	6.25	22.42	1.52	0.74	0.49	105.60	110.25
15:11:13	12.70	3.14	5.83	7.12	26.66	3.41	0.95	0.41	136.80	84.40
15:11:15	16.31	0.32	6.84	7.29	18.31	4.85	0.54	0.39	123.50	112.40
15:11:16	12.66	2.23	6.71	7.00	31.38	1.50	0.55	0.33	103.00	96.60
15:11:18	16.60	4.77	8.12	7.07	19.94	4.83	0.86	0.49	148.60	87.60

Individual values in a sample that significantly deviate from the vast majority of observations in the sample to which they belong form anomalous ''noise points'' in the data, also known as outliers. This noise does not represent actual changes in the monitored object and does not contribute to the monitoring task. In fact, they are useless data and must be disposed off. In general, outliers in the data should be dealt with before analysis in order to prevent interference. For example, outliers can distort the correlation between X and Y and regression relationships and lead to wrong conclusions. Other research methods are also subject to interference from outliers, which can distort conclusions.

B. PRINCIPLES OF ISOLATED FOREST-BASED ANOMALY DETECTION FOR MINE WATER QUALITY DATA

1) ISOLATED FOREST CONSTRUCTION BASED ON MINE WATER QUALITY DATA

An isolated forest is an anomaly detection algorithm based on random binary trees for the fast detection of outliers. It is applied to feature-continuous mine water time series data and has linear time complexity and high accuracy. The core task of the algorithm is to select samples for random partitioning, construct a multiset binary tree structure iTree until all sample points are isolated, and measure the anomaly index by the distance from each sample point to the root node [40]. iForest's implementation consists of the construction of an n element isolated forest and the anomaly detection of the data.

Let there be a large-scale mine water quality dataset D with randomly sampled ψ training data x as a subsampled set D' and a binary tree describing the mine water quality data, with a node set N:

$$N_{ijd} \subseteq D', \quad d = l \text{ or } r \tag{2}$$

where i denotes the number of levels of the node in the binary tree, j denotes the number of node bits from left to right in the level above the node, d denotes the direction of nodes at the same level, l denotes the left node, and r denotes the right node. In particular, N_0 denotes the root node, which is equal to the data set as D' on data inclusion.

For dataset D'_{ij} contained in layer i, sample attribute q and its value domain are randomly chosen to take the spatial value p to divide the corresponding node set:

$$h(D) = \begin{cases} D'_{(i+1)j^*}, & q < p \\ D'_{(i+1)(j^*+1)r}, & q \geq p \end{cases} \tag{3}$$

where j^* denotes the left to right node position at layer $i+1$. The basis for determining a complete binary tree is as follows: (1) the mine water quality data tree reaches a set maximal value of $log_2(\Psi)$; and (2) nodes contain only one data point or the same data points. If the above conditions are met and splitting is stopped, an iTree is constructed. If n iTrees are constructed according to the above method, an isolated forest containing n iTrees based on mine water quality data can be constructed.

2) ABNORMAL DATA DETECTION

The iTree depth established above is normalized and the training data x of each iTree are iteratively retrieved. Then the number of layers x that falls in each iTree, i.e., the distance function $h(x)$ from x to the root node (also as a depth function) is calculated. Finally, the average of all distance functions is set to $E(h(x))$.

Let the average value of the path length for a given number of training samples $\psi bec(\psi)$ be:

$$c(\psi) = \begin{cases} 2H((\psi-1) - 2(\psi-1)/n), & \psi > 2 \\ 1, & \psi = 2 \\ 0, & \psi < 2 \end{cases} \tag{4}$$

$$H(k) = \ln(k) + \xi \tag{5}$$

where $H(k) = ln(k) + \xi$ and ξ is Euler's constant, taken as $\xi = 0.5772156649$.

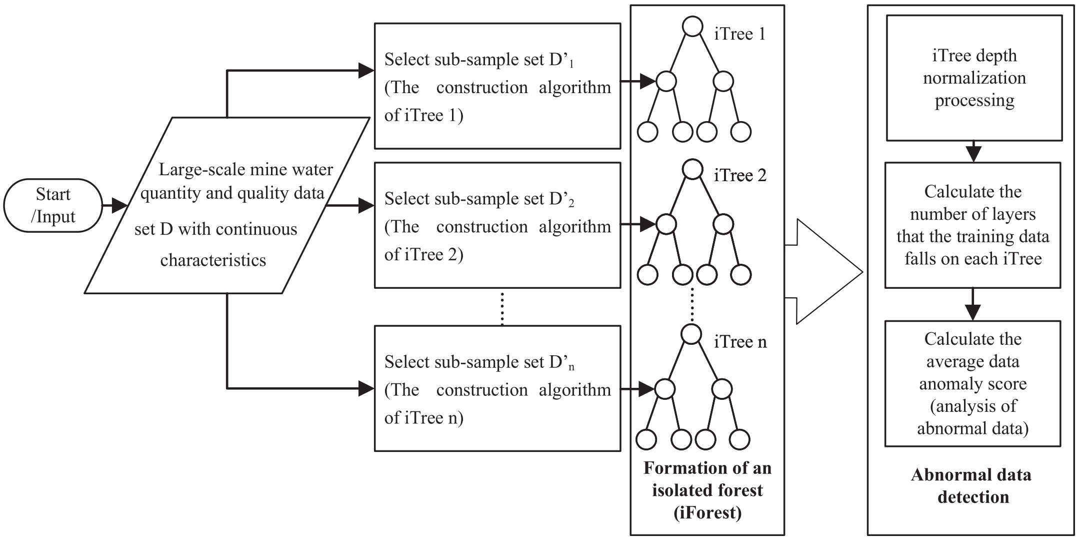

FIGURE 17. **Flowchart of an anomaly detection algorithm for mine water quantity and quality information based on isolated forest.**

The anomaly score s is calculated as follows:

$$s(x, \psi) = 2^{-\frac{E(h(x))}{c(\psi)}} \tag{6}$$

The larger the anomaly score s is, the more likely it is that the data are anomalous and the smaller s is, the more likely it is that the data are normal. From the formulas: $E(h(x)) \rightarrow 0, s \rightarrow 1$: the more s tends to 1, the higher the probability of anomaly; $E(h(x)) \rightarrow \psi - 1, s \rightarrow 0$: the more s tends to 0, the higher the probability of the data being normal; and $E(h(x)) \rightarrow c(\psi), s \rightarrow 0.5$: no abnormal data when the majority is 0.5.

C. ISOLATED FOREST-BASED ANOMALY DETECTION FOR MINE WATER QUALITY DATA

The process of detecting anomalies in mine water quality data based on the isolated forest is shown in Fig.17. The data for the detection come from the monitoring data of the experimental platform designed in this paper. The first step is to construct an isolated forest according to the method in Section.IV-B2. Then the anomaly score for each point is separately calculated, and the outliers are filtered out. In practice, a score of 0 is used as the cut-off point, and any score below 0 is judged as abnormal, while the rest is judged as normal.

V. EXPERIMENTAL DESIGN AND VALIDATION

The experimental object is the experimental platform of ten groups of sensor detection data totaling 3080 data points collected on 4 July 2021 at $21:30-22:33$. The experimental computing environment was $Windows10, 2.60\ GHz/16.0\ GB(CPU/RAM)$, and the computing tool was Pycharm (an environment for developers with an inclination for open source software).

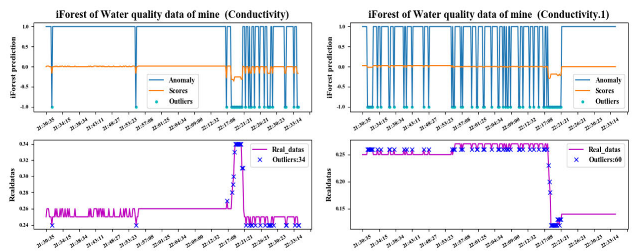

FIGURE 18. **Cond sensor anomaly monitoring results.**

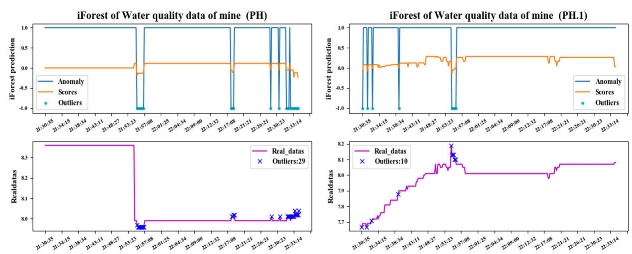

FIGURE 19. **Abnormal pH sensor monitoring results.**

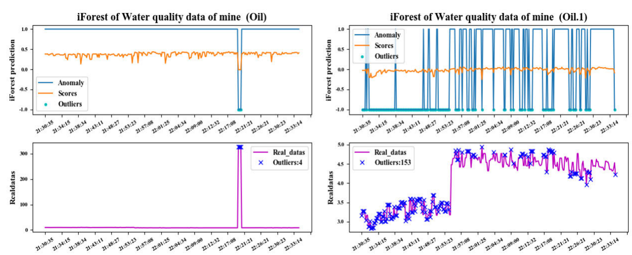

FIGURE 20. **Oil sensor anomaly monitoring results.**

Five sensors were set up for collecting the above detection data; each sensor detected two sets of data, and the continuous

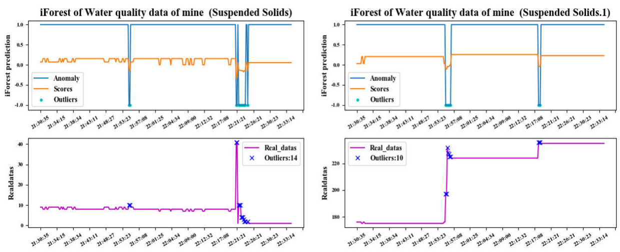

FIGURE 21. SS sensor anomaly monitoring results.

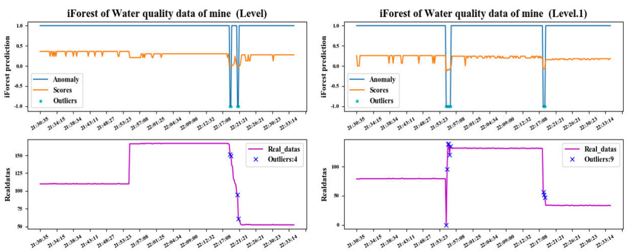

FIGURE 22. Level sensor anomaly monitoring results.

collection time was 1 hour to detect the abnormal value of each sensor. The detection results of the experimental platform are shown in figures below:Fig.18 shows the abnormal monitoring results of the Cond sensor, Fig.19 shows the abnormal monitoring results of the pH sensor, Fig.20 shows the abnormal monitoring results of the oil sensor, Fig.21 shows the abnormal monitoring results of the suspended solids sensor, and Fig.22 shows the abnormal monitoring results of the level sensor.

The iForest prediction part of each graph represents the content of the isolated forest anomaly detection algorithm, and the yellow line indicates the assigned score for each data point according to the isolated forest, where a positive number is the normal fluctuation range. The larger the score is, the higher the normal probability. A negative number is an abnormal value; the smaller the score is, the larger the abnormal fluctuation. The blue line indicates the abnormal detection results based on the assigned scores, where 1 indicates the final identification as normal data, and −1 indicates the final identification as abnormal data. The scattered part indicates the abnormal points detected by the algorithm. The Realdatas part represents the actual sensor detection data, and "x" marks the actual time when the abnormal points occurred. These marked anomalies and the anomalies detected by the algorithm fit well, which verified the effectiveness of the isolated forest-based anomaly detection algorithm for mine water quality data.

Fig.18 shows that the number of abnormal points of Cond sensor 0 (without number) was 34, and the percentage of abnormality was 11.04%; the number of abnormal points of Cond sensor No. 1 (with number) was 68, and the percentage of abnormality was 19.48%. Fig.19 shows that the number of abnormal pH sensor points for No. 0 (without number)

TABLE 3. Sensor data anomaly statistics and effect evaluation.

Sensors	Anomalies Number		Anomaly Index		Accuracy
	Detection	Actual	Detection	Actual	
Cond	34	43	11.04 %	13.96 %	79.07%
Cond.1	60	64	19.48 %	20.78 %	93.75%
pH	29	29	9.42 %	9.42 %	100.00%
pH.1	10	12	3.25 %	3.90 %	83.33%
Oil	4	5	1.30 %	1.62 %	80.00%
Oil.1	153	173	49.68 %	56.17 %	88.44%
SS	14	17	4.55 %	5.52 %	82.35%
SS.1	10	12	3.25 %	3.90 %	83.33%
Level	4	5	1.30 %	1.62 %	80.00 %
Level.1	9	10	2.92 %	3.25 %	90.00%

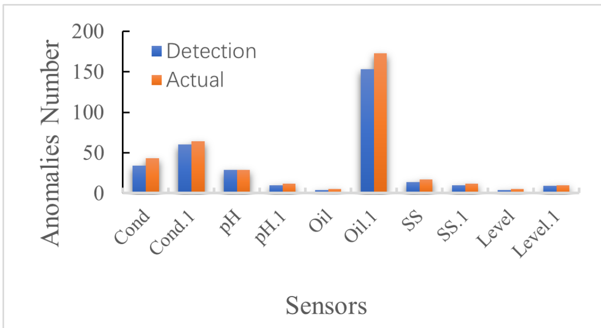

FIGURE 23. Number of anomalies.

was 29, and the percentage of abnormality was 9.42%; the number of abnormal pH sensor points for No. 1 (with number) was 10, and the percentage of abnormality was 3.25%. Fig.20 shows that there were four oil sensor anomalies in No. 0 (without number), with an anomaly ratio of 1.30%; there were 153 oil sensor anomalies in No. 1 (with number), with an anomaly ratio of 49.68%. Fig.21 shows that the number of SS sensor anomalies in No. 0 (without number) was 29, and the percentage of anomalies was 9.42%; the number of SS sensor anomalies in No. 1 (with number) was 10, and the percentage of anomalies was 3.25%. Fig.22 shows that there were 29 level sensor anomalies in No. 0 (without number), with an abnormality ratio of 9.42%, and 10 level sensor anomalies in No. 1 (with number), with an abnormality ratio of 3.25%.

Abnormal sensor detection data are further analyzed as follows. Table3 shows the number of abnormal points and the percentage of abnormalities for the five groups of data. Fig.23 and Fig.24 show that the number of abnormalities discovered in mine water quality data using an isolated forest-based anomaly detection method was not much different from actual tagging. With a detection accuracy of up to 100% and an average accuracy of 86.03% for the ten-sensor data, the accuracy of the online mine water monitoring data is ensured. Most abnormal fluctuations of the sensors were within the lower range of 5%, which is particularly stable; a small number were between 5% and 20%, which is stable; and a small number were close to 50%, which indicates that the sensor is less stable or has more stringent requirements for

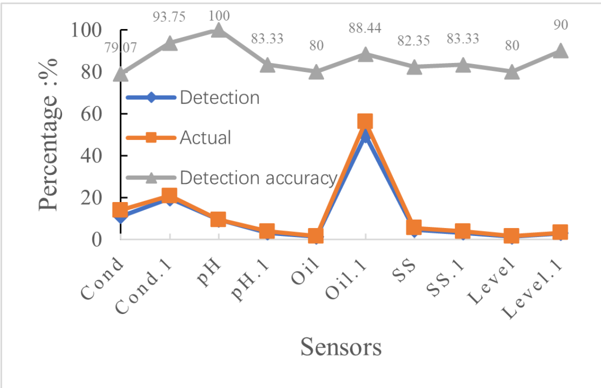

FIGURE 24. Effectiveness of isolated forest anomaly detection.

the detection object. The detection results can be used as a reference factor to test the stability of the sensor, and combined with the time and working station that generated the abnormal data, they can provide an important reference for the practical application of mine water quality information monitoring and the optimization of the experimental platform.

VI. CONCLUSION

This paper combines the industrial IoT framework with the efficient and comprehensive utilization pathway of mine water. It deeply integrates the IoT theory with the mine water treatment scenario, and solves the technical problems associated with the scenario such as the difficulty of data centralization and sharing faced by the collaborative and efficient utilization of mine water up-hole-surface.

In this study, we first established a fast and effective online monitoring system for mine water based on isolated forests and the IoT. Starting from the actual process requirements of mine water, we studied the sensing and detection network, communication system and abnormal data detection of the mine water online monitoring platform. We then used the LoRa network as an example and combined it with process design to produce a simulation experimental platform for the online monitoring system of mine water IoT. Finally, we used unsupervised learning methods to improve the effectiveness of the collected data by isolated forest-based anomaly detection of mine water quality data. Online monitoring and anomaly detection experiments were carried out for five types of water quality in the actual mine water treatment system. The experimental results show that the frequency of updating various types of data is approximately 1 s/time. The detection rate of the pH value can reach 100%, and the average detection rate, 86.03%. The system can detect most of the abnormal data of mine water and meet the requirements of mine water treatment and utilization scenarios for detection timeliness. In addition, the experimental platform is able to collect, transmit and store real-time quantity and quality information of mine water. It can quickly and accurately reflect the dynamic changes of mine water properties. Furthermore, it meets the requirements of mine water treatment and utilization with high speed and robustness, low time delay, high accuracy, low power consumption and high permeability.

The experimental platform, through data cleaning and distribution, can provide data support for inductive training of dispatching mine water big data and provide an effective data driven construction of digital mines and smart mines.

In addition, we have also conducted production scenario based simulation experiments to enhance our feasibility study of efficient mine water utilization pathways and technologies. Subsequent research will be carried out on water point precision control systems and to eventually realize the integration of mine water treatment and monitoring and even expand into intelligent systems.

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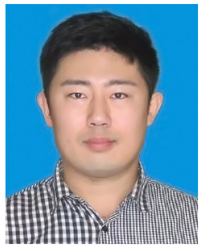
LEI BO received the bachelor's degree in electrical engineering and its automation from the China University of Mining and Technology, Beijing, in 2018, where he is currently pursuing the Ph.D. degree in electrical engineering. His research interests include mine water optimization treatment, filling automation, and artificial intelligence.



YANG LIU received the Ph.D. degree in power electronics and power transmission from the China University of Mining and Technology, Xuzhou, China, in 2014. He is currently a Lecturer with the School of Mechanical Electronic and Information Engineering, China University of Mining and Technology (Beijing). His research interests include mine wireless communication and distribution system planning.

ZIHANG ZHANG received the bachelor's degree in electrical engineering and automation from the North China University of Water Resources and Electric Power, in 2018, and the master's degree from the China University of Mining and Technology (Beijing), in 2021, where he is currently pursuing the Ph.D. degree. His research interests include mine water optimization treatment, filling automation, and artificial intelligence.

DONGXU ZHU received the bachelor's degree in electrical engineering and automation from the China University of Mining and Technology (Beijing), in 2018, where he is currently pursuing the master's degree. His research interests include mine water optimization treatment, filling automation, and artificial intelligence.

YIYING WANG was born in Baoding, Hebei, China, in 1985. He received the M.S. degree in computer science and technology from the Hebei University of Engineering, Handan, China, in 2009, and the Ph.D. degree in control theory and engineering from the China University of Mining and Technology (Beijing), Beijing, China, in 2017. He is currently working with the Hebei University of Engineering. His research interests include wireless communication, wireless sensor networks, modular robot, and power electronics.