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Improving Intelligence and Efficiency of Salt Lake Production by Applying a Decision Support System Based on IOT for Brine Pump Management

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Abstract: At present, due to their geographical distribution, environmental conditions and traditional monitoring technologies, the manual inspection of brine pumps in Qinghai Saline Lake can not be effectively carried out in real time, so the pumps have a high failure rate. This has seriously affected the chemical production of this saline lake. The paper designed a remote real-time monitoring terminal and a decision support system based on LoRa technology, GPRS (General Packet Radio Services) remote communication technology and remote-control technology. The system integrated the liquid-level sensing model and the decision support model for brine pump management. The system monitored and analyzed the voltage, current, and liquid-level parameters in real time to determine the operating status or failure of the brine pump. The ID3 (Iterative Dichotomiser 3) method was used to establish the correlation models between the dynamic monitoring information and the brine pump failure, which is the core of the decision support model. The remote controller was implemented to display and control the running status of the brine pumps when the maintenance personnel received the warning information. PHP (Hypertext Preprocessor) language and a MySQL database were implemented to realize the data display, management and decision support system.

Keywords: salt lake brine mining; LoRa wireless sensor network; remote real time monitoring; decision support model; remote control

1. Introduction

Salt lake resources, as an important part of China's mineral resources, contain rich inorganic salt resources, which are formed from liquid minerals in the unique natural geographical environment. There are more than 100 salt lakes in Qinghai province, which is the largest salt lake resource in China. It has been reported that Qinghai would promote salt lake resources development as part of a national strategy. Most Qinghai salt lake resources are located in Qaidam Basin, affected by the storage conditions of underground brine, water physical properties, hydraulic characteristics and distribution, and the mining area is vast and the brine pumps are disperse [1,2]. According to the burial characteristics of the underground brine and the water-rich level of the aquifer, salt lake chemical enterprises realize the large-scale exploitation and utilization of the underground brine by adopting well-mining technology [3].

The brine pump is responsible for extracting the underground brine from the brine well to the surface and is scattered throughout various mining areas, which increases the difficulty of the daily management of brine pumps. At present, the monitoring and failure response of the brine pumps in Qinghai Saline Lake chemical industry depends on manual inspection. Enterprises send jeeps and patrol workers every day to inspect the operation of brine pumps in various mining areas. Because the brine pumps are installed below the ground, it is difficult for the inspection workers to judge whether they are blocked by salt crystals, because the brine level is insufficient with naked eyes. Even if the patrol workers find the brine pump to be faulty, they can only deal with small faults. Those brine pumps that cannot be repaired immediately, should stop at once. This traditional manual monitoring method is constrained by the geographical environment, climate and production cost of the mining area. Therefore, it does not involve real-time and accurate monitoring. This disadvantage causes brine pump damage and great losses to the production enterprises. Therefore, the saline lake chemical industry requires urgently a set of automated and intelligent systems to manage brine pumps, reduce the failure rate and improve production efficiency.

A monitoring system for industry is always one of the main requirements. Especially for the brine mining industry, the monitoring system is an indispensable part. The background of this paper is a special project case that is rare among research papers. Pedro Morillo proposed a monitoring system for meal distribution based on a wireless sensor network (WSN) and the Internet of Things (IoT) [4]. Xiaofan Jiang presented a monitoring system for pharmaceutical lyophilization based on radio frequency (RF) technology [5]. Farihah Shariff implemented a monitoring system for grid-connected photovoltaics based on Zigbee technology [6]. Matteo Cerchecci designed a monitoring system for waste management by a LoRa low power wide area network (LPWAN) [7]. Jose Ignacio Suarez developed a monitoring system for air quality based on Bluetooth and smartphones [8]. Tao Wang introduced a monitoring system for transformer fault diagnosis based on radio-frequency identification (RFID) tags [9]. These monitoring systems all chose wireless technology for data transmission. The comparison of the monitoring systems is in Table 1.

Table 1. Comparison of main wireless-technology and applications about monitoring systems.

Application	Wireless-Tech	Distance	Advantage	Disadvantage	Literature
Meal distribution trolleys	WSN * + IOT *: IEEE * 802.15.4	<100 m	Real-Time, Compared WSN and IoT	Temperature only	[4]
Pharmaceutical Lyophilization	RF *: nRF52832	<1 m	Multi-point sensors' measurement	Close range transmission	[5]
Grid-connected photovoltaic	Zigbee: SKXBEE	10~75 m	Web-based	Robustness of the system	[6]
Waste Management	LoRa LPWAN *: SX1272	>1000 m	Energy efficient solution	Power consumption	[7]
Air quality	Bluetooth: RN42VX	<10 m	Miniaturized gas-sensing	Close range transmission	[8]
Transformer Fault Diagnosis	RFID *: VISN-V3	<100 m	Stacked denoising autoencoder	Close range transmission	[9]

* WSN: Wireless Sensor Network; IoT: Internet of Things; IEEE: Institute of Electrical and Electronics Engineers; RF: Radio Frequency; LoRa LPWAN: LoRa Low Power Wide Area Network; RFID: Radio-Frequency Identification.

This paper also designs a decision support system for the salt lake production. Such a decision support system has applications in industry with successful results, as shown in Table 2. El Hassan developed an expert classification system by fuzzy rules, which can simulate human reasoning [10]. Marina proposed an intelligent system of image annotation based on fuzzy knowledge, which can deal with fuzzy knowledge and an image with the concept of different abstraction, which is more like a human [11]. Adel Sabry proposed an innovative combination method by the ID3 (Iterative Dichotomiser 3) algorithm together with the bee algorithm (BA) to choose the best subset of intrusion detection system features [12]. Mario proposed a traffic light dynamic control system, which works in parallel with fuzzy controllers by combining traffic monitoring in real time of the IEEE (Institute of Electrical and Electronics Engineers) 802.15.4 network [13]. Costea described a fuzzy-knowledge control system architecture for cement pulverization used fuzzy control strategies to regulate feed [14]. According to fuzzy set theory and a minimum–maximum combination, Petrović proposed a technical system fault risk assessment model [15].

Table 2. Comparison of methods, applications and advantages about decision support systems.

Methods	Application	Advantage	Disadvantage	Literature Studies
A fuzzy rule-based expert classification system	Automatic classification of seismic events	Making the classifier more transparent and adjustable	The multi-parameter optimization problem	[10]
A fuzzy knowledge-based intelligent system	Automatic image annotation	Enriched with new, more general and abstract concepts	Cannot be immediately used for new applications or domains	[11]
A selection model based on ID3 * and bees algorithm	Intrusion detection system	Higher values of DR * and AR * and lower values of FAR *	Searching the most efficient possible location	[12]
Multiple fuzzy logic controllers	Dynamic traffic lights management	Better performance, fault-tolerance	The WSN * node power consumption	[13]
A system architecture based on fuzzy logic	Cement milling	Changing within range: 40–60%	Only simulated using a MATLAB-Simulink	[14]
The fuzzy logic theory and traditional RPN * application	Mining equipment failure	The possibility to operate imprecise and insufficient data	Replacement time and downtime of the conveyor	[15]

* ID3: Iterative Dichotomiser 3; DR: Detection Rate; AR: Accuracy Rate; FAR: False Alarm Rate; WSN: Wireless Sensor Network; RPN: Risk Priority Number method.

This paper combines sensor technology, LoRa wireless sensor network technology, and GPRS (General Packet Radio Services) remote communication technology, and uses PHP (Hypertext Preprocessor) language and MySQL database to design a set of automated decision support systems for salt lake production. The system uses voltage, current and brine level inquired by sensors to establish a data classification model to determine the fault status of brine pumps. Moreover, the remote control function of the brine pump is realized by installing a remote controller in the distribution cabinet, which can send control commands via mobile phone and web browser. These can improve the accuracy of brine pumps and real-time monitoring data, reduce the risk of production, and save manpower costs.

The rest part is described as follows. First, Section 2 is about the system functional/technology requirements and system architecture design. Then it is implemented by information transmission, information acquisition and data classification models, respectively, in Section 3. Section 4 is for the tests, evaluation and performance of this system. Section 5 is for conclusions.

2. System Requirements Analysis and Architecture Design

This section analyzes existing problems of a salt lake chemical enterprise to clarify the goal, function and technology demand in the process of constructing a decision support system, which designs the overall architecture, functional structure and central database of the automated system.

2.1. Decision Support System Requirements Analysis

2.1.1. Field Observation and Interview

A field observation and an interview were conducted for brine mining in West Taijinar Saline Lake Resources Company, which is a famous saline lake chemical enterprise in Qinghai province. The interviews were conducted face-to-face with 5 production managers and 10 inspection workers over 7 days. All of the interviewees have over 3 years of working experience in the company. Each interview lasted for around 40 min, and interviewees were asked a series of questions about monitoring demands and functional requirements:

- What kind of monitoring equipment is used in the enterprise, which monitoring method is adopted, which parameters are monitored and what is the monitoring period?
- Whether the existing monitoring parameters can fully characterize the operation status of the brine pump, whether there is a new monitoring requirement for the brine pump, and which parameters should be added with the existing parameters to describe the operation status of these brine pumps.

- How do maintenance workers judge whether the brine pump is faulty or not, and how do they deal with the fault when the failure occurs?
- What kind of equipment is used to record dynamic monitoring data, static information, maintenance information and fault information?
- Where the enterprise intends to install the remote monitoring equipment and the number of items of equipment installed.

2.1.2. System Functional Requirements

From the field observation, the key problems in current production management and future needs are extracted and summarized as shown in Table 3. These key problems often caused the occurrence of brine pump failures that affected the production and economic benefits of the chemical industry.

Table 3. Existing problems and system requirements of salt lake chemical enterprises.

Existing Problems	Future System Requirements	Hierarchy of Needs
The manual inspection method is used to monitor the dynamic information of the brine pump, which has low efficiency and high human cost.	Automatic collection of dynamic information for the brine wells.	Information acquisition
Brine pumps are large in number (more than 300) and scattered in distribution (the distance between pumps is about 500 m), the desert environment is sandy, there is strong sun exposure and big diurnal temperature difference, and so the implementation of traditional monitoring methods is difficult.	Combined with long-range wireless communication technology to achieve acquisition and transmission of dynamic information.	Information transmission
There is no management information system to manage the data produced during the operation of the brine pumps and the production process of the chemical enterprises. The enterprise records the data by manual means, and it is easy to lead to errors due to the large amount of data and non-standard data.	Design and development decision support system to realize the management and maintenance of data such as static information, dynamic monitoring data of the brine pump, fault repair and mining status of the mining area.	Information management
There is no decision model to judge the operation status of brine equipment meaning users cannot identify and predict brine pump operating status.	The voltage, current and brine level of the equipment can be intelligently analyzed, which provides decision support for the analysis and judgment of the brine pump.	Data mining and decision support
As there are large distances, when the brine equipment fails maintenance workers cannot rush to the scene troubleshooting but can only rely on manual inspection periodically.	Using remote-control technology, through the mobile phone or Web browser to realize remote control of a pumping station and brine equipment.	Remote control

2.1.3. System Technical Requirements

As the underground brine is in the supersaturated state, the agitation and temperature change of brine will lead to corrosion and crystallization in the contact area between the liquid-level sensor and brine. Therefore, the liquid-level sensor needs to avoid direct contact with the brine in the measurement process; if it is unavoidable that it will contact directly with the brine, it is necessary to adopt anti-corrosion materials or take protective measures to ensure the normal operation of the liquid-level sensor. At present, common level measurement methods are divided into contact and non-contact: contact types including differential pressures, input type, etc. and non-contact types including laser, radar and so on. As shown in Table 4, the basic parameters of some common contact and non-contact level sensors are compared.

Table 4. Contact and non-contact liquid level sensors.

Measurement Method	Species	Range	Accuracy	Beam Angle	Brine Level Calculation Method
Non-contact	Laser sensor	0–30 m	±3 mm	—	$h = h_f$
	Radar sensor	1.5–40 m	±1 mm	4°	
	Ultrasonic sensors	0.9–40 m	±1 mm	6°	
Contact	Pressure Sensor	0–50 m	2 cm	—	$h = L_j - h_j$

The distribution structure and power supply characteristics of the brine wells are very consistent with the long-distance star topology of the LoRa network. That is, brine wells are distributed along a straight brine drainage which transports the brine mined by brine pumps to the brine storage tank. There are also a number of straight brine drainages distributed in the range of 10 km in an east–west span, 20 km from the north–south span, and there is no obscurity in the range of sight distance, and the interval between the brine wells is about 500 m. This means that the range of data transmission is at least 600 m for good operations. According to Table 1, that is why LoRa is chosen for data transmission. Furthermore, module SX1278 matches the technical requirements of sensors according to Table 5. The sink node uses STC12C5A60S2 as the micro controller because it matches the technical requirements of SX1278 according to Table 6. The maximum throughput that a single device can achieve is 37.5 bytes according to the datasheet [7]. Although the system is designed for so-called "real-time" monitoring, the actual latency constraints are somewhat flexible. For this purpose, select the 5-s latency time (from sensing to sending) as the actual timing constraint. Longer delays will provide greater flexibility in communication scheduling and power management opportunities. Its power source is provided by the far-end power plant in the factory. The 10 kV high-voltage electric power plant is transported to the near-end step-down transformer of the brine by the large distance. After being converted to 380 V AC, it is sent to the distribution room and assigned to the nearest three brine wells.

Table 5. Module SX1278 technical requirements for sensors [16].

Parameter	Minimum Settings	Recommended Settings	SX1278	Match
Range	600 m(Rural)	1000 m (Rural)	15,000 m (Rural)	√
Data Rate	2 kbps	10 kpbs	0.3–37.5 kbps	√
Band	433 MHz	433 MHz	433 MHz	√
Payload Length	12 bytes	16 bytes	64 bytes	√
AES 128 bits	AES decryption in software	Secure Element 2	AES decryption in software	√

Table 6. Module MCU technical requirements for SX1278 [16,17].

Parameter	Minimum Settings	Recommended Settings	STC12C5A60S2	Match
MCU * RAM *	8 KB	16 KB	16 K (Expandable)	√
MCU Flash	128 KB	256 KB	128 KB (Expandable)	√
AES * 128 bits	AES decryption in software	Secure Element 2	AES decryption in software	√
Radio DIO *s connected to MCU IRQ * inputs	DIO0, DIO1, DIO2	DIO0, DIO1, DIO2, DIO3	DIO0, DIO1, DIO2	√
SPI * (4 wires: SCK *, MOSI *, MISO *, NSS *)		Mandatory		√
RTC * (32.768 kHz XTAL *)	Recommended for accurate time keeping	Mandatory for Class B nodes and FUODA *	Recommended for accurate time keeping	√
IEEE * EUI *-64 (OUI *: 24 or 30 bits, SN *: 40 or 34 bits)		Mandatory		√

* MCU: Microcontroller unit; RAM: Random-access memory; AES: Advanced Encryption Standard; DIO: Digital in and out; IRQ: Interrupt request; SPI: Serial Peripheral Interface; SCK: Serial Clock; MOSI: SPI Bus Master Output/Slave Input; MISO: SPI Bus Master Input/Slave Output; NSS: Slave select; RTC: Real-Time Clock; XTAL: External Crystal Oscillator; FUODA: Firmware Upgrade Over The Air; IEEE: Institute of Electrical and Electronics Engineers; EUI: Extended Unique Identifier; OUI: Organizationally Unique Identifier; SN: Serial Number.

Therefore, according to the characteristics of the aforementioned brine mining area, as shown in Figure 1, the monitoring system architecture is defined, and three brine wells and their adjacent distribution room are defined in the form of star topology to construct wireless sensor networks. Among them, the sensor nodes are responsible for collecting the operational information of brine pumps, which are deployed in three brine wells respectively and powered by solar cells. The gateway node is then deployed in the nearest distribution room, which can be powered by the power distribution cabinet to realize the two-way data forwarding service between the LoRa network and the network server. The network server is responsible for MAC (Medium Access Control) layer processing, including sensor node online activation, adaptive rate selection, gateway management and MAC layer mode loading [18]; the application server mainly solves the problem of information data processing and service provision. The dynamic monitoring information from the network server is transferred into the decision support system for processing. The system can provide a wealth of services for all types of users through a variety of equipment, such as application status display, real-time warnings, and so on. Correspondingly, the working levels of the terminal nodes, the gateway, the network server and the application server on the LoRa hierarchical communication protocol are presented respectively.

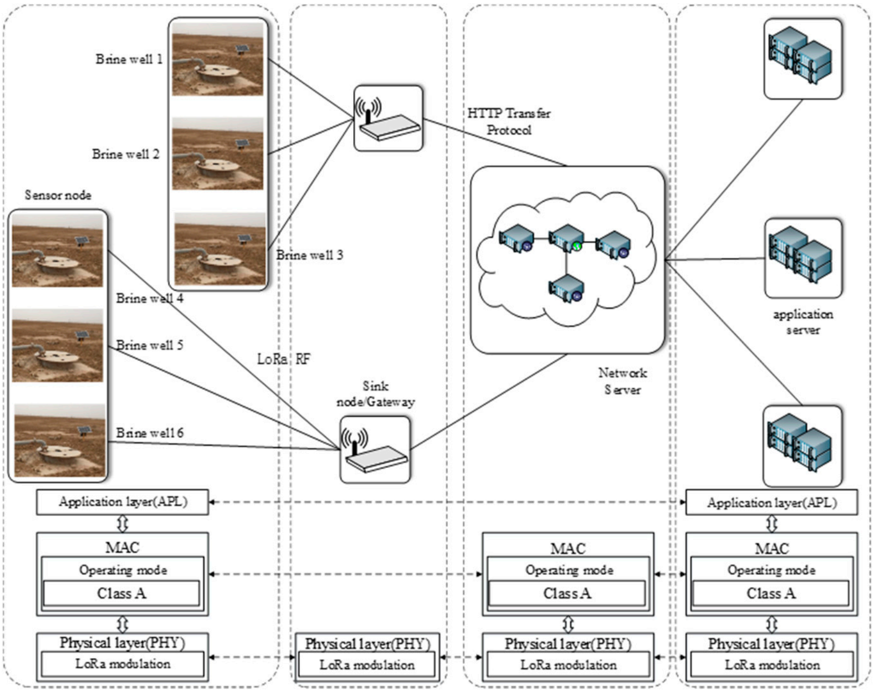

Figure 1. Wireless sensor network architecture based on LoRa.

2.2. Decision Support System Architecture Design

According to the analysis of the system requirements, the B/S mode (short for Web browser-Web server -database server) distribution structure is used to design the overall structure of the decision support system. This model simplifies the development, maintenance and the system by centralizing the core of system functions to the server. It mainly includes a data acquisition layer, data layer, application layer and UI (User Interface) layer, which is for displaying the fixed information of the pump station, dynamic monitoring information of the pump station, remote control and the running status prediction of the pumping station, and providing auxiliary decision for the automation and efficient operation of the pump station.

2.2.1. System Overall Architecture Design

This paper designs a decision support system which is based on a hierarchical structure, adopts software architecture, carries on the function level abstraction, establishes the frame model and technology, which can improve the stability, flexibility and robustness of the software system. Data warehouse (DW or DWH), a system for reporting and data analysis for brine pumps, is considered a core component of the decision support system. The model database is a template database that can be used as a template for building a database. It contains the basic objects, such as system tables, view tables, login information, and more. An algorithm library stores the core algorithm model of the decision support system. The central database (CDB) is a database that is located, stored, and maintained in a single location that is typically a central computer, such as a large server computer. The expert database contains data from questionnaire surveys of experts in the field. The knowledge base mainly stores knowledge rules about the failure of the brine pumps. Figure 2 shows the overall design architecture of this system.

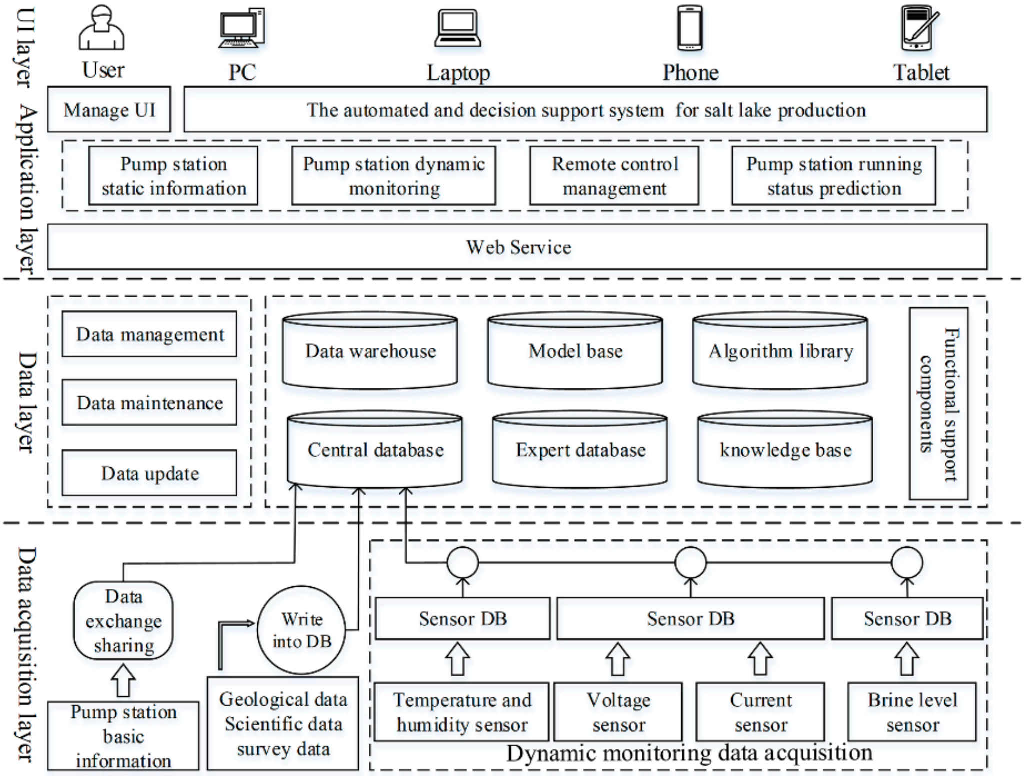

Figure 2. System architecture of decision support system.

2.2.2. System Functional Structure Design

The automated and decision support system based on IOT for the salt lake production is a platform for the management of salt lake automation decision management [19–22], and the functional framework of the decision support system is shown in Figure 3. It is composed of four subsystems: the pump station static information subsystem, pump station dynamic monitoring subsystem, remote control management subsystem, and pump station running state prediction subsystem. In this application system platform, the basic information of the pump station can be stored and queried, the operation status of brine pump can be analyzed and judged, and the running status of the brine pump can be controlled.

- Pump station static information subsystem: this includes the type of pump station, the location and the equipment in the pump station, such as the location of the brine wells and well depth, brine pump and mixed flow pump nameplate, downhole depth, manufacturers and purchase prices, etc.
- Pump station dynamic monitoring subsystem: this is responsible for collecting, transmitting, storing and processing information of the brine pump running status (voltage, current and liquid level of the brine well equipment) in the pump station, and entering the meteorological and geological information in the mining area.
- Remote-control management subsystem: this is in charge of remotely controlling and inquiring about the running status of the brine equipment. According to the early warning information received from the decision support system, staff can realize the control function of the brine equipment through two ways, mobile phone or Web browser.
- Pump station running state prediction subsystem: this provides monitoring data, fault information, basic information and other decision-making information for the management of the enterprise at all levels, in order to quickly and scientifically make appropriate decision-making programs. According to the operation status information (voltage, current and liquid level), the subsystem can carry out the early warning, which includes the system early warning and the

SMS (Short Message Service) warning to ensure that the warning information can be conveyed to the brine equipment maintenance personnel and management personnel. Among them, the system early warning is connected with the server in the web browser to pop up in the dialog box to notify the watch and management personnel; the SMS warning is through an SMS message in time to send early warning information to the early warning contact. After the user logs in to the system, they can set the early warning strategy, the early warning retransmission time, the alarm contact address book, and so on [23,24].

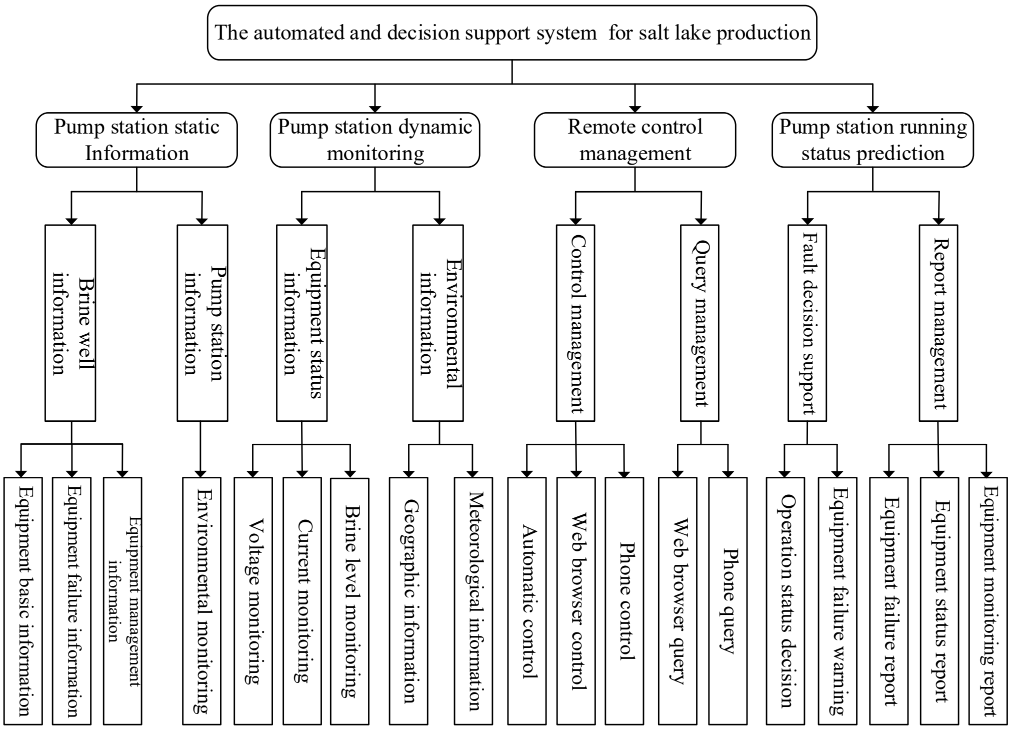

Figure 3. Functional framework of decision support system.

2.2.3. System Center Database Design

In the process of database design, we not only consider the system data requirements, but also the characteristics of the information of the brine mining production site and how to meet the management information system needs. Therefore, the following two points need to be considered: (1) information requirements: the user wants to get the information from the database content and their nature, which can decide what data is stored in the database [25]; (2) processing requirements: the user's requirement for processing functions, response time, and processing methods.

The system entity includes user rights, pump station maintenance information, pump station fault information, pump station static information, control equipment, data acquisition equipment, equipment warning information, equipment control information, pumping station monitoring information and plant meteorological information, combined with the functional requirements of the decision support system for salt lake production; the database is shown in Figure 4.

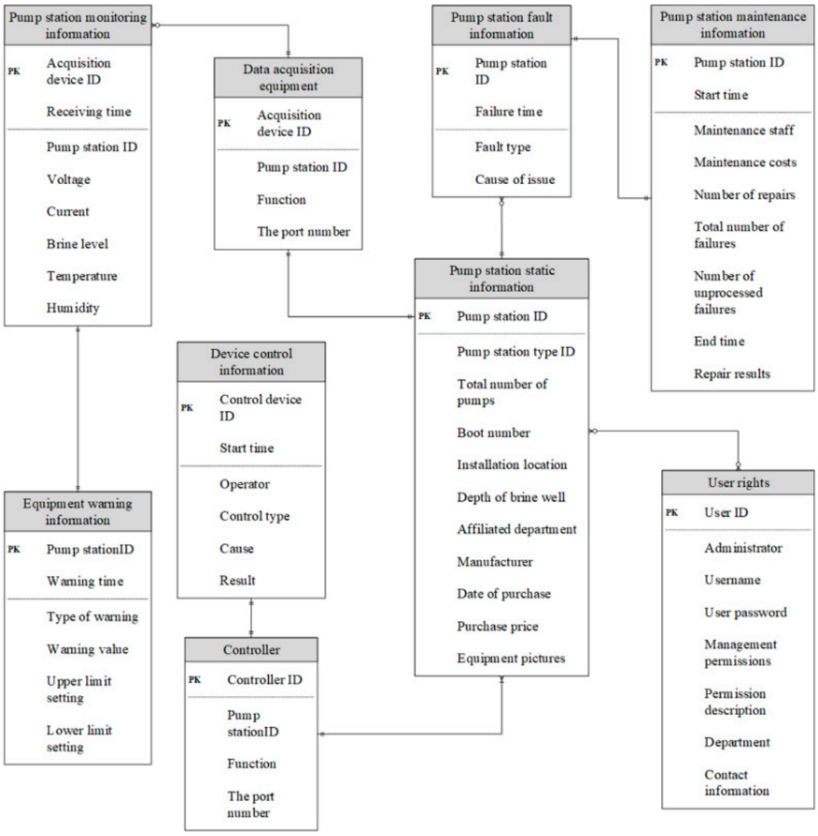

Figure 4. Entity relationship diagram for database.

3. Key Models of the Decision Support System

3.1. Measurement Model of Dynamic Liquid Level in Brine Well

For the salt lake chemical enterprise in Qinghai, the brine pumps and the mixed flow pumps are the key equipment for collecting and transporting raw brine. The running state stability of brine pumps has great influence on the production of the potash. In the brine mining process, a brine pump becomes damaged because staff do not discover in a timely manner that the liquid level in brine well is lower than the intake of brine pump, which interrupts production and causes human workload and economic loss. So it is critically important to measure and detect the liquid level in time and accurately. According to brine level monitoring requirements and application characteristics, this paper uses pressure sensors to monitor the brine level.

The Wheatstone bridge is responsible for sensing the brine pressure in the brine well and converting the pressure signal into a weak voltage signal to supply the signal conditioning circuit. The pressure sensor is made based on the piezoresistive effect of monocrystalline silicon for using impurity diffusion or an ion implantation method to form a force-sensitive resistor that is connected to the Wheatstone bridge, as shown in Figure 5 [26].

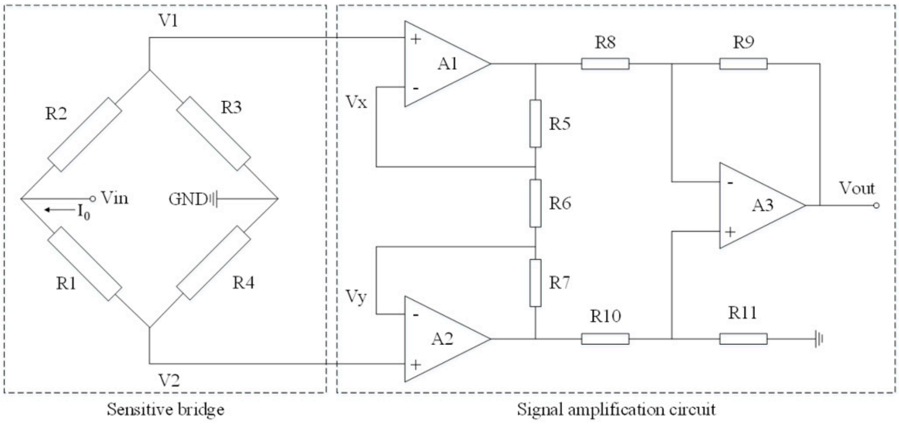

Figure 5. Wheatstone bridge and amplifier circuit.

(1) Dynamic model of pressure sensor sensitive bridge. The Wheastone bridge consists of 4 force sensitive resistors R_1, R_2, R_3 and R_4, where R_2 and R_4 have positive piezoresistive coefficients, and R_1 and R_3 have negative piezoresistive coefficients [27]. Compared with the constant voltage source power supply, the output of constant current source power supply has nothing to do with temperature. Therefore, when using a constant current source power supply, the bridge output is:

$$V_2 - V_1 = \frac{R_2R_4 - R_1R_3}{R_1 + R_2 + R_3 + R_4} \times I_0 \quad (1)$$

(2) Weak signal amplification model. Before the analog-to-digital converter samples the electrical signal from the sensitive bridge, the weak analog voltage signal must be amplified and filtered by a signal conditioning circuit so that the analog quantity is suitable for the voltage conversion range of the analog-to-digital converter. As shown in Figure 5, the signal amplifying circuit adopts a differential amplifier circuit with high input impedance, A1 and A2 are two in-phase operational amplifiers, and are then connected with the differential operational amplifier A3 in series to form a 3-amplifier differential amplifier circuit. The relative resistance in the circuit is strictly symmetrical. The model of a weak signal circuit amplification is shown below:

$$V_{out} = (V_2 - V_1)(R_5 + R_6 + R_7)/R_6 \quad (2)$$

(3) Mathematical model of analog digital conversion. The analog-to-digital converters are used for converting the 1~5 V analog voltage signal into a digital quantity of 0~2000 proportional to it, as the output supply to the microprocessor. Take the V_{REF} reference voltage, n bit precision analog-to-digital converter as an example. When the output data is increased by one, the analog input variable V_{out} is $V_{REF}/2^n$, and when the analog input is V_{out}, the formula for calculating the output data x is as follows:

$$x = \frac{V_{out}}{V_{REF}} \times 2^n \quad (3)$$

(4) Response output of pressure sensor. After the analog–digital conversion circuit, the pressure sensor output digital signal data range is 0~2000, corresponding to its range 0~FS (this paper selects the full range of the sensor 250 KPa). When the output data is x, the sensor pressure output is:

$$P = \frac{x}{2000} \times 250 \quad (4)$$

The pressure of the sensor is given by $P = \rho gh + P_0$. When the sensor is fed into the brine, the hydraulic pressure is introduced into the positive pressure chamber of the sensor. P is the brine hydraulic pressure. The atmospheric pressure P_0 in the air is connected with the negative pressure chamber of the sensor through the cable airway to cancel the P_0 on the front of the sensor so that the pressure of the sensor is ρgh. With the combination of (4), the measured value of the pressure sensor can be expressed as:

$$h = \frac{\frac{x}{2000} \times 250}{\rho g} \tag{5}$$

where, h is the depth of the pressure sensor in brine. ρ is the brine liquid density. g is the local gravity acceleration. The altitude in the Ge ermu region is about 2800 m, which has little acceleration when it comes to gravity. Therefore, the approximate value of g usually takes 9.8 $\mathrm{m/s^2}$.

3.2. Decision Model of Brine Pump Operation Condition

The operation status of a brine pump (fault state and normal running state) can be characterized by voltage, current and brine level, so that a data classification method is needed to establish a classification model for the above 3 categories of data and their descriptive attributes. Then, the classification model can be used to classify the data of the operation status of the brine pump, to identify and predict the operation status of the brine pump and to release the warning information to the saline lake chemical enterprise. At present, there are many theories and techniques for data classification, such as the naive Bayesian classification, support vector machine, rough set classification algorithm, decision tree, and so on. Therefore, the decision tree which is based on the ID3 algorithm is advantageous for having no need to master the application domain knowledge or parameter setting, has simple principles, suitable for dealing with large-scale learning problems, and is easy to transform into classification rules, which is more suitable for classifying the dynamic monitoring data of the brine pump [28,29].

3.2.1. Decision Model Architecture Based on Iterative Dichotomiser 3

The ID3 decision tree algorithm includes the master algorithm and the contribution algorithm, and combining the fault analysis of brine pumps, the establishment process of the fault prediction model of brine pumps based on the ID3 algorithm is shown in Figure 6. The running state training sampling set of brine pumps is composed of a subset of the normal operation state (positive example set) and a subset of the failure running state (negative example set), which are expressed as PE and NE, and their subsets PE′, NE′ and PE″, NE″, respectively.

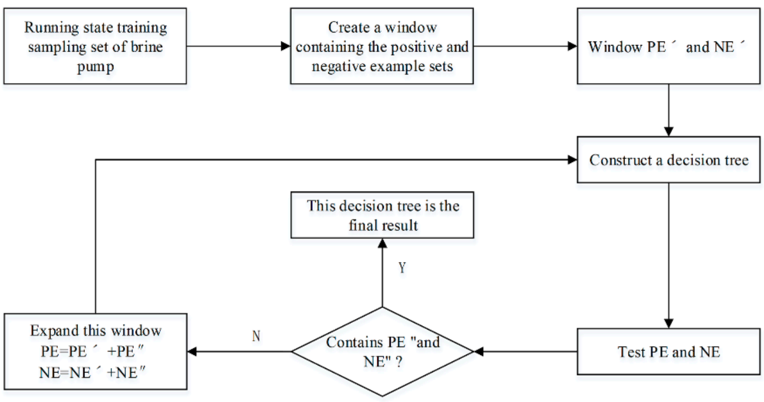

Figure 6. ID3 main algorithm flow chart.

The ID3 algorithm constructs a decision tree for the current window, and the decision tree is built as follows:

(1) Calculate the mutual information (information gain) of each description attribute for the positive example set and negative example set [30]. The calculation method is shown in Table 7.

Table 7. Mutual information of description attribute calculation method.

Category	Calculation Formula	Description
Information entropy (unconditional entropy)	$E(C) = -\sum_{i=1}^{u} p(c_i)log_2 p(c_i)$	The information entropy reflects the uncertainty of category attribute C
Conditional entropy	$E(C, A_k) = -\sum_{j=1}^{v} \frac{s_j}{n}\left(-\sum_{i=1}^{u} \frac{s_{ij}}{s_j} log_2 \frac{s_{ij}}{s_j}\right)$	The conditional entropy represents the classification ability of the category attribute C for the training data set S in the case of the known description attribute A_k
Mutual information (information gain)	$G(C, A_k) = E(C) - E(C, A_k)$	Mutual information is used to measure the extent to which attribute attributes are reduced

Note: $p(c_i) = \frac{s_i}{n}$ represents the probability that the attribute class c_i appears.

Assume that the training sample set is the relational data table S that contains n tuples and m + 1 attributes, whereby A_1, A_2, ..., A_m are the description attribute or condition attribute, and C is the category attribute. The category attribute C has u different values whose range is (c_1, c_2, ..., c_u). In the relation table S, the number of tuples whose category attribute is c_i ($1 \leq i \leq u$) is s_i. For the description attribute A_k ($1 \leq k \leq m$), the number of different values of it is v whose range is (a_1, a_2, ..., a_v). When the description attribute A_k is a_j ($1 \leq j \leq$ v), the number of tuples is s_j, so that in the sub-region where A_k is a_j, when the class attribute C is c_i, the number of tuples is s_{ij}.

(2) Select the maximum mutual information of description attribute A_k as the root node of the tree (or subtree).
(3) Divide tuples that take the same value at the description attribute A_k into the same subset, and take that value as a branch of this root node. The number of subsets equals the number of branches.
(4) Recursive call contribution algorithm for the above subsets.
(5) If the subset contains only positive or counter-examples, the corresponding branch is marked P or N.
(6) Repeat step (5) to check the unprocessed subset one by one until all subsets have marked the category (P or N).

3.2.2. Construction of Decision Tree Using Iterative Dichotomiser 3

Table 8 shows a set of training samples for the running status of the brine pump, where the 14 tuples are used as windows to derive the classification decision tree from the ID3 (Iterative Dichotomiser 3) algorithm.

Table 8. Brine pump running status-training sample set S.

Attribute Value	Description Attribute			Category Attribute
No.	**Current**	**Voltage**	**Brine Level**	**Failure**
1	Low	Medium	Low	P
2	Low	Medium	Medium	N
3	Low	Medium	High	N
4	Low	High	Medium	N
5	Medium	Low	Low	P
6	Medium	Low	Medium	P
7	Medium	Medium	Low	P
8	Medium	Medium	High	N
9	Medium	High	Low	P
10	Medium	High	Medium	N
11	High	Low	Low	P
12	High	Low	High	P
13	High	Medium	Medium	P
14	High	Medium	High	P

Since the attribute value of the ID3 algorithm is discrete and the current, voltage and brine level are continuous, it is necessary to discretize the attribute value by data transformation. The description attribute categories and its discretization rules are as follows:

- Description attribute 1: current, low (Less than 0.8 times the rating value I); medium (0.8 times the rating value ~1.2 times the rating value I); high (Greater than 1.2 times the rating value I).
- Description attribute 2: voltage, low (Less than −10% of the rated value U); medium (−10% of the rated value U ~10% of the rated value U); high (Greater than 10% of rated value U).
- Description attribute 3: brine level, low (less than 2 m); medium (2 m~5 m) high (higher than 5 m).

The decision tree for fault classification of the brine pump can then be built, which is described in Figure 7.

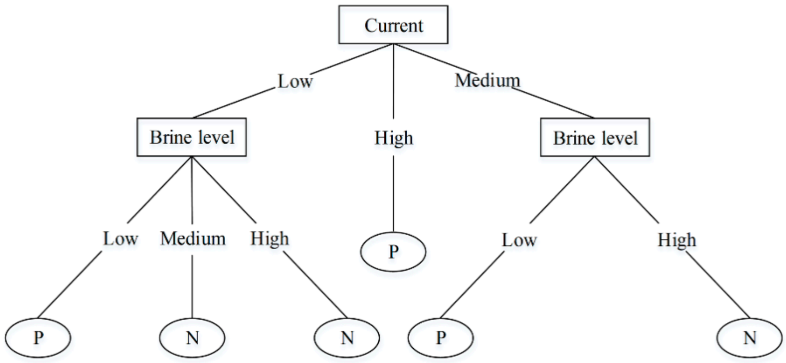

Figure 7. Decision tree for fault classification of brine pump.

3.2.3. Extract Classification Rules from Decision Tree

In order to establish a rule-based classifier, it is necessary to extract a set of rules to identify the key relationships between the description attribute and the category attribute in the data set. In this paper, an indirect method is used to extract the classification rules from the classification model of the running state of the brine pump. An IF-THEN classification rule can be created for each path from the root node to the leaf node, that is, one of the rules (the IF part) is formed along each path, each internal attribute-value pair (internal node-branch pair) item is formed, and the leaf node is formed after the rule (THEN part). For the status decision tree of a brine pump in Figure 7, it can be converted to the following IF-THEN classification rules, as shown in Table 9.

Table 9. Classification rules for brine pump failure.

No.	Antecedent of Rules	Consequent of Rules
1	IF the Current is "low" AND the Brine level is "low"	THEN the failure is "P"
2	IF the Current is "low" AND the Brine level is "medium"	THEN the failure is "N"
3	IF the Current is "low" AND the Brine level is "high"	THEN the failure is "N"
4	IF the Current is "medium" AND the Brine level is "low"	THEN the failure is "P"
5	IF the Current is "medium" AND the Brine level is "high"	THEN the failure is "N"
6	IF Current = "high"	THEN the failure is "P"

4. System Implementation, Test Evaluation and Discussion

This section mainly tests and evaluates the automated and decision support system based on IOT for salt lake production. A wireless sensor network adopts STC12LE5A60S2 as a microcontroller and LoRa wireless transceiver module as a radio front-end to complete the implementation of the wirless hardware and software of the acquisition node and gateway node [31,32].

4.1. System Implementation

4.1.1. Realization of Information Acquisition and Transmission

The composition of the wireless sensor nodes of the low-power network includes the micro-control unit STC12LE5A60S2 which shows the advantages of high-speed, low power consumption and high anti-jamming, LoRa RF front-end with long range wireless single hop communication, a dynamic information acquisition sensor (voltage, current and liquid level), and a solar power supply unit [33–35].

The sink node uses STC12C5A60S2 as the micro controller, and the LoRa wireless communication module as the RF front-end, as shown in Figure 8. In the implementation of the access network part, the GPRS module of the GPRS232-7S2 model is used as the gateway of the LoRa network, which is communicated with the microcontroller through the UART (universal asynchronous receiver/transmitter) port [36,37]. A power distribution room is responsible for the power supply of three adjacent brine pumps, and from the middle of the brine pump closer. Therefore, the gateway can be deployed in the distribution room, through the distribution cabinet to provide a constant power supply [38].

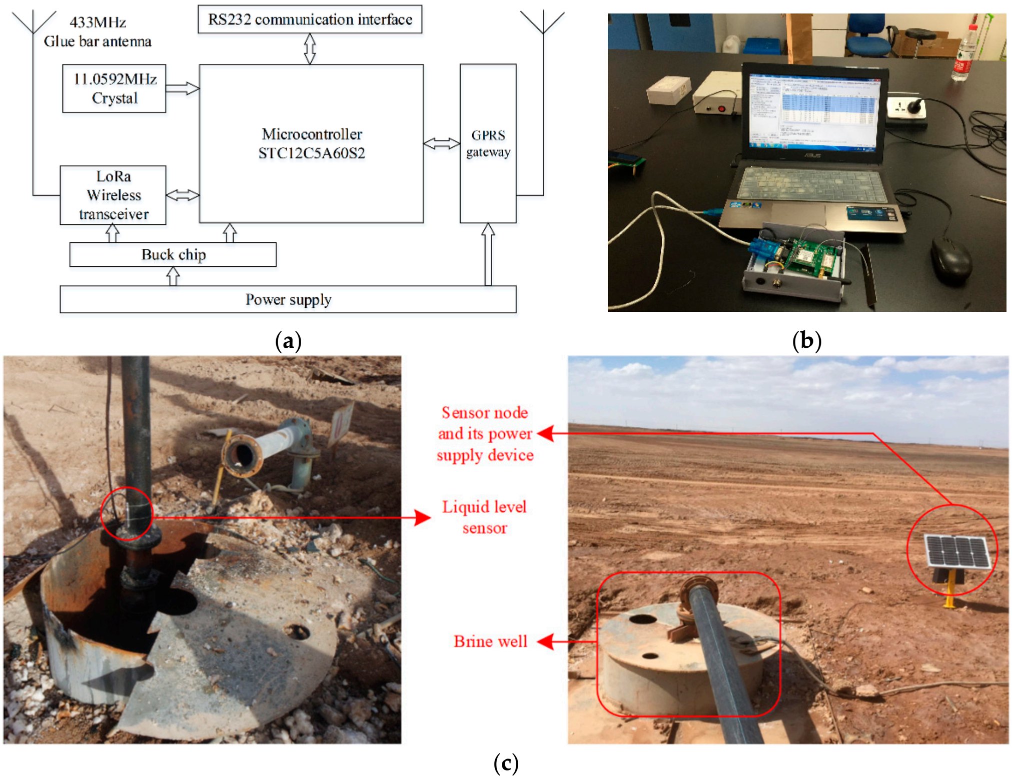

Figure 8. The implementation of gateway and installation of sensor nodes: (**a**) principle diagram of gateway; (**b**) gateway physical map; (**c**) physical diagram of sensor node installation.

4.1.2. Realization of the Decision Support System Software

The user of the brine pump static information management interface, as shown in Figure 9, can see the all the brine pump data of the current system, including equipment ID, equipment number, equipment category, affiliated companies, production companies, installation location and other basic information, and the equipment nameplate information.

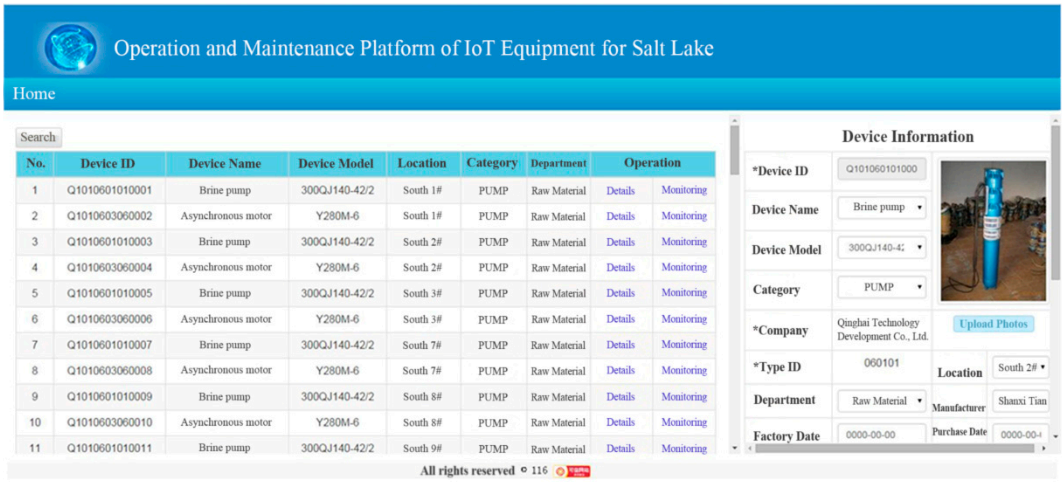

Figure 9. Device static information list.

In the dynamic monitoring interface, as shown in Figure 10, the user can view the dynamic curve and real-time data list of the brine pumps to monitor the current, voltage and brine level of the brine pumps.

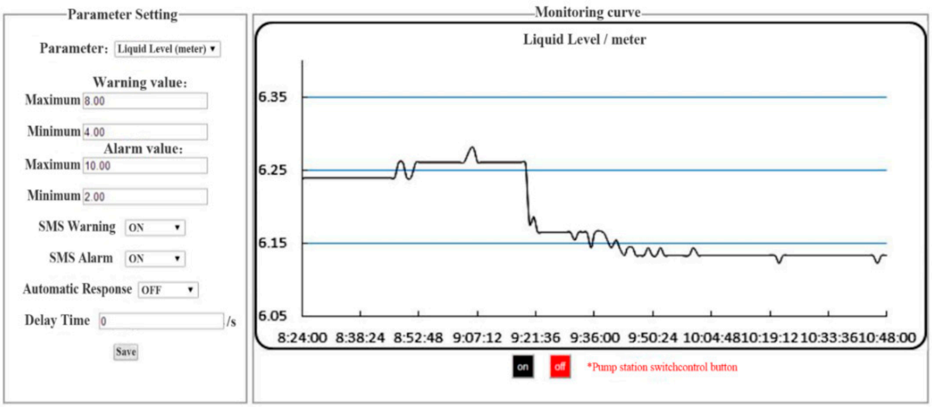

Figure 10. Dynamic monitoring information of brine pumps.

4.2. System Test and Evaluation

The decision support system based on IOT for brine pump management was tested and evaluated in West Taijinar Saline Lake Resources Company located in Qaidam Basin, Qinghai Province. In view of the actual deployment environment and system requirements of wireless sensor networks, the testing content included a communication coverage test of sensor nodes, a link quality test, and a reliability test of information acquisition and the transmission link.

4.2.1. Sensor Measurement Test

Figure 11 shows the results of the pressure sensor measurements. Three brine wells numbered 74, 75 and 79 were measured with the initial brine level of 6.37 m, 6.20 m and 1.88 m, respectively, and the height of the water surface is indicated clearly by the curve. As can be seen, from 9 to 12 o'clock in the morning, there is a clear drop in brine level, which is the same as field research. The results from the figure indicate that the system could display accurate brine level monitoring information. Furthermore, it could provide more effective safety guarantee for the brine pumps against the no-load operation.

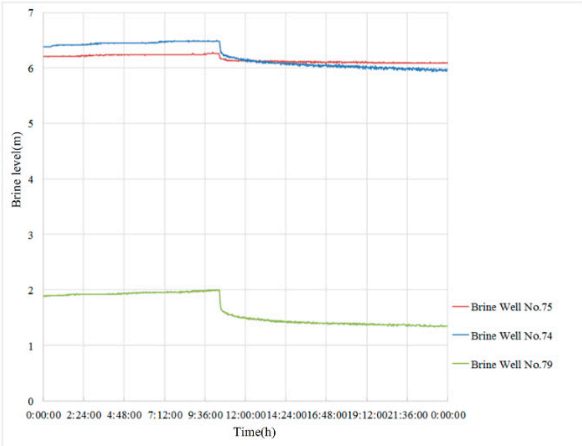

Figure 11. Measuring results of the brine level.

4.2.2. Reliability Test of Communication Link

Test scenario 1: Communication distance under the condition of constant transmit power

Considering that this is a new technology, although there are many technical extensions about LoRa, there is no practical experience in the use and effectiveness of this technology. The evaluation scheme is used as a practice exercise to familiarize LoRa with performance and reliability in a typical environment. The link-quality indicator (LQI) and RSSI are typically applied for measuring the quality of wireless links during the network operation. Since the LQI is calculated from the original RSSI, by linearly adjusting between the minimum and maximum defined RF power levels of the radio, the RSSI was measured to research how it affected the physical layer of the LoRa wireless network and how it is affected by the well-mining conditions [39,40].

In the paper, the wireless communication module with LoRa technology was used to test the coverage, and field tests were carried out to verify whether LoRa long-distance wireless communication performance meets the demand of communication distance in the brine mining area. A total of 14 different communication distances (50 m, 100 m, 150 m, . . . 650 m, 700 m) were set up to test the node packet loss rate and RSSI. The packet length was 20 bytes, the data volume was 300 frames, and the transmission period was 5 s. In order to make the test scene as close as possible to the actual installation, the sensor node was fixed on the device 1 m high from the ground.

As shown in Figure 12, the test results showed that the received signal strength decreased with the increase of communication distance, and the packet loss rate was increasing, which was consistent with other scholars' test and evaluation of LoRa wireless communication technology performance [34,41], although a different application environment will have different effects on link quality and packet loss rate. From the test results, the wireless sensor network based on LoRa technology can realize the reliability of communication in the harsh climate of the brine mining field and meet the practical application requirements.

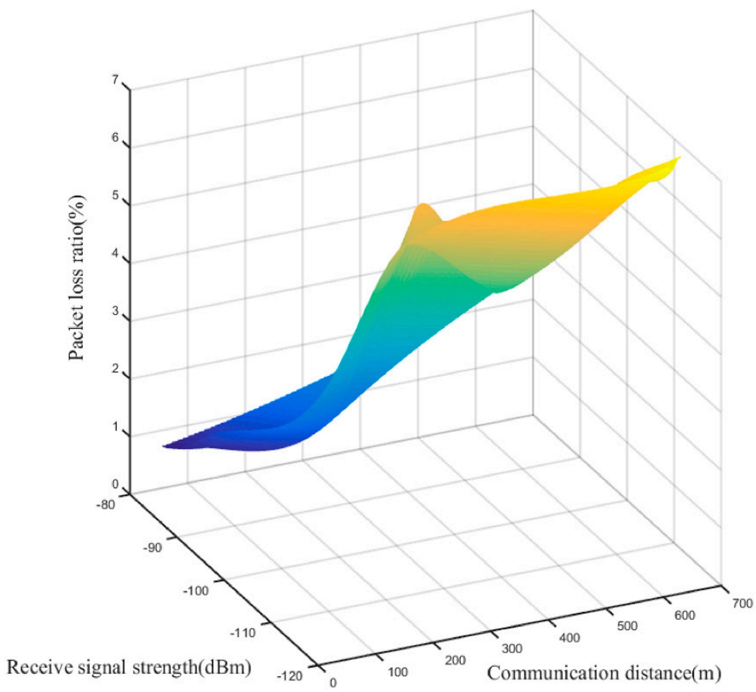

Figure 12. Influence of different communication distance on link quality.

Test scenario 2: Effect of transmitting power on link quality under communication distance

Because of the harsh environment (temperature difference and sandstorm) in the salt lake, the path loss of the communication channel is easily affected by the change of the surrounding environment when the communication distance is constant. The electromagnetic wave emitted by the sensor node is attenuated rapidly in the transmission process, and the gateway node cannot detect the signal wave and the decoded signal correctly when the signal intensity is reduced to below the receiver sensitivity, which results in a decrease in signal-to-noise ratio and an increase in packet loss rate. However, the wireless communication module with LoRa is a long-distance single-hop link, and there is no possibility of using multi-hop communication to generate longer links to improve the strength of the received signal. Therefore, the LoRa sensor node can adopt appropriate transmission power to improve the communication capacity of the LoRa network, which enable the gateway node to receive enough signal strength and ensure good reception quality when the channel environment deteriorates [31].

In the paper, the wireless communication module with LoRa is tested in 7 different transmission power to verify the influence of transmission power on link quality (the packet loss rate and RSSI of the sensor node) in the brine mining area. The packet length is 20 bytes, the data volume is 300 frames, and the transmission period is 5 s. In order to make the test scene as close as possible to the actual installation, the sensor node is fixed on the device 1 m high from the ground.

As shown in Figure 13, the test results show that as the node transmission power increases, the received signal strength tends to rise and the packet loss rate decreases. However, the higher the transmit power, the greater the power consumption of the node and the more the interference with other nodes in the environment. Therefore, the transmit power should be reduced as far as possible under the condition of satisfying the reliability of the communication.

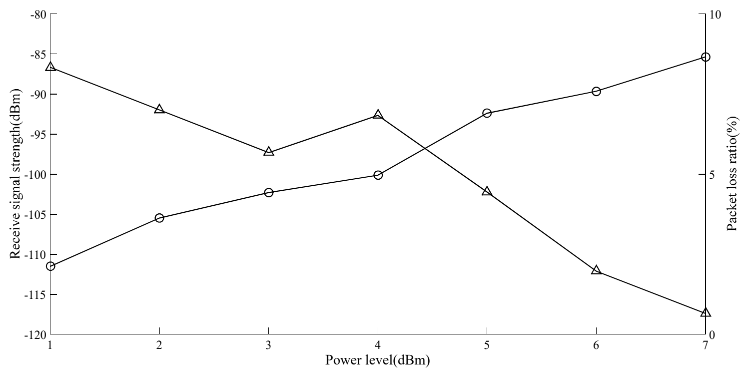

Figure 13. Influence of different transmitting power on link quality.

Test scenario 3: Reliability test of communication link based on LoRa and GPRS

The reliability of wireless links from sensor nodes to the server is evaluated by measuring the packet loss rate of the LoRa network within 30 days at the brine mines [41]. First, the sensor node transmits a 20-byte packet with a fixed transmission power of 15 dBm at a transmission interval of 60 s. Then, the GPRS gateway forwards data received from the sensor node to the server. Furthermore, during the evaluation, the sensor nodes did not request a confirmation message from the network service, nor did it use any mechanism to send the lost packet.

As shown in Figure 14, the packet loss rate of the communication link based on LoRa and GPRS fluctuates with time, and the quality of the channel varies greatly with different weather conditions. When windless or wind speed is small, the packet loss rate is 5%; but when the wind speed increases, the packet loss rate increases to 12.4%.

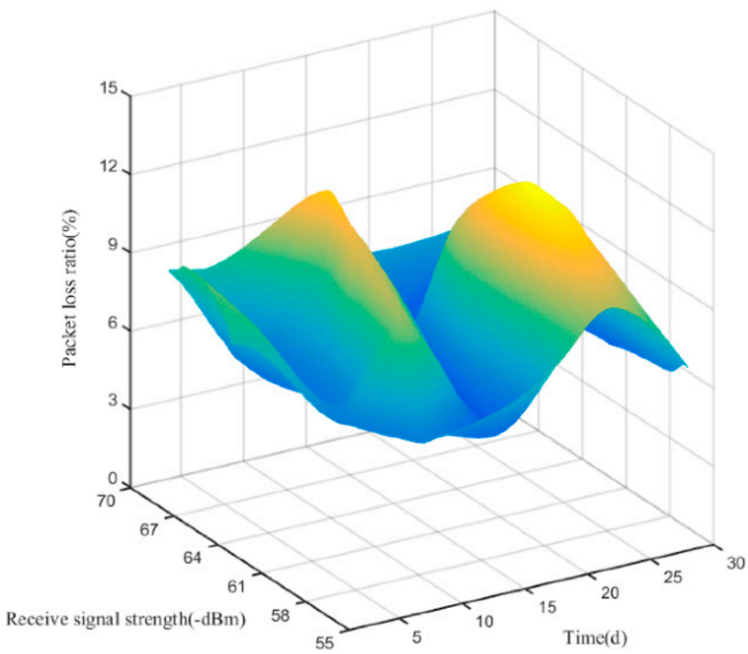

Figure 14. Communication link reliability based on LoRa and GPRS.

4.2.3. System Assessment Results

The use and technical performance of the system before and after implementation was evaluated, and the results are shown in Table 10. By inviting corporate managers and operators to participate in the system evaluation, we discussed the system performance and formed a consensus on how to develop the system to improve the efficiency of salt lake brine production management [42].

Table 10. Functional analysis before and after the implementation of the system.

Function	Before the Project	After the Project
Voltage monitoring	Manual inspection	Automated monitoring
Current monitoring	Manual inspection	Automated monitoring
Brine level monitoring	Manual inspection	Automated monitoring
Static information management	Paper record and manual input	management information service
Fault discrimination	Manual inspection	Decision support
Fault warning	Null	Real-time warning
Fault response	Manual inspection	Remote control

This research compares and analyzes the statistical data of brine pump failures before the implementation of the system (from July to October 2016) and after the implementation of the system (from July to October 2017). We cooperated with the factory workers to make sure that the brine pumps worked as usual after system implementation. Table 11 lists the number of failures and causes of the brine pump before and after the implementation of the system, respectively. Notice from Table 11, after the system is implemented, that through the comprehensive analysis of voltage, current and liquid level, the system can provide early warning of brine pump failure, and the number of burned down brine pumps is obviously reduced. However, because the ID3 algorithm based on the classification model is over-fitting, a small number of brine pumps were still burned.

Table 11. Fault analysis of brine pump before and after system implementation.

Date	Total Number of Failures	Causes of Failure and Number of Faults	Repair Results
25 July 2016–24 August 2016	12	No-load: 5 Electric leakage: 1 Impeller crystallization: 5 Non-full-phase: 1	Repair: 8 Burn out: 4
25 August 2016–24 September 2016	13	No-load: 5 low voltage: 4 Impeller crystallization: 4	Repair: 9 Burn out: 4
25 September 2016–24 October 2016	12	No-load: 6 Non-full-phase: 1 Impeller crystallization: 5	Repair: 7 Burn out: 5
25 July 2017–24 August 2017	6	No-load: 2 Impeller crystallization: 2 low voltage: 2	Repair: 4 Burn out: 2
25 August 2017–24 September 2017	7	No-load: 3 Impeller crystallization: 1 Electric leakage: 2 Non-full-phase: 1	Repair: 4 Burn out: 3
25 September 2017–24 October 2017	6	No-load: 2 Impeller crystallization: 3 Non-full-phase: 1	Repair: 4 Burn out: 2

5. Conclusions

For solving the problems of a lack of timeliness, slow fault response, high failure rate and high maintenance cost caused by manual inspection methods through a combination of sensor technology, LoRa wireless sensor network technology, and GPRS remote communication technology, this paper has proposed a decision support system through real-time monitoring. Using the PHP language and MySQL database technology, this research also has implemented the decision support system for salt lake production with the function of information management and fault diagnosis of brine pumps. The main conclusions of this research are as follows:

In the aspect of brine level acquisition, this paper designed a piezoresistive sensor with anti-corrosion characteristics. The signal response and processing models of the pressure sensor were established according to four aspects: signal acquisition, signal amplification, A/D (Analog-to-Digital) conversion and output response. At the same time, the static response characteristics of the pressure sensors were calibrated to improve the measurement accuracy and temperature stability of the liquid-level sensors.

Distinguishing whether the brine pump is at fault or not, this research establishes a data classification model by adopting the ID3 algorithm for the dynamic monitoring data of brine pumps. The key link between the description attribute of the dynamic monitoring data and the failure category of the brine pump is identified by the classification rule extracted from the decision tree classification model, which provides the corresponding decision for the early warning of the brine pump. This improves the equipment maintenance department's decision-making ability to improve the inspection efficiency of equipment, and reduce the failure rate and loss rate of the brine pumps.

The system was tested in a brine mining area for one month to verify the communication link reliability of LoRa sensor nodes and LoRa WAN wireless networks in a typical environment. The test results show that the wireless sensor network based on LoRa can provide a complete and accurate dynamic monitoring information of the brine pumps. It provides more effective safety guarantees for the management of brine pumps and fully meets the needs of the system.

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References

1. Yu, J.; Hong, R.; Gao, C.; Cheng, A.; Zhang, L. Pinnoite Deposit in DaQaidam Saline Lake, Qaidam Basin, China: Hydroclimatic, Sedimentologic, and Geochemical Constraints. *Minerals* **2018**, *8*, 258. [CrossRef]
2. Zheng, M.; Liu, X. Hydrochemistry of Salt Lakes of the Qinghai-Tibet Plateau, China. *Aquat. Geochem.* **2009**, *15*, 293–320. [CrossRef]
3. Kong, R.; Xue, F.; Wang, J.; Zhai, H.; Zhao, L. Research on Mineral Resources and Environment of Salt Lakes in Qinghai Province based on System Dynamics Theory. *Resour. Policy* **2017**, *52*, 19–28. [CrossRef]
4. Morillo, P.; Orduña, J.M.; Fernández, M.; García-Pereira, I. Comparison of WSN and IoT approaches for a real-time monitoring system of meal distribution trolleys: A case study. *Future Gener. Comput. Syst.* **2018**, *87*, 242–250. [CrossRef]
5. Jiang, X.; Zhu, T.; Kodama, T.; Raghunathan, N.; Alexeenko, A.; Peroulis, D. Multi-Point Wireless Temperature Sensing System for Monitoring Pharmaceutical Lyophilization. *Front. Chem.* **2018**, *6*. [CrossRef] [PubMed]
6. Shariff, F.; Rahim, N.A.; Hew, W.P. Zigbee-based data acquisition system for online monitoring of grid-connected photovoltaic system. *Expert Syst. Appl.* **2015**, *42*, 1730–1742. [CrossRef]
7. Cerchecci, M.; Luti, F.; Mecocci, A.; Parrino, S.; Peruzzi, G.; Pozzebon, A. A low power IoT sensor node architecture for waste management within smart cities context. *Sensors* **2018**, *18*. [CrossRef] [PubMed]
8. Suárez, J.I.; Arroyo, P.; Lozano, J.; Herrero, J.L.; Padilla, M. Bluetooth gas sensing module combined with smartphones for air quality monitoring. *Chemosphere* **2018**, *205*, 618–626. [CrossRef] [PubMed]
9. Wang, T.; He, Y.; Li, B.; Shi, T. Transformer Fault Diagnosis Using Self-Powered RFID Sensor and Deep Learning Approach. *IEEE Sens. J.* **2018**, *18*, 6399–6411. [CrossRef]
10. Ait Laasri, E.H.; Akhouayri, E.S.; Agliz, D.; Zonta, D.; Atmani, A. A fuzzy expert system for automatic seismic signal classification. *Expert Syst. Appl.* **2015**, *42*, 1013–1027. [CrossRef]
11. Ivasic-Kos, M.; Ipsic, I.; Ribaric, S. A knowledge-based multi-layered image annotation system. *Expert Syst. Appl.* **2015**, *42*, 9539–9553. [CrossRef]
12. Eesa, A.S.; Orman, Z.; Brifcani, A.M.A. A new feature selection model based on ID3 and bees algorithm for intrusion detection system. *Turk. J. Electr. Eng. Comput. Sci.* **2015**, *23*, 615–622. [CrossRef]

13. Collotta, M.; Lo Bello, L.; Pau, G. A novel approach for dynamic traffic lights management based on Wireless Sensor Networks and multiple fuzzy logic controllers. *Expert Syst. Appl.* **2015**, *42*, 5403–5415. [CrossRef]
14. Costea, C.R.; Silaghi, H.M.; Zmaranda, D.; Silaghi, M.A. Control System Architecture for a Cement Mill Based on Fuzzy Logic. *Int. J. Comput. Commun. Control* **2015**, *10*, 165–173. [CrossRef]
15. Petrović, D.V.; Tanasijević, M.; Milić, V.; Lilić, N.; Stojadinović, S.; Svrkota, I. Risk assessment model of mining equipment failure based on fuzzy logic. *Expert Syst. Appl.* **2014**, *41*, 8157–8164. [CrossRef]
16. Semtech SX1276/77/78/79 Datasheet. 2015, p. 132. Available online: http://www.mouser.com/ds/2/761/sx1276_77_78_79-1021978.pdf (accessed on 14 August 2018).
17. STC MCU Limited. STC12C5A60S2 Series MCU STC12LE5A60S2 Series MCU Data Sheet. 2011. Available online: http://www.buydisplay.com/download/ic/STC12C5A60S2(STC12LE5A60S2)-ENG.pdf (accessed on 14 August 2018).
18. Vangelista, L.; Zanella, A.; Zorzi, M. Long-range IoT technologies: The dawn of LoRaTM. *Lect. Notes Inst. Comput. Sci. Soc. Telecommun. Eng. LNICST* **2015**, *159*, 51–58. [CrossRef]
19. Cetinkaya, O.; Akan, O.B. A DASH7-based power metering system. In Proceedings of the 2015 12th Annual IEEE Consumer Communications and Networking Conference (CCNC), Las Vegas, NV, USA, 9–12 January 2015; pp. 406–411. [CrossRef]
20. Chen, Y.Y.; Wang, Y.J.; Jan, J.K. A novel deployment of smart cold chain system using 2G-RFID-Sys. *J. Food Eng.* **2014**, *141*, 113–121. [CrossRef]
21. ElShafee, A.; Alaa Hamed, K. Design and implementation of a WiFi Based Home automation system. *Int. J. Comput. Electr. Autom. Control Inf. Eng.* **2012**, *6*, 1074–1080. [CrossRef]
22. Mangalvedhe, N.; Ratasuk, R.; Ghosh, A. NB-IoT deployment study for low power wide area cellular IoT. In Proceedings of the 2016 IEEE 27th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC), Valencia, Spain, 4–8 September 2016. [CrossRef]
23. Bharati, P.; Chaudhury, A. An empirical investigation of decision-making satisfaction in web-based decision support systems. *Decis. Support Syst.* **2004**, *37*, 187–197. [CrossRef]
24. Alalwan, J.A.; Thomas, M.A.; Weistroffer, H.R. Decision support capabilities of enterprise content management systems: An empirical investigation. *Decis. Support Syst.* **2014**, *68*, 39–48. [CrossRef]
25. Khan, M.A.; Zeb, K.; Sathishkumar, P.; Ali, M.U.; Uddin, W.; Hussain, S.; Ishfaq, M.; Khan, I.; Cho, H.-G.; Kim, H.-J. A novel supercapacitor/lithium-ion hybrid energy system with a fuzzy logic-controlled fast charging and intelligent energy management system. *Electronics* **2018**, *7*, 63. [CrossRef]
26. Singh, R.; Ngo, L.L.; Seng, H.S.; Mok, F.N.C. A silicon piezoresistive pressure sensor. In Proceedings of the First IEEE International Workshop on Electronic Design, Test and Applications, Christchurch, New Zealand, 29–31 January 2002; pp. 181–184. [CrossRef]
27. Stornelli, V.; Ferri, G.; Leoni, A.; Pantoli, L. The assessment of wind conditions by means of hot wire sensors and a modifed Wheatstone bridge architecture. *Sens. Actuators A Phys.* **2017**, *262*, 130–139. [CrossRef]
28. Yan, R.; Ma, Z.; Zhao, Y.; Kokogiannakis, G. A decision tree based data-driven diagnostic strategy for air handling units. *Energy Build.* **2016**, *133*, 37–45. [CrossRef]
29. Sökmen, N.; Çebi, F. Decision-Tree Models for Predicting Time Performance in Software-Intensive Projects. *Int. J. Inf. Technol. Proj. Manag.* **2017**, *8*, 64–86. [CrossRef]
30. Umano, M.; Okamoto, H.; Hatono, I.; Tamura, H.; Kawachi, F.; Umedzu, S.; Kinoshita, J. Fuzzy decision trees by fuzzy ID3 algorithm and its application to diagnosis systems. In Proceedings of the 1994 IEEE 3rd International Fuzzy Systems Conference, Orlando, FL, USA, 26–29 June 1994; pp. 2113–2118. [CrossRef]
31. Wixted, A.J.; Kinnaird, P.; Larijani, H.; Tait, A.; Ahmadinia, A.; Strachan, N. Evaluation of LoRa and LoRaWAN for wireless sensor networks. In Proceedings of the 2016 IEEE SENSORS, Orlando, FL, USA, 30 October–3 November 2016; pp. 5–7. [CrossRef]
32. Kim, D.H.; Lim, J.Y.; Kim, J.D. Low-power, long-range, high-data transmission using Wi-Fi and LoRa. In Proceedings of the 2016 6th International Conference on IT Convergence and Security (ICITCS), Prague, Czech Republic, 26 September 2016; pp. 1–3. [CrossRef]
33. Zhang, C.; Fu, Y.; Deng, F.; Wei, B.; Wu, X. Methane Gas Density Monitoring and Predicting Based on RFID Sensor Tag and CNN Algorithm. *Electronics* **2018**, *7*, 69. [CrossRef]
34. Aref, M.; Sikora, A. Free space range measurements with Semtech LoRa^{TM} technology. In Proceedings of the 2014 2nd International Symposium on Wireless Systems within the Conferences on Intelligent

Data Acquisition and Advanced Computing Systems, Offenburg, Germany, 11–12 September 2014; p. 19. [CrossRef]
35. Augustin, A.; Yi, J.; Clausen, T.; Townsley, W. A Study of LoRa: Long Range & Low Power Networks for the Internet of Things. *Sensors* **2016**, *16*, 1466. [CrossRef]
36. Li, J.; Xie, J.; Yang, Z.; Li, J. Fault Diagnosis Method for a Mine Hoist in the Internet of Things Environment. *Sensors* **2018**, *18*, 1920. [CrossRef] [PubMed]
37. Liu, X.; Wang, F.; Zeng, Z. Design and Implementation of Indoor Environmental Quality Monitoring System based on ZigBee. In Proceedings of the International Conference on Computer Information Systems and Industrial Applications, Bangkok, Thailand, 28–29 June 2015; pp. 297–300. [CrossRef]
38. Casari, P.; Castellani, A.P.; Cenedese, A.; Lora, C.; Rossi, M.; Schenato, L.; Zorzi, M. The "Wireless Sensor networks for city-Wide Ambient Intelligence (WISE-WAI)" project. *Sensors* **2009**, *9*, 4056–4082. [CrossRef] [PubMed]
39. Tran, A.T.; Mai, D.D.; Kim, M.K. Link Quality Estimation in Static Wireless Networks with High Traffic Load. *J. Commun. Netw.* **2015**, *17*, 370–383. [CrossRef]
40. Baccour, N.; Koubâa, A.; Mottola, L.; Zúñiga, M.A.; Youssef, H.; Boano, C.A.; Alves, M. Radio link quality estimation in wireless sensor networks. *ACM Trans. Sens. Netw.* **2012**, *8*, 34. [CrossRef]
41. Petäjäjärvi, J.; Mikhaylov, K.; Yasmin, R.; Hämäläinen, M.; Iinatti, J. Evaluation of LoRa LPWAN Technology for Indoor Remote Health and Wellbeing Monitoring. *Int. J. Wirel. Inf. Netw.* **2017**, *24*, 153–165. [CrossRef]
42. Nolan, K.E.; Guibene, W.; Kelly, M.Y. An evaluation of low power wide area network technologies for the Internet of Things. In Proceedings of the Paphos, Cyprus, 5–9 September 2016; pp. 439–444. [CrossRef]