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A Motor Fault Diagnosis Method Based on Industrial Wireless Sensor Networks

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Abstract. Nowadays, with the development of the Internet of Things (IoT), the relationship between sensor manufacturing technology and wireless network communication technology is getting closer. It is a great direction that diagnosing motor fault using the sensors with information perception, data processing, and wireless communication capabilities. To reduce the memory requirements, and improve the accuracy and stability of the fault diagnosis, we propose a motor fault diagnosis method based on the industrial wireless sensor network. Our proposed method includes an early warning method based on Bloom filter and a fault diagnosis based method based on decision tree-Bayesian network. Simulation results show that our proposed early warning method can reduce the memory requirements compare to the tradinational early warning method based on a hash table. In addition, simulation results also show that our proposed fault diagnosis method can achieve higher diagnostic accuracy compared to the fault diagnosis method based on traditional Bayesian network and diagnostic Bayesian networks. Moroever, we evaluate our proposed method by experiments. Experimental results show that our proposed method can effectively solve the problem of information data uncertainty in the field of motor fault diagnosis, which verifies that our proposed motor fault diagnosis method can achieve high stability.

Keywords: industrial wireless sensor networks, motor fault diagnosis, Bloom filter, decision tree-Bayesian network

1 Introduction

In the production site of modern standard factory buildings, various large-scale motor equipment is widely deployed. Generally, the motor equipment has the following characteristics: large volume, high power, large data, high speed, high pressure, and high requirements for timeliness of operation and maintenance. In addition, the working environment for the motor equipment is usually in high temperature, high pressure/ultra-high pressure, easily corroded. The factors mentioned above may easily lead to the occurrence of sudden equipment failures, which may cause the cessation of industrial production, and bring great economic losses. Moreover, the continuity between the production chains of each production line is very strong in a complex industrial environment. Therefore, once the equipment fails, the production line will be completely stagnated, which seriously affects product safety and cause production accidents. Hence, it is necessary to develop a motor fault diagnosis method that can diagnose a motor fault with high accuracy.

Nowadays, with the development of the Internet of Things (IoT), the relationship between sensor manufacturing technology and wireless network communication technology is getting closer. It is a great direction that diagnosing motor fault using the sensors with information perception, data processing, and wireless communication capabilities. The application of wireless sensor networks in industrial production environments can solve a lot of problems of traditional wired networks, such as poor self-organization, weak self-adaptablity, weak inability to deploy flexibly, and poor scalability. Therefore, it is of great significance to study and apply the method of motor fault diagnosis based on an industrial wireless sensor networks.

In traditional fault diagnosis method, the host computer software stores the collected parameters through a hash table. A hash table is a data structure that implements an associative array abstract data type, a structure that can map keys to values. Its advantage is that whether the corresponding parameters exist in the historical record can be judged quickly by finding them from the hash table, to achieve quick and accurate early warning. However, the hash table occupies a large storage space. When the data set is large, the efficiency of the hash table

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method becomes low, and cannot be applied to the computers with limited memory. To solve this disadvantage, we propose an early warning method based on the Bloom filter, which occupies less memory and can diagnose fault quicker. In addition, there are some fault diagnosis methods based on traditional Bayesian network, Bayesian network diagnosis combing fault tree analysis method, decision tree diagnosis method, and neural network. The traditional Bayesian network diagnosis method is a fault diagnosis method based on Bayesian network inference. The Bayesian network diagnosis combing fault tree analysis method is a fault diagnosis method that combines a bottom-up fault tree with a Bayesian network fault diagnosis method. The neural network diagnosis method is a method of diagnosing motor faults through the training of the neural network. However, adopting a certain network model alone will have some drawbacks. To maximize the reliability and stability of the fault diagnosis system, a method combing decision tree and Bayesian network model, namely decision tree-Bayesian network model based motor fault diagnosis method is proposed. The main contributions of this paper are summaried as follows.

(1) To reduce the memory occupation and improve the reliability and stability of the motor fault diagnosis, we propose a motor fault diagnosis method based on industrial wireless sensor networks, which includes a motor fault early warning method based on Bloom filter and a motor fault diagnosis method based on decision tree-Bayesian network.

(2) We design a wireless sensor network-aided motor fault diagnosis system based on our proposed motor fault diagnosis method.

(3) We test our proposed motor fault diagnosis method using our designed motor fault diagnosis system, which verify that our proposed motor fault diagnosis method can reduce memory occupation, and effectively diagnose the motor fault.

The rest of this paper is organized as follows. Section 2 introduces the related work. Section 3 presents our proposed motor fault diagnosis method. Section 4 analyzes the performance of our proposed method evaluated by our designed motor fault diagnosis system. Section 5 concludes the paper.

2 Related Work

2.1 Motor Fault Diagnosis based on Wireless Sensor Network

As shown in Fig. 1, the structure of motor fault diagnosis based on the industrial wireless sensor network consists of two parts, i.e., wireless sensor network and fault early warning diagnosis. In the wireless sensor network, terminal nodes are deployed around the motor to collect data from the motor, and the coordinator node gathers the data collected by the terminal node and sending it to the fault warning diagnosis part. The fault warning diagnosis part includes the motor fault early warning and the motor fault diagnosis model. The workflow chat of the motor fault diagnosis based on the industrial wireless network is shown in Fig. 2.

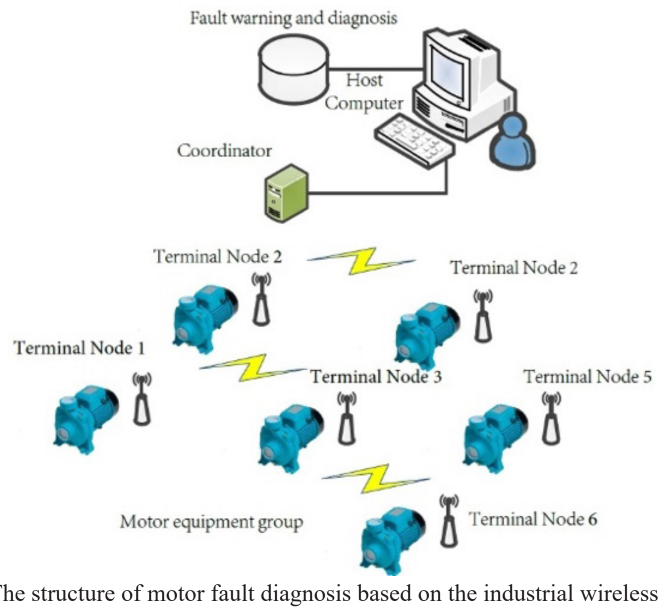

Fig. 1. The structure of motor fault diagnosis based on the industrial wireless network

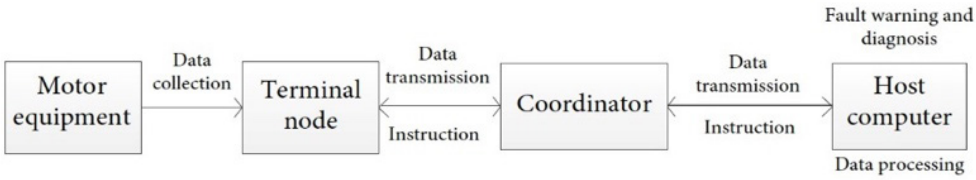

Fig. 2. Workflow chart

2.2 Communication Techniques

In recent years, the communication techniques used in motor fault diagnosis based on the industrial wireless network mainly includes Bluetooth, infrared data communication, WIFI technology, and Zigbee technology [1-3]. The comparison of the wireless communication techniques, including protocol standard, maximum transmission rate, energy consumption, and so on, is given in Table 1.

Table 1. Comparision of communication techniques

Parameters	Bluetooth	Infrared	WIFI	Zigbee
Protocol standard	IEEE802.15	Infrared	IEEE802.11	IEEE802.15.4
Maximum transmission rate	1M	16M	600M	250K
Energy consumption	Several days	Several days	Several hours	Several months
Transmission distance	10m	100m	50-100m	10-75m
Frequency（GHz）	2.4	/	2.4	2.4
Network characters	Point to side	Peer to peer	Ad-hoc	Star, tree, mesh
The number of network devices	7	2	32	65000

2.3 Existing Motor Fault Diagnosis Methods

(1) *D-S evidence theory*: The D-S evidence theory defines the trust function and basic probability distribution. When the electrical equipment is running, the same operating state may be generated before different faults occur, and the operating state shown when the fault occurs is not unique. D-S evidence theory is to solve the uncertainty problem of fault diagnosis, and the probability of each fault is expressed by the trust function Bel. Wireless sensor nodes collect operating data of motors and obtain the probability value corresponding to each kind of fault detected by each node, that is, the trust function of each kind of fault symptom. Then, the trust function value of each kind of fault symptom is processed based on the DS evidence theory. According to the fusion trust function value, the operating state of the motor is diagnosed to determine whether a fault has occurred [4-7].

(2) *Probabilistic reasoning method*: The probabilistic reasoning method is an uncertainty reasoning method based on the Bayesian method. It can effectively solve the uncertain problem of whether the event occurs. In the uncertainty problem, the uncertainty of whether an event occurs is universal. Hence, the probabilities reasoning method has a wide range of applications, such as motor fault diagnosis.

(3) *Bayesian network reasoning method*: The Bayesian network reasoning method is also a common fault reasoning method based on the Bayesian method. It is a probabilistic network. The Bayesian network is a directed acyclic graph, and each node has a probability distribution, which represents the dependence between the nodes. The Bayesian network can vividly describe the joint probability distribution among the nodes.

3 Motor Fault Early Warning and Diagnosis Methods

To reduce the memory occupation and improve the reliability and stability of the motor fault diagnosis, we propose a motor fault diagnosis method based on industrial wireless sensor networks, which includes a motor fault early warning method based on Bloom filter and a motor fault diagnosis method based on decision tree-Bayesian network. In the rest of this section, we introduce these methods sequentially.

3.1 Motor Fault Early Warning Method based on Bloom Filter

In this method, a Bloom filter for a motor is established firstly. The idea of this method is to put the collected data into the Bloom filter for filtering and judge whether the collected data exists in the blacklist of the Bloom filter.

The blacklist is the data when the fault occurred or to occur. If the collected data is on the blacklist, it will be judged that the motor is going to fault and an early warning will be given. As shown in Fig. 3, the establishment process of the Bloom filter can be summarized as follows.

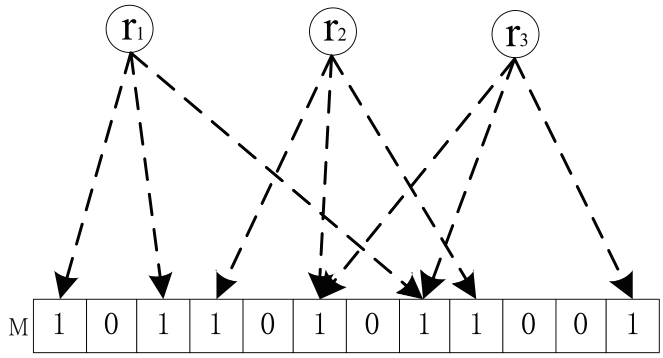

Fig. 3. Establishment of Bloom filter

(1) Generating a vector M with length m. We denote a hash function set and a category of fault blacklist as $H = \{h_1, h_2, \ldots, h_{k'}, \ldots, h_k\}$ and $R = \{r_1, r_2, \ldots, r_j, \ldots, r_1\}$, respectively. Generating Bloom filter using k hash functions.

(2) Setting the m values in vector M as 0, and set a counter $j = 1$.

(3) The j-th fault sample parameter is operated with k hash functions to obtain k hash values $h_1(r_j)$, $h_2(r_j)$, …, $h_{k'}(r_j)$, …, $h_k(r_j)$ with a value range in [1, $m-1$].

(4) Then, $\{h_1(r_j), h_2(r_j), \ldots, h_{k'}(r_j), \ldots, h_k(r_j)\}$ is expressed by the vector M. We define that the corresponding representative bit of $h_{k'}(r_j)$ in M is $m[h_{k'}(r_j)]$. If $m[h_{k'}(r_j)]$ is zero, then set it to 1; Otherwise, keep zero.

(5) If $j < j$, set $j = j + 1$, and go to step (3); Otherwise, the process is finished, which means that all elements in the fault blacklist are written into the Bloom filter.

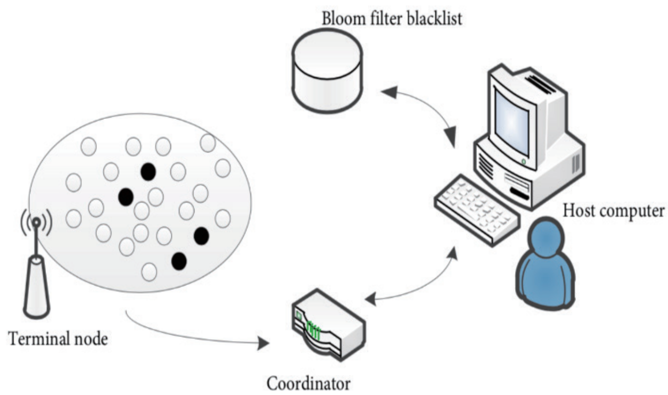

Fig. 4. Early warning process

As shown in Fig. 4, the work process of the proposed early warning method based on the Bloom filter can be summarized as follows. The operating parameters of the motors are collected firstly. Then, the collected data are is transmitted to the host computer software through the coordinator. Finally, host computer software performs the Bloom filter to determine whether the collected parameters are in the blacklist. The detailed early warning process is shown in Fig. 5, which can be summarized as follows.

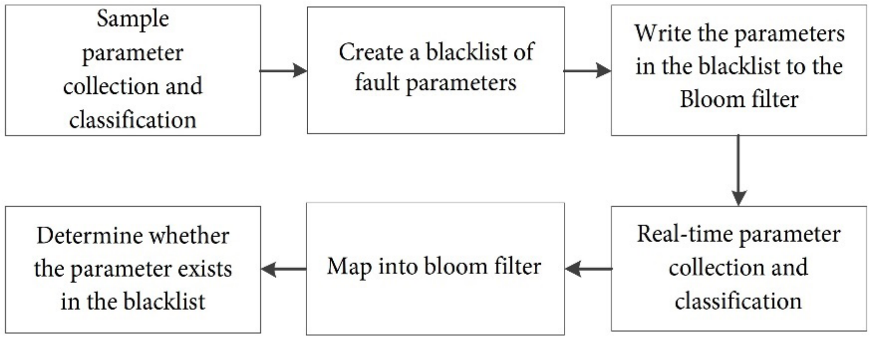

Fig. 5. The detailed early warning process

(1) The sample parameters when the motor is in a fault state are collected and classified firstly. The specific method of the sample parameters classification is summarized as follows. The classification method adopts the cosine similarity classification method of the law of cosines. First, the feature vector of each category is defined (the feature vector of each category is determined through the operation manual of the motor and the expert knowledge base), the parameters are vectorized, and then the cosine value between the parameter and the eignen-vector is calculated. Finally, the decision is made. When the cosine value is greater than the set threshold, it is determined that the parameter vector is acquainted with the eigenvector, that is, the parameter belongs to the category corresponding to the eigenvector. The specific cosine value can be derived by

$$S = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{x_1^2+x_2^2+\cdots+x_n^2}\times\sqrt{y_1^2+y_2^2+\cdots+y_n^2}}\ , \tag{1}$$

where x_i is the i-the lement in the parameter vector, y_i is the i-th element in the feature vector. Since each variable in the vector is a positive number, the value of the cosine is between 0 and 1. When the value of the angle between the two vectors is close to 1, the two vectors are similar and can be classified into one category. The above threshold can be set to 0.9.

(2) Selecting the fault sample parameters in each category, and build a blacklist of faults in different categories. The specific construct method is based on the Bloom filter that has been introduced above.

(3) Making an ID for each fault sample parameter in the fault blacklist, and map these Ids to the bloom filter of the corresponding category, which means that all the fault sample parameters in the fault blacklist are written into the Bloom filter of the corresponding category.

(4) Collecting real-time motor parameters and classify them. The specific classification method is shown in Eq. (1).

(5) Marking IDs for the real-time parameters in each category, and map these IDs to the Bloom filter of the corresponding category. If the value of all representation bits is 1, the real-time parameter is in the fault blacklist, that is, the real-time parameter is abnormal, then a warning of motor failure is issued.

3.2 Motor Fault Diagnosis Method based on Decision Tree-Bayesian Network

We propose a decision tree-Bayesian network model as the fault diagnosis and reasoning method in this paper, which combines the decision tree model and the Bayesian network model. Decision tree is a decision support tool that uses a tree-like model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. It is one way to display an algorithm that only contains conditional control statements. A Bayesian network is a probabilistic graphical model that represents a set of variables and their conditional dependencies via a directed acyclic graph. Assuming that the type of fault is F_1, F_2, F_3, …, F_m and the state set of motors is $S = \{S_1, S_2, S_3, \ldots, S_n\}$. As shown in Fig. 6, the basic idea of the fault diagnosis method is summarized as follows. First, collecting the original data when the motor fails by constructing an industrial wireless sensor network, and organizing and analyzing the state phenomenon when the motor fails, and build an expert knowledge base. Then, establishing the fault decision tree model, and calculating the prior probability $P(S_i)$, $P(F_m)$, $P(S|F_i)$, of each node in the decision tree according to the expert knowledge base. Then, the conditional probability $P(F_i|S)$ $(i = 1, 2, \ldots, m)(j = 1, 2, \ldots, n)$ is calculated using Bayesian formula. Next, the decision tree model is transformed into a decision tree-Bayesian network model according to the decision tree to Bayesian network model method; So far, the decision tree-Bayesian network fault diagnosis model proposed in this paper has been established. Next, collect the real-time data of the motor through the constructed industrial wireless sensor network, and use the expert knowledge base and work manual to determine the motor fault status phenomenon, and calculating the posterior probability of the occurrence of these fault status phenomena, and bring the status phenomenon nodes into the established decision tree-Bayesian network model uses the clump tree inference method to make inferences to form a fault type diagnosis report [8-10].

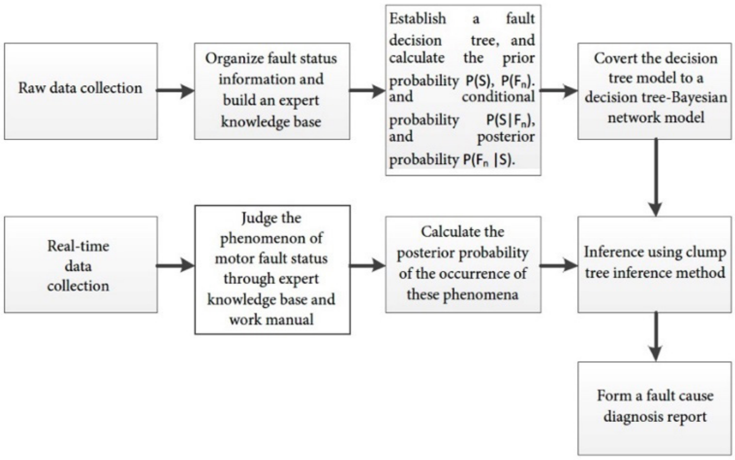

Fig. 6. Decision tree-Bayesian network model

As shown in Fig. 7, the implementation process of our proposed fault diagnosis is mainly as follows. The terminal node in the industrial wireless sensor network collects the real-time operating parameters of the motors. Then, the collected data is aggregated into the coordinator, and the coordinator uploaded the data to the host computer through communication technology. The host computer processes and analyzes the data, and inputs the processed data into the established decision tree-Bayesian network model for reason, and form a fault diagnosis report.

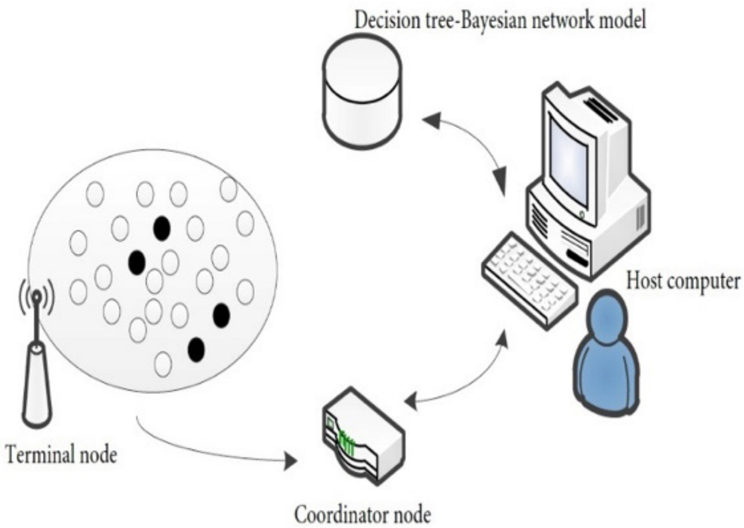

Fig. 7. Motor fault diagnosis method

When building a fault diagnosis model, first of all, we can know that the fault type of a motor can often be manifested by several different status phenomena through work experience. Table 2 shows the relationship between fault types and fault status phenomena.

Table 2. The relationship between fault types and fault status phenomena

Fault number	Fault types	Fault status phenomena
F_1	Low DC bus voltage	Phase voltage is abnormal (S_1)
F_2	UVW signal failure	UVW signal line is abnormal (S_2)
F_3	AB signal count failure	AB signal line is abnormal (S_3)
F_4	Z signal failure	Phase voltage is abnormal (S_1), Z siganal line is abnormal (S_4)
F_5	Motor power failure	Phase voltage is abnormal (S_1), Z signal line is abnormal (S_4), abnormal current detection (S_5)
F_6	ABZ signal failure	AB signal line is abnormal (S_3), Z signal line is abnormal (S_4)

The reasoning of the whole decision tree model is summarized as follows. Since the decision tree is a top-down tree, we can make the following reasoning according to the fault type and the occurrence phenomenon shown in Table 2.: If the state S1 occurs and the state S4 does not occur, then, a fault occurs F1 is more likely; if S1, S4, and S3 all occur, then failure F6 is more likely; if S1, S4 occurs, S3 does not occur, and S5 occurs, then failure F5 is more likely to occur; if only S1 and S4 occur, then the fault F4 is more likely to occur; if only the S2 state occurs, then the fault F2 is more likely to occur; if only the S3 state occurs, the fault F3 is more likely to occur. Then, the decision tree model is transformed into a decision tree-Bayesian network model. By analyzing the probability value of each node of the established decision tree-Bayesian network model, and combining the Bayesian network reasoning method to perform motor fault reasoning to determine the fault type of the current faulty motor.

4 Performance Evaluation

4.1 Boom Filter based Early Warning Method

We first evaluate the memory requirements for our proposed motor fault early warning based Bloom filter, and compare it to that based on a hash table by MATLAB. The numbers of data used for judgment are set as 500, 1000, 1500, 2000, 2500, 4000, 5000, 6000, 8000, and 100 million. In theory, Bloom filters account for about 1/8 of the hash table under the same storage amount. Comparing the memory usage of the Bloom filter based method and the hash table based method under the same storage amount, we can intuitively see from Fig. 8 that in the same situation, the memory usage of the Bloom filter based method is indeed much smaller compared with the hash table based method. Since the type of judgment data used is motor operating data, although the Bloom filter based method occupies more than 1/8 of the hash table based method under the same stored data in actual simulation, it is also good enough. In addition, because the time required to insert data and query data in the storage set in the Bloom filter is constant $O(k)$, compared with the method based on the hash table, the motor fault warning method based on the Bloom filter has advantages in both time and space.

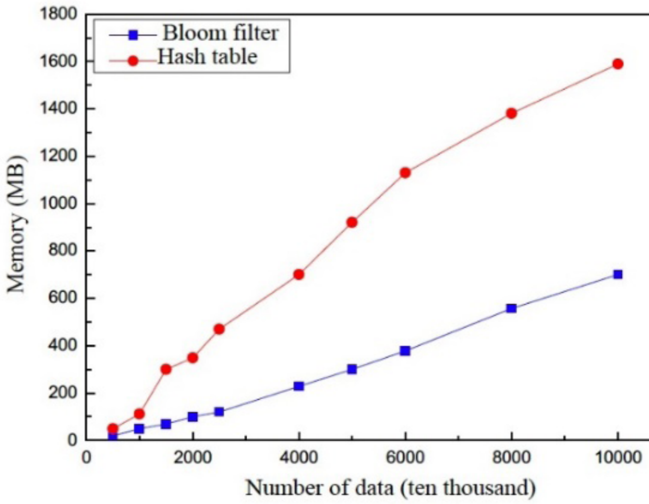

Fig. 8. Occupied memory

4.2 Motor Fault Diagnosis Method based on Decision Tree-Bayesian Network

We then evaluate our proposed motor fault diagnosis method based on the decision tree-Bayesian network and compare it to the traditional Bayesian network method, and the diagnostic Bayesian network based method. The diagnostic Bayesian network method is a method that combines the fault tree from the bottom to up and the Bayesian network fault diagnosis method. In the simulation, we use the same number of samples and the same experimental environment. Fig. 9 shows the diagnostic accuracy of each model under each sample. The number of diagnosis cases used in the simulation are 20, 70, 120, 170, 220, 2.7, and 3.2 million, respectively. The accuracy of three different diagnosis models is compared when the same number of cases was diagnosed. From Fig. 9, we can see that as the number of detected cases of the model increases, the diagnostic accuracy of all models is also continuously improved. The reason is that the network model can be adjusted well as the increase of the number of detected cases, which can improve the diagnose accuracy. The number of detected cases means that the number of times that we have detected. In addition, the diagnostic accuracy of our proposed decision tree-Bayesian network based motor fault diagnosis is higher than that of the traditional Bayesian network model because it is based on Bayesian inference that is good at the processing of uncertain problems. In addition, it can be seen from the figure that the diagnostic accuracy of the decision tree-Bayesian network model is higher than that of the diagnostic Bayesian network model because the decision tree-Bayesian network has a stronger learning ability compared with the diagnostic Bayesian network. In general, our proposed decision tree-Bayesian network model based fault diagnosis method has obvious advantages in diagnostic accuracy.

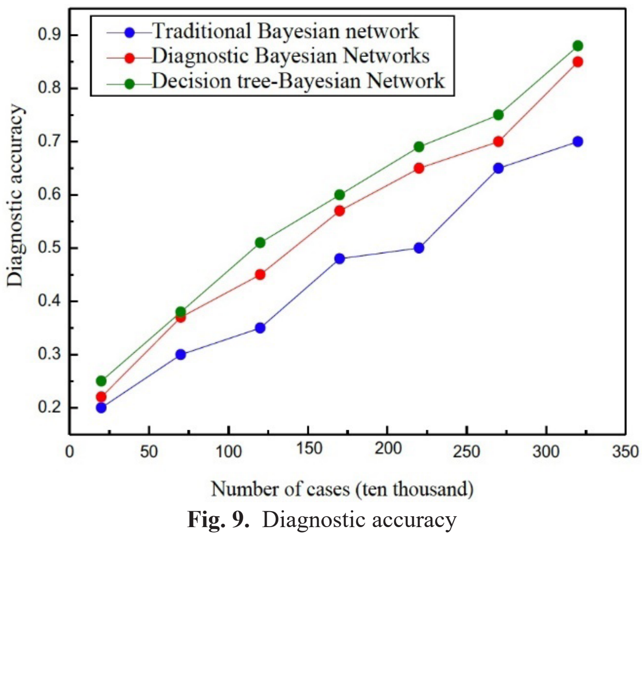

Fig. 9. Diagnostic accuracy

4.3 Overall System Test

To test our proposed methods, we build a star-shaped wireless sensor network as shown in Fig. 10. The hardware used in our system test includes a laptop with a windows 10 system, 15 designed wireless sensor nodes, an RS232 serial port data line, and an emulator. Among 15 designed wireless sensor nodes, there is one coordinator node, and the remaining nodes are terminal nodes. Firstly, we write the terminal and coordinator program to the terminal nodes and coordinator nodes, respectively. After the confirmation of network build, we diagnose the fault.

Fig. 10. Experimental deployment

The normal ranges of the fault status are summarized in Table 3 while the fault diagnosis results are shown in Table 4. Then, the following conclusions can be drawn from the experimental results.

(1) When the abnormal value of the phase voltage is greater than or equal to 0.36, the motor may fault with low DC bus voltage.

(2) When the abnormal value of the UVW signal line is greater than or equal to 0.1, the motor may have a UVW signal failure.

(3) When the abnormal value of AB signal line is greater than or equal to 0.69, the motor may have abnormal with AB signal counting failure.

(4) When the abnormal value of the phase voltage is greater than or equal to 0.43, and the abnormal value of the Z signal line is greater than or equal to 0.58, the motor may experience abnormal Z signal failure.

(5) When the abnormal value of the phase voltage is greater than or equal to 0.54, the abnormal value of the Z signal line is greater than or equal to 0.25, and the value of the abnormal current detection is greater than or equal to 0.46, the motor may have a motor power failure.

(6) When the value of AB signal line disconnection is greater than or equal to 0.21, and the value of Z signal line disconnection is greater than or equal to 0.32, the electrical equipment may have ABZ signal failure.

In summary, the motor fault diagnosis method based on the industrial wireless sensor network can effectively solve the problem of information data uncertainty in the field of motor equipment fault diagnosis, which means that our proposed method can make accurate decisions on the type of failures using the uncertainty data without fixed values collected by sensors.

Table 3. Normal ranges of fault status

Fault status	Normal rannges
Phase voltage is abnormal（S_1）	0.23-0.30
UVW signal line is abnormal（S_2）	0.04-0.06
AB signal linne is abnormal（S_3）	0.08-0.15
Z signal line is abnormal（S_4）	0.13-0.25
Current dection is abnormal（S_5）	0.02-0.05

Table 4. Fault diagnosis results

Types / Characteristic	F_1	F_2	F_3	F_4	F_5	F_6
S_1	0.36	0	0	0.43	0.54	0
S_2	0	0.1	0	0	0	0
S_3	0	0	0.69	0	0	0.21
S_4	0	0	0	0.58	0.25	0.32
S_5	0	0	0	0	0.46	0

5 Conclusion

The paper researched the motor fault diagnosis based on the industrial wireless sensor network. We proposed an early warning method based on Bloom filter, and a fault diagnosis based method based on decision tree-Bayesian network. Simulation results showed that our proposed early warning method can reduce the memory compared to a hash table. In addition, simulation results showed that our proposed fault diagnosis can achieve higher diagnostic accuracy. Moreover, we evaluated our proposed method by experiments. Experimental results showed that our proposed method can effectively solve the problem of information data uncertainty in the field of motor equipment fault diagnosis.

Acknowledgement

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