Fault diagnosis for wind power generation system based on association rule mining

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Abstract

This paper concentrates on the problem of fault diagnosis for wind power generation system, which is a crucial problem for wind power industry. Firstly, framework of the fault diagnosis system for wind power generation is presented. This framework is made up of two main parts, that is, "local device module" and "remote diagnosis center". In the local device module, wind turbines are connected to other servers through lower computers, and then data is transmitted to the remote diagnosis center. Furthermore, the remote diagnosis center can receive the data transmitted by the local devices and then discover faults by the proposed association rule mining algorithm. Secondly, in the proposed association rule mining algorithm, the opportunity and effectiveness of a specific rule is represented as the number of chances to utilize this rule and the average utilization ration of this rule, and then the rules with higher probability are preserved to conduct the Fault Diagnosis. Finally, specific wind power generation equipment is used to test the effectiveness, and experimental results show that the proposed method can discover different kinds of faults in the power generation system with high accuracy.

Keywords: wind power generation system, fault diagnosis, association rule mining, support, confidence

1 Introduction

Wind power is an important way to use the wind energy, striving to develop clean energy (e.g. wind power) is a strategic method of the government. Wind electric technical equipment construction is belonged to wind power industry [1]. As far as we know that countries around the world have taken many effective measures to enhance the development of domestic wind power technology and equipment industry [2]. In recent years, China's wind power technology and wind power generation equipment has developed fast. Particularly, a great deal of high quality wind electrical equipment constructing enterprises have appeared in China. Moreover, according to statistics yearbook of China (2010), China's installed capacity of wind power positions at the first location in the world [3-6].

However, areas with rich wind energy resources are generally more far from cities and locate in rugged environment [7, 8]. Particularly, wind turbines distribution is more dispersed with more monitoring parameters, which may greatly influence the control of the wind power system. To fully utilize wind power generation, we should take effective measures to detect faults in wind power generation system [9]. If the faults in wind power generation can be discovered in time, we can effectively improve the reliability of wind farm operation [10].

The main creative ideas of this paper lie in that we introduce the association rule mining technology in wind power generation system fault diagnosis. Association rule mining is belonged one of the typical data mining technologies, and data mining is a very hot research field in the field of computer science [11-12]. The objective of data mining aims to discover comprehensible, useful, and non-trivial knowledge from large-scale datasets. Association rule mining denotes the searching attribute - value conditions which may happen with high frequency together in a same dataset. Association rule mining can extract the close relationships between data elements in transactional data, and it has been successfully utilized in many applications such as Smoking cessation treatment, Privacy Preserving, Composite Granules, Regional Pharmacovigilance Center, Determine promising secondary phenotyping hypotheses, Software defect prediction, semantic image classification .

2 Framework of the fault diagnosis system for wind power generation

In this section, we will show the architecture of our fault diagnosis system (shown in Figure 1). As the wind turbines almost locate in remote areas, we install the diagnosis center using the remote control mode.

As is shown in Figure 1, in the local device module, several wind turbines are connect to other servers via lower computer, and then data is output to the remote diagnosis center after being processed by some local servers. On the other hand, remote diagnosis center can receive the data transmitted by the local devices. Furthermore, our proposed algorithm is implemented in the overall diagnosis server, which works with the support of "Diagnosis center workstation", "Remote database servers" and "Remote Web server".

3 Association rule mining based fault diagnosis for wind power generation system

Association rule mining uses two frequency based measures, that is, support and confidence. Support is represented as $\sup(A \to C)$, which denotes the ration of particular transactions including both A and C. On the other hand, confidence is represented as $conf(A \to C)$, which refers to the strength of a rule. Then, an association rule can be represented by the following equation:

$$\{a_1,a_2,\cdots,a_m\}\rightarrow\{c_1,c_2,\cdots,c_n\}(s\%,c\%),\qquad(1)$$

where $s\%$ and $c\%$ mean the support and confidence respectively.

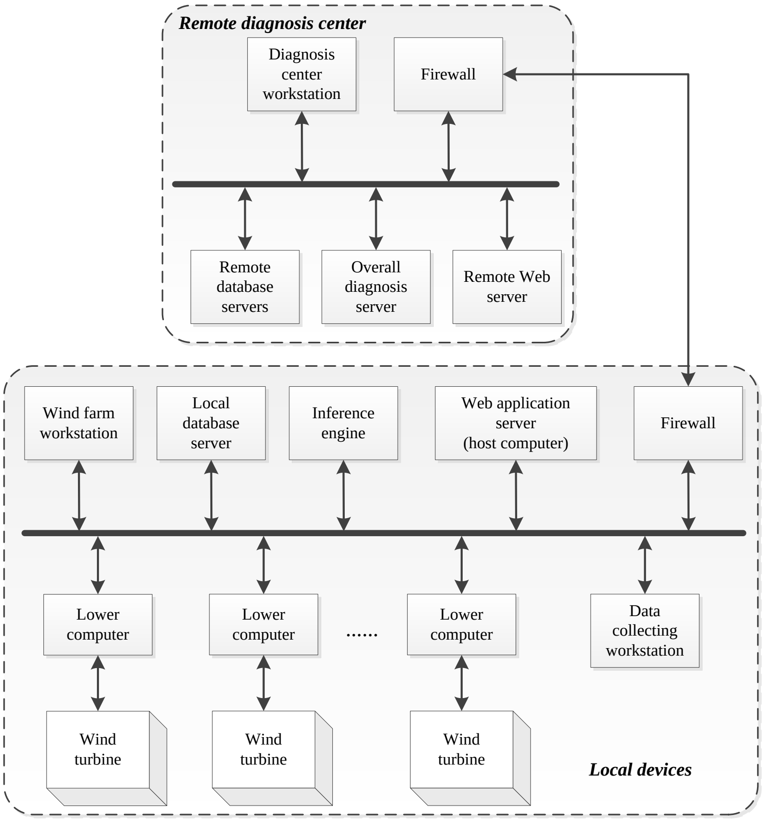

FIGURE 1 Framework of the fault diagnosis system for wind power generation

Supposing that $R=\{r_1,r_2,\cdots,r_n\}$ refers to a set of records, in which each one is characterized by a set of attributes $(a_1,a_2,\cdots,a_m)$. In there are $N(R_k)$ chances to utilize the k^{th} rule R_k, the expected utilization rate is $E(R_k)$. Then for the l^{th} application, its expected utilization rate can be represented as follows.

$$E(R_k)=\sum_{l=1}^{N(R_k)}E_l(R_k)=\sum_{l=1}^{N(R_k)}\left(U_l(R_k)\cdot P_l(R_k)\right),\qquad(2)$$

where $U_l(R_k)$ and $P_l(R_k)$ are the utility and the probability of the rule R_k in the l^{th} application. To make the problem be easier, we assume that each application has the same probability, and then $E(R_k)$ can be represented as follows.

$$E(R_k)=P_l(R_k)\cdot\left(\sum_{l=1}^{N(R_k)}U_l(R_k)\right),\qquad(3)$$

Afterwards, the element $\sum_{l=1}^{N(R_k)}U_l(R_k)$ can be converted to the product of the application chance number $N(R_k)$, and the average utilization ratio of the rule R_k can be represented as $avg(U_l(R_k))$. Hence, $E(R_k)$ can be calculated as follows.

$$E(R_k)=N(R_k)\cdot avg(U_l(R_k))\cdot P(R_k).\qquad(4)$$

Moreover, the opportunity and effectiveness of a specific rule can be illustrated as the number of chances to exploit this rule and the average utilization ration of this rule. Hence, expected utilization rate $E(R_k)$ can also be represented as follows.

$$E(R_k)=Op(R_k)\cdot Ef(R_k)\cdot P(R_k),\qquad(5)$$

where $Op(R_k)$ and $Ef(R_k)$ refer to the opportunity and effectiveness of the rule R_k respectively. Next, in our fault diagnosis for wind power generation system, a rule's probability can be represented as the confidence as follows.

$$E(R_k)=|T|\cdot\sup(R_k)\cdot e\cdot conf(R_k),\qquad(6)$$

where $|T|$ is the number of items in the transaction database, $\sup(R_k)$ and $conf(R_k)$ denote the support and confidence of R_k respectively, and the rules with higher probability are preserved.

As is shown in Figure 2, we represent the above association rule mining algorithm in a flowchart. In this flowchart, the association rule mining process is made up of three steps, and then association rules for wind power generation fault diagnosis can be mined.

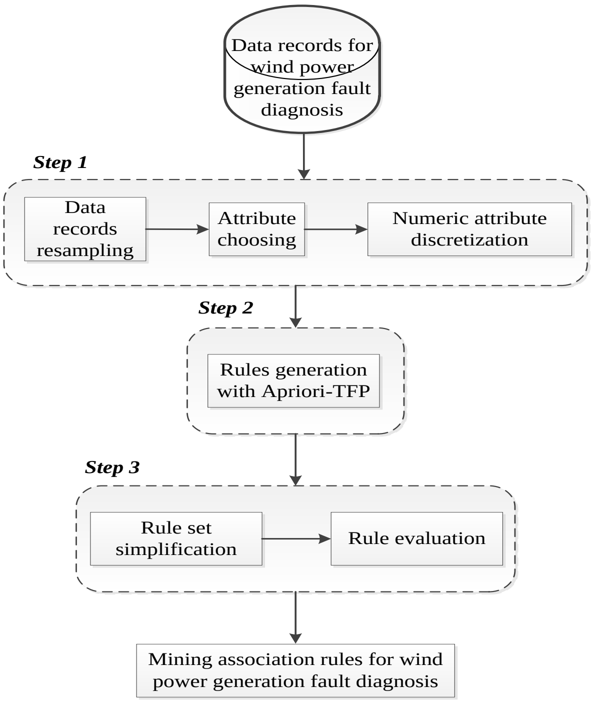

FIGURE 2 Flowchart of the association rule mining process

4 Experiment

In this section, we conduct experiments to verify the proposed algorithm using a specific wind power generation equipment, and the parameters of this equipment are listed in Table 1.

Afterwards, we extract five kinds of items from the fault transactions, that is, I_1: Host shutdowning by overcurrent, I_2: Faults in the wind turbines, I_3: Faults in the Governor, I_4: Host sudden stopping, I_5: Faults in host communication. In this experiment, the minimum support degree is equal to 0.22, and we choose a frequent item set $L=\{I_1,I_2,I_5\}$ with minimum confidence 0.7 as an example to demonstrate the performance of our algorithm. Thus, the association rules is generated by L, and the non-empty sub-set of L include $\{I_1,I_2\}$, $\{I_1,I_5\}$, $\{I_2,I_5\}$, $\{I_1\}$, $\{I_2\}$, $\{I_5\}$. In Table 2, some items in the fault transaction database are provided.

TABLE 1 Parameters of wind power generation equipment used in this experiment

Parameter	Mechanical (W)	Rotor flux (Wb)	Generator power (V/A)	Friction coefficient
Value	39800	0.195	39800	0.001875
Parameter	Pitch angle	Optimal tip speed ratio	Stator resistance	Fan radius R (m)
Value	0	7.8	0.05	16
Parameter	Inductance (H)	Wind speed range (m/s)	Pole logarithmic (P)	Maximal wind power utilization coefficient
Value	0.000578	$[5-12]$	32	0.46

TABLE 2 Parts of the fault transaction database

ID	List of the items
1	I1, I2, I5
2	I2, I3
3	I2, I4
4	I1, I4
5	I1, I2, I3, I5
6	I1, I2, I4
7	I1, I3
8	I1, I2, I3
9	I2, I5
10	I4, I5

Using the above wind power generation equipment and the fault transaction database shown in Table 2, we use the proposed algorithm to mine some association rules in Table 3.

TABLE 3 Association rules mined by the proposed algorithm

Association rule	Confidence degree
$I_1 \wedge I_2 \Rightarrow I_5$	0.5
$I_1 \wedge I_5 \Rightarrow I_2$	1
$I_2 \wedge I_5 \Rightarrow I_1$	1
$I_1 \Rightarrow I_2 \wedge I_5$	0.4
$I_2 \Rightarrow I_1 \wedge I_5$	0.3
$I_5 \Rightarrow I_1 \wedge I_2$	1

Next, we integrate the experimental results together to evaluate the precision of the fault diagnosis for the wind power generation system, and the experimental result is shown in Figure 3.

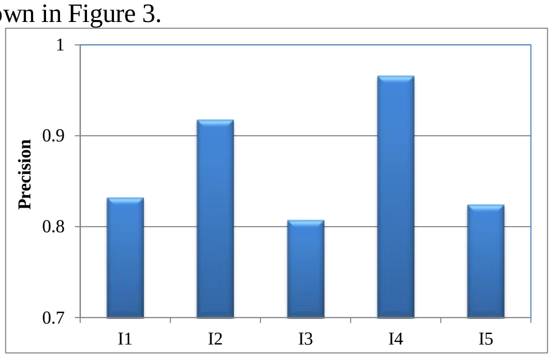

FIGURE 3 Fault diagnosis precision for the wind power generation system

Figure 3 demonstrates the precision of fault diagnosis for the wind power generation system, the average fault diagnosis precision is 86.9%. Hence, it can be seen that our method can detect faults in the power generation system with high accuracy.

5 Conclusions

In this paper, we study on how to discover fault diagnosis in wind power generation system. The framework to detect fault diagnosis consists of two modules: "local device module" and "remote diagnosis center". In the local device module, wind turbines are connected to other servers through lower computers. The remote diagnosis center is designed to receive the data from the local devices and faults can be discovered by the proposed association rule mining algorithm. Particularly, in the proposed algorithm, the opportunity and effectiveness of a given rule is represented as the number of chances to utilize this rule and the average utilization ration of this rule, and then the rules with higher probability are used to implement the fault diagnosis.

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