The research of elevator health diagnosis method based on Bayesian network

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Abstract. Elevator, as a complex mechanical system, is hard to determine the factors that affect components’ status. In accordance with this special characteristic, the Elevator Fault Diagnosis Model is proposed based on Bayesian Network in this paper. The method uses different samples of the elevator and adopts Monte Carlo inference mechanism for Bayesian Network Model structure and parameter learning. Eventually, an elevator fault diagnosis model based on Bayesian network is established, which accords with the theory of elevator operation. In this paper, we use different kinds of fault data samples to test the method. Experimental results demonstrate the higher accuracy of our method. This paper provides a good assistant method by means of Fault prediction and Health diagnosis of elevator system at present.

1 Introduction
The Elevator System with complex structure consists of seven major subsystems, and the interaction between the system components is complex. It is difficult to establish the corresponding mathematical model according to its operation state. In the field of elevator fault diagnosis, there are a lot of signals for fault state of the elevator system. Due to the fault prediction is the research of the important signal before the failure occurred, the diagnosis objects are complex, the testing methods are limited, and the knowledge is not accurate, which make many uncertainties exist in the fault diagnosis of elevator. The uncertainties mainly includes: Indicators have a lot of correlation and interconnection; The same fault may be caused by one or several abnormal signals, or the same abnormal signal may cause single or multiple faults simultaneously. At present, most of the literatures are about the fault diagnosis of simple system, and achieved some scientific research fruits, but there are few reports about the fault prediction of elevator system at home and abroad.

Bayesian Network based on probabilistic inference is developed in recent years, which used for solving the uncertainty and incompleteness problem. It has the great advantage in solving the fault caused by the uncertainty and interconnection of complex equipment, and arouses widespread attention in many fields [1,2]. As a directed acyclic graph to describe probability, Bayesian Network combine with prior information, and use probability theory to solve the problem of uncertainty caused by different signal and signal correlation in the system. After the calculation of posterior probabilities [3], Bayesian network can be used to the decision-making problem, which depend on many factors. At present, Bayesian Network has been applied to the field of fault diagnosis [4,5].

On the above analysis, this paper proposed a health diagnosis method of elevator based on Bayesian Network. The method adopts Bayesian Network Algorithm, and conjunction with the
structure and working principles of elevator to sets up Bayesian Network Model for Faults Prediction. Then we can get fault prediction of elevator and fault rate of main components through backward reason, which is according to the new state signal. Thus assess the health state of elevator equipment at work. Finally the improve method is verified by an actual case of the Guangzhou subway company chebei station Thyssen elevator.

2 The fault feature selection of elevator

The traction elevator is a kind of elevator that is widely applied in the building perpendicular transportation [6]. It contains Traction system, Guide system, Door system, Car system, Weight balance system, Electrical drive system, Electrical control system and Safety protection system. It can be clearly seen from the structures of elevator system that as a complex engineering system of mechanical and electrical equipment, faults may occur in all sub-systems of the elevator. And the sorts of faults are various, which include quantifiable fault characteristics indicators, non-quantifiable fault characteristics indicators and status value that can’t be measured in real time. So it is important to select the reasonable elevator fault indices for the construction of Bayesian Network elevator fault diagnosis model.

According to the comprehensive safety assessment method [7] and discarding standard in China, this paper analysis the main component that plays an important role in elevator safety running [8, 9]. The main components mainly include Traction machine, Brake, Car frame and car, Counterweight, Door, Safety protection, Electrical control and Guide Rail. The main part apt to faults and fault features listed in Table 1. The main fault characteristics of elevator listed in Table 2.

| Elevator system | The main part | fault features |
|-----------------|--------------|---------------|
| Traction system | Electric motor | Wear degree of motor bearing |
|                 |              | Wear degree of stator and the rotor |
|                 |              | Decrease of insulation resistance |
|                 |              | Working temperature |
|                 |              | Abnormal degree of brush device |
|                 | Reduction gearbox | Bearing wear of reduction gearbox |
|                 |              | Temperature of reduction gearbox |
|                 |              | Oil permeability of axle stretch end |
|                 | Brake | Abnormal degree of brake torque |
|                 |              | Brake release gap |
|                 | Traction sheave | Working temperature of magnetic coil |
|                 |              | Abnormal degree of traction force |
|                 |              | Wear degree of traction sheave |
|                 |              | Abnormal degree of groove |
|                 |              | Abnormal degree of wire rope |
| Suspension      | Wire rope | Breakage of wire, wear degree, distortion degree, corrosion degree |
|                 | Traction belt | Breakage of wire, Wear degree |
|                 | Rope hitch | Abnormality rate |
| Car             | Car frame | Structure abnormality rate |
|                 | Car | Structure abnormality rate |
| Door system     | Car door and Hall door | Corrosion degree |
|                 |              | Deformation magnitude |
|                 |              | Damage rate |
| Safety protection system | Door lock device | Short-circuited |
|--------------------------|------------------|-----------------|
| Speed governor           | Action reliability | Lubrication conditions of rotating part |
|                          | Abnormal degree of speed governor protection device |
| Safety gear              | Flexibility |
|                          | Consistency with Guide rail clearance |
| Overload protector       | Abnormal degree |
| Buffer*                  | Abnormal degree |
| Terminal limit protection device | Completeness of limit switch |
|                          | Reliability of limit switch |
| Electrical control       | Control cabinet | Electrical components reliability |
|                          | Traveling cable | Cable anomaly |

*Different types of buffers have different indices. The degree of abnormality should be determined according to the types of devices.

Table 2: The main fault characteristics of elevator

| Sudden stop of elevator                           | Over speed of elevator       |
|---------------------------------------------------|-------------------------------|
| Constant acceleration in elevator operation       | Elevator running speed is too slow |
| Electrical contacts cannot be removed             | Elevator running speed between fast and slow |
| Can not open the door after reaching a certain level | Call button lock              |

3 The elevator fault diagnosis based on Bayesian Network Algorithm

3.1 Bayesian Network Theory

Bayesian Network is a network model, which is based on probability theory and graph theory and used for uncertainty knowledge representation, casual inference and diagnosis inference \cite{10}. It can combine the causation between the state and result and the knowledge of the probability. Network can be described as B(G,P). G is a directed acyclic graph that has a number of nodes. Each node in the graph represents a variable, and nodes are connected by directed edges, denoting causal dependence between the nodes \cite{11}. P is Conditional Probability Table(CPT), P(X_i/X_a) is used to describe the degree of correlation between each node. The following paper briefly describe the probability theory about Bayesian Network \cite{12}.

The prior probability: The probability values obtained by the evaluation of professional or historical documents. A priori probability is divided into two types according to the source. The first is objective probability, specifically refers to the probability data from people’s practical experiment. The data in this paper comes from the elevator instructions, the recorded data of metro company, and the previous studies about elevator and so on. The second is subjective probability, which obtained the data without practices or the information is incomplete, specifically refers to the probability that concluded from the long-term practice experience of experts in elevator field.

The posterior probability: According to Bayesian formula, posterior probability make Bayesian Network more realistic by amends the prior probability.

Bayesian formula:
\[ P(B_i/A) = \frac{P(A \mid B_i)P(B_i)}{\sum_{j \in i} P(A \mid B_j)P(B_j)} \] (1)

In this paper, we research the Bayesian Network elevator health diagnosis method in order to get the probability of faulty nodes, which need Bayesian network learning and real-time status of fault characteristics nodes.

### 3.2 The Elevator Fault Diagnosis Model based on Bayesian Network

Since the complex structure of elevator system, a complete Bayesian Network model has a large number of nodes. This paper will take the traction system as an example to expound the elevator health diagnosis model based on Bayesian Network.

#### The establishment of Bias Network model

There are two types of nodes in Bayesian Network model: (1) Specific fault node; (2) Fault characteristics nodes. Fault characteristic node is connected with itself and specific fault node. The specific fault contained in the model listed in Table 3. Preliminary fault characteristics nodes and pertinent specific fault node listed in Table 4. The values of characteristic nodes are divided into three grades: Slight, Critical and severe, and the values are 0/1/2 respectively. Specific fault nodes are divided into two grades: normal and fault, and the values are 0/1 respectively. By means of the auxiliary MATLAB tools, a traction system fault diagnosis Bayesian Network was preliminarily established on the platform of Full BNT-1.04 \(^{(13)}\), as shown in Figure 1.

| Fault name                                           | Label |
|------------------------------------------------------|-------|
| Double brake arm asynchronous when the gate opening and closing | Q1    |
| Braking force shortage after closing the gate         | Q2    |
| The traction machine has serious oil spill           | Q3    |
| The wire rope and the traction wheel slip             | Q4    |
| Worm wheel speed reducer of traction heat/smoke      | Q5    |
| Fail of releasing electro-hydraulic shoe brake        | Q6    |
| Elevator running speed is too slow                   | Q7    |
| Sudden stop of elevator                              | Q8    |
| Abnormal of elevator speed                           | Q9    |

![Figure 1: Traction system fault diagnosis Bayesian Network](image)

### 3.3 Bayesian Network Learning Algorithm of Elevator \(^{(14)}\)

Elevator appearance diagnosis has its particularity because of the mechanical, electrical and safety
And the data collected from the key parts of the fault and the fault characteristics are very different (include approximate continuity and dispersion). Thus the data need to divided into three grades before the establishment of Bayesian Network, this method is complicated. And as a high safety performance system, some parts of the elevator can not get the state data frequently, that means exist a possibility of loss or distortion of the data. According to this characteristic, in the process of establishing the Bayesian Network model of elevator system, this paper use the structure learning algorithm and the EM(expectation-maximization) algorithm.

### 3.3.1 Structure learning algorithm

Bayesian network structure learning is to find a structure best match with the training sample set D under the premise of a data set D.

| First-level nodes of Characteristic node data | Second-level nodes of Characteristic node data | related Fault node data |
|-----------------------------------------------|-----------------------------------------------|------------------------|
| **Electric motors F(1)**                     | Wear degree of motor bearing F(1-1)            | Q2 Q3 Q7 Q8 Q9         |
|                                               | Wear degree of stator and the rotor F(1-2)     | Q2 Q3 Q7 Q8 Q9         |
|                                               | Decrease of insulation resistance F(1-3)       | Q5 Q7 Q8 Q9            |
|                                               | Working temperature F(1-4)                     | Q3 Q7 Q8 Q9            |
|                                               | Abnormal degree of brush device F(1-5)         | Q2 Q7 Q8 Q9            |
| **Reduction gearbox F(2)**                    | Bearing wear of reduction gearbox F(2-1)       | Q2 Q5 Q3 Q5 Q7 Q8 Q9  |
|                                               | Temperature of reduction gearbox F(2-2)         | Q3 Q5 Q7 Q8 Q9         |
|                                               | Oil permeability of axle stretch end F(2-3)     | Q3 Q5 Q7 Q8 Q9         |
| **Brake F(3)**                               | Abnormal degree of brake torque F(3-1)         | Q1 Q6 Q7 Q8 Q9         |
|                                               | Brake release gap F(3-2)                       | Q1 Q2 Q6 Q7 Q8 Q9     |
|                                               | Working temperature of magnetic coil F(3-3)     | Q1 Q2 Q6 Q7 Q8 Q9     |
| **Traction sheave F(4)**                      | Abnormal degree of traction force F(4-1)       | Q2 Q3 Q6 Q7 Q8 Q9     |
|                                               | Wear degree of traction sheave F(4-2)          | Q2 Q3 Q4 Q6 Q7 Q8 Q9  |
|                                               | Abnormal degree of groove F(4-3)               | Q2 Q3 Q4 Q6 Q7 Q8 Q9  |
|                                               | Abnormal degree of wire rope F(4-4)            | Q2 Q4 Q7 Q8 Q9         |

There are some literatures have proved that[15], Bayesian Network space increases rapidly with the increase of the number of nodes n. Bayesian network structure learning has been proved to be a
NP-Hard problem \[^{[16]}\]. In this paper, Bayesian network structure learning algorithm chooses K2 Score Metric \[^{[17]}\]. And uses P (G,D) as a scoring function:

\[
B(G, D) = P(G, D) = P(G)P(D | G)
\]

\[
= P(G) \prod_{i=1}^{n} P(x_i | f_G)
\]

\[
= P(G) \prod_{i=1}^{n} \frac{(r_i-1)!}{(N_q + r_i - 1)!} \prod_{i=1}^{n} N_{q_i}!
\]

P(G) is the priori probability of network structure G. \(X_i\) is network nodes, \(X_i \in \{x'_i, \cdots x''_i\}\). the parent node set \(\prod_i\) correspond to the nodes \(X_i\). \(\pi_i\) is the configuration of \(\prod_i\). The arrangement order of \(\pi_i\) is 1,2,\(\cdots\),\(q_i\). \(N_q = \sum_{i=1}^{q_i} N_{q_i}\), \(N_{q_i}\) is the number of cases that satisfy \(X_i = x'_i\) and \(\pi_i = j\) in the data set D.

For example, if an expert suggests the existence of a particular edge or a local structure, then the given network structure should be given a higher priori probability. If there is no priori probability of the network structure, or there is no special priority network structure, then the priori probability P(G) assumed to be uniformly distributed. Given a network structure G, conditional probabilities \(\hat{\theta}_i\) can be estimated by the Bias estimator:

\[
\hat{\theta}_i = E(\theta_i | D, G) = (N_{q_i} + 1)/(N_q + r_i)
\]

Where E is Expectation. Bayesian posterior score can be interpreted as: for all network structures G, if a network structure G\(_0\) meet P(G\(_0\),D)\(\geq P(G, D)\), then G\(_0\) is the most consistent network structure with the current data set D. In the process of algorithm implementation, \(log(P(G, D))\) is usually used instead of P(G,D), to get the decomposition form of scoring function:

\[
f_{k2}(G : D) = \sum_{x_i} f_{k2}(x_i, \prod_{j=1}^{n} N_{q_i}, \prod_{j=1}^{n} r_i, x_i, y_i, S_i)
\]

\[
= \sum_{x_i} \left( \frac{(r_i-1)!}{(N_q + r_i - 1)!} \right) \prod_{i=1}^{n} \sum_{\pi_i} \log(N_{q_i})
\]

3.3.2 Parameter learning algorithm. In this paper, the parameter learning of Bayesian Network is to seek the probability distribution of each node in the network, which is based on the sample data. This paper uses the network topology, training sample set and the prior knowledge to determine the conditional probability density of Bayesian Network model at each node, denoted as P (\(\theta | D, G\)). Bayesian Network parameter learning algorithm is actually a process to solve the convergence of the local node optimal parameter \(\hat{\theta}_i\). First initialize the configure of \(\hat{\theta}_i\), then iterate E and M two steps to find the maximum posteriori probability and the optimal value. Derive the maximum likelihood estimation of the model parameters. The specific steps \[^{[18]}\] are as follows:

1) E-steps (Expectations)

\[
E_{\theta_i | D, \theta_j, s^k}(N_{q_i}) = \sum_{x_i} P(x'_i, \pi'_i | y_i, \theta_i, S_i), \quad h,i,j,k,l \in \mathbb{N}
\]

Where E is Expectation. D is a training sample. \(\hat{\theta}_i\) is the optimal parameters. \(x_i \in \{x'_i, \cdots x''_i, \cdots x''_i\}\).

The arrangement order of \(\pi_i\) is 1,2,\(\cdots\),\(q_i\). \(N_q = \sum_{i=1}^{q_i} N_{q_i}\), \(N_{q_i}\) is the number of cases that satisfy \(X_i = x'_i\) and \(\pi_i = j\) in the data set D. \(y_i\) is the number of missing data in D. \(s^k\) is the Bayesian network structure selection hypothesis.

2) M-steps (Maximization)

Maximum likelihood estimation function:

\[
\hat{\theta}_i = \frac{E_{\theta_i | D, \theta_j, s^k}(N_{q_i})}{\sum_{x_i} E_{\theta_i | D, \theta_j, s^k}(N_{q_i})}
\]
MAP estimation:

$$\theta_k = \frac{N_{ijk} \cdot E_{\theta_k(\theta_k)}(N_{ijk})}{\sum_{k} (N_{ijk} \cdot E_{\theta_k(\theta_k)}(N_{ijk}))}$$

(7)

$$N_{ijk}$$ is the priori sufficient statistical factor. $$N_{ijk}$$ is the full statistical factor of sample data. $$i, j, k, h, q \in N$$.

3.4 Bayesian Network approximate inference algorithm

Due to the complex structure of the elevator system and the large number of fault states and fault feature nodes, the complexity of the exact inference in Bayesian Networks increases exponentially with the increase of the number of nodes in the network. Network may exceed the scope of hardware implementation. In order to improve the computational efficiency of multi node complex Bayesian Networks, this paper uses the stochastic sampling approximate inference algorithm Monte Carlo algorithm. This method needs no other auxiliary structure such as junction tree, it only uses a random number generator and the conditional probability distribution table of the Bayesian model to determine the status of each elevator fault feature node. Then generate a large number of samples. Each variable to save a count, while recording the number of variables in each state, and then calculate the probability after generating all the samples.

4 Example of Thyssen TE-evolution1 machine roomless elevator fault diagnosis model based on Bayesian Network

In this section, we will establish a Bayesian Network model of elevator according to the characteristics of elevator faults and the collected fault data. Then verify the validity of the model to the fault diagnosis of elevator system. Simulation research will use Full BNT-1.04 platform. We use the elevator system in Figure 1 (Section 3.2) to simulate.

4.1 Accuracy verification experiment

According to the actual operation data of the Thyssen elevator in Guangzhou Subway Company Chebei Station, we can get the Bayesian Networks with known parameters. This paper mainly study the accuracy of the algorithm. So, in theory, we can assume that the network is the true value and use it as a control. According to the Bayesian Networks with known parameters, 5000 groups of sample data can be obtained by using the probability sampling method. The sample data is divided into 10 experiments, and the amount of data for each experiment is 500 groups. The first 480 groups are used as training data, and the last 20 groups are used as test data. Table 5 lists the training and test data of one experiment. Training the new Bayesian Networks with 480 sets of training data, this process uses the K2 Score Metric and EM algorithm. Input the feature node data of 20 groups of test data into the trained Bayesian Network. Then get the fault node prediction results of 20 groups of data. Compared with the original 20 groups of data corresponding fault node state, we can calculate the correct rate of prediction. Take Q1 as an example, if the number of the data, which has correct predicted results, is M, and the total data number is N=20, the accuracy of Q1 is $$P_{Q1} = M / N$$. In this way, we can calculate the accuracy of 9 fault nodes separately from Q1 to Q9. In this paper, we choose one of the nine specific fault nodes Q2 (braking force shortage after closing the gate) as an example. The prediction results of Q2 node after 10 experiments are shown in Table 6. For other fault nodes, the experimental results are similar.

Table 5: 480 sets of training data and 20 sets of test data in the first experiment

| Characteristic node data | Fault node data |
|--------------------------|----------------|
| F(1-1) | F(1-2) | F(1-3) | ... | F(4-4) | Q1 | Q2 | ... | Q8 | Q9 |
| training data | | | | | | | | | |
| 1 | 0 | 0 | 0 | ... | 1 | 0 | 0 | ... | 0 | 1 |
2 | 1 | 0 | 0 | ... | 0 | 0 | 0 | ... | 0 | 0
3 | 0 | 0 | 1 | ... | 0 | 0 | 1 | ... | 0 | 0
...
479 | 0 | 0 | 0 | ... | 0 | 0 | 0 | ... | 1 | 0
480 | 0 | 1 | 2 | ... | 1 | 1 | 0 | ... | 0 | 0

| experiment times | 1 | 2 | 3 | 4 | 5 |
|------------------|---|---|---|---|---|
| accuracy /%      | 81.11 | 83.27 | 87.79 | 86.62 | 89.83 |

| experiment times | 6 | 7 | 8 | 9 | 10 |
|------------------|---|---|---|---|---|
| accuracy /%      | 88.04 | 90.11 | 86.70 | 82.73 | 84.29 |

It can be seen from the data in Table 6 that, the average accuracy of 10 experiments is 86.049%. The average training time of Bayesian Network is about 328s. Based on the complete data, the trained Bayesian Network has a high accuracy and the fast speed of programs running.

In actual operation of the elevator, all the characteristics of the state of the node cannot be fully monitored, so the data obtained is incomplete. There are about 10% of the data is not available in actual operation. Therefore we hide ten percent of 5000 groups of training samples to learn and train the network. Hidden data is represented by NAN. Similarly, we choose one of the nine specific fault nodes Q2 (braking force shortage after closing the gate) as an example. The prediction results of Q2 node after 10 experiments are shown in Table 7. For other fault nodes, the experimental results are similar.

| experiment times | 1 | 2 | 3 | 4 | 5 |
|------------------|---|---|---|---|---|
| accuracy /%      | 71.13 | 67.28 | 73.91 | 77.16 | 74.11 |

| experiment times | 6 | 7 | 8 | 9 | 10 |
|------------------|---|---|---|---|---|
| accuracy /%      | 72.86 | 66.66 | 69.53 | 72.33 | 75.37 |

It can be seen from the data in Table 7 that, the average accuracy of 10 experiments is 72.034%. The average training time of Bayesian network is about 359s.

The comparison chart of the fault diagnosis performance of the Bayesian Network prediction is drawn as follows.

![Comparison of fault diagnosis accuracy of Bayesian network with complete data and incomplete data](image)

Figure 2: Comparison of fault diagnosis accuracy of Bayesian network with complete data and incomplete data

From figure 2 we can see that compared with the ideal state with complete data, in the actual condition of incomplete data, the correct rate of Bayesian Network fault diagnosis model is slightly decreased, but the correct rate is still high. While there is a slight drop of accuracy of fault diagnosis.
model based on Bayesian Network, which through the method researched in this paper, the change was not significant.

4.2 Experiments under the different amount of data
The purpose of this experiment is to find the amount of training data, which is suitable for the Bayesian Network in this paper. We generate 10000 groups of data from the known network by probability sampling. The data is divided into 10 experiments, and the amount of data for each experiment is 1000 groups. The first 980 groups are used as training data, and the last 20 groups are used as test data. The steps of the experiment are the same as the steps of the experiment with incomplete data in section 4.1. Hide ten percent of training samples to learn and train the network. Similarly, we choose one of the nine specific fault nodes Q2 (braking force shortage after closing the gate) as an example. The prediction results of Q2 node after 10 experiments are shown in Table 8. The average training time of Bayesian Network is about 873s. For other fault nodes, the experimental results are similar.

Table 8: Prediction accuracy of 1000 groups of data

| experiment times | 1    | 2    | 3    | 4    | 5    |
|------------------|------|------|------|------|------|
| accuracy /%      | 84.46| 82.29| 88.31| 86.64| 79.33|
| experiment times | 6    | 7    | 8    | 9    | 10   |
| accuracy /%      | 84.69| 82.24| 84.11| 82.33| 80.12|

We generate 15000 groups of data from the known network by probability sampling, and repeat the above experiment. The prediction results of Q2 node are shown in Table 9. The average training time of Bayesian Network is about 1736s.

Table 9: Prediction accuracy of 1500 groups of data

| experiment times | 1    | 2    | 3    | 4    | 5    |
|------------------|------|------|------|------|------|
| accuracy /%      | 76.66| 81.17| 83.30| 79.34| 76.86|
| experiment times | 6    | 7    | 8    | 9    | 10   |
| accuracy /%      | 84.42| 80.11| 83.35| 81.19| 79.94|

According to Table 7-Table 9, we can get the line chart and see the influence of different amount of data on the accuracy of Bayesian Network fault diagnosis system.

![Figure 3: The accuracy of Bayesian Network fault diagnosis system under different amount of data](image)

From the Figure 3 and Figure 4 we can see that as the algorithm used in network learning in this paper contains iterations, with the increase of data though the accuracy of Bayesian Network increased slightly, the time of training grow significantly. So, the suitable amount of data needed to train the
Bayesian Network is about 1000.

5 Conclusion
This paper proposes a method for Elevator Fault Diagnose of Bayesian Network given incomplete data. The paper analyses the elevator structure and selects failure indicators, then calculate the conditional probabilities of fault characteristics and fault states by probability inference. Compared with other diagnostic methods, the elevator fault diagnosis model based on Bayesian Network takes account of the mutual constraints between state variables in complex systems, which makes it both more scientific and rigorous. It is proved that this method can achieve high prediction rate through the existing data samples. Therefore, the Elevator Fault Diagnosis Model based on Bayesian Network is very valuable in the field of elevator health diagnosis and has broad application prospects.

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