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## COMPLICATED MECHANICAL EQUIPMENT DIAGNOSIS BASED ON BAYESIAN NETWORKS

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### ABSTRACT

Mechanical equipment fault diagnosis is a complicated process. Due to the complex structure, the different operating environment, the different detection means and testing equipment, the difference between the operator and other factor, that well lead to many uncertainties. In order to solve these problems, this paper established a Bayesian Network-based mechanical equipment fault diagnosis model. The evaluation function and firefly algorithm are introduced to optimize the model. Introduce a priori knowledge to self-learning during model establishment, reduce the uncertainty caused by the test object information. Improve the reliability of mechanical equipment fault detection, finally verified by an example.

## 1. INTRODUCTION

The development of science and technology in the modern era is accelerating. The level of modern industrial technology has also been continuously improved. Industrial areas developed constantly to automation and intelligent. Constantly to automation and intelligent development. At the same time, the machinery and equipment, as an industrial infrastructure, have become more efficient, elaborate and sophisticated [1]. These characteristics of modern machinery and equipment determine that the failure detection of mechanical equipment becomes more and more difficult. Among them, the main reasons include the differences of testing technicians, the difference of professional level of testing personnel, the difference of working environment of equipment, the difference of personnel's operation level, and so on [2]. That's way the reason of equipment failure is uncertain. Therefore, the scientific fault detection method for the detection of complex equipment has become very important. Complex machinery and equipment for unknown reasons for fault diagnosis. In view of the above problems, this paper uses the combination of Bayesian Network and firefly algorithm to diagnose the unknown causes of complex mechanical equipment.

## 2. BAYESIAN NETWORK

Bayesian Network is a probability graph model, also known as directed acyclic graph model. The model consists of directed edges and nodes, and all the nodes are represented as the set of random variables  $\{X_1, X_2, \dots, X_n\}$ . In this paper, nodes represent the fault state sets. The directed edges between nodes represent the inter-node relationships or unconditional independence. The value of the variable corresponds to the evidence and hypothesis, the degree of dependence of variables depends on is represented as the conditional probability [3]. Bayesian Network based on probability reasoning is proposed to solve the problem of uncertainty and incompleteness. It has a great advantage to solve the problem caused by the complexity and relevance of complex devices. For the complexity of mechanical equipment's structure and the cause of the failure of the uncertainty of the fault reason, the uncertain factors of the diagnostic object and its running environment are represented by network nodes. The correspondence between fault and fault symptom is

represented by directed edges between nodes. Gathering experts in the field of knowledge and applying to Bayesian Network, using evaluation function and Firefly Algorithm to construct Mechanical Equipment Fault Diagnosis Bayesian Network Model [4].

The Bayesian Network can be expressed as  $G = (X, E)$ ,  $G$  represents a directed acyclic graph,  $X$  represents the set of all nodes in the graph, and  $E$  represents the directed edge set in the graph. The joint probability distribution of a node  $X$  is:

$$P(X) = P(X_1, X_2, \dots, X_n) = \prod_{i=1}^n P[X_i | Pa(X_i)] \quad (1)$$

In formula:  $X_i$  represents the no.  $i$  node in the graph,  $n$  represents the number of all nodes, and  $Pa(X_i)$  is called the father of  $X_i$ , which represents the cause of  $X_i$ . According to the nature of Bayesian Networks,  $X_i$  is independent of all nodes except  $Pa(X_i)$ .

For the Bayesian Network  $B = (X, E, P)$  is constructed in this paper,  $X$  represents the set of fault nodes;  $E$  represents the directed edge set between the parent node and the child node; and  $P$  represents the conditional probability distribution parameter set of any node in the network. Under the condition of known  $Pa(X_i)$ , the conditional probability of node  $X_i$  is  $P(X_i) = P[X_i | Pa(X_i)]$ .

## 3. FIREFLY ALGORITHM

### 3.2 Standard firefly algorithm

The Firefly Algorithm is a meta-heuristic algorithm inspired by the fact that firefly individuals in nature find their way to attract their fellow courtship or foraging behaviors by emitting light. Fireflies attract each other as well as the location of the iterative process of updating is the search and optimization process. The problem of finding the brightest fireflies is the problem of finding the optimal value. Continue to use the best position to replace the poor position to complete the search process. In a certain search area, all the weak light fireflies move to the glowing fireflies. In order to achieve the location optimization. Each firefly should

be as an individual. Individuals, which mainly have "location, brightness, attractiveness" and other attributes. There are two important factors: brightness  $I$  and attraction degree  $\beta$ . The brightness is high, indicating that the position is good, and attract the individuals with low brightness to close. When the attraction is high, fireflies move far away. Starting from FA, the individuals of fireflies are randomly distributed within the specified region, and the brightness of individuals is determined by the objective function.

Let  $I_0$  indicate the individual brightness of fireflies,  $\gamma$  brightness medium absorption coefficient, the relative distance  $r_{ij}$  for any two individuals of  $i$  and  $j$  (general Euclidean distance),  $\beta_0$  firefly individual inherent attraction, with individual light intensity changes of  $I$  expressed as the distance  $r$ :

$$I = I_0 e^{-\gamma r^2} \tag{2}$$

Then, the mutual attraction between firefly  $i$  and firefly  $j$  is calculated as follows:

$$\beta = \beta_0 \times e^{-\gamma r_{ij}} \tag{3}$$

Let  $x_i(t)$  and  $x_j(t)$  represent the positions of firefly  $i$  and firefly  $j$  at time  $t$ . The distance between the two is calculated as:

$$r_{ij} = \|x_i(t) - x_j(t)\|_2 = \sqrt{\sum_{m=1}^d (x_{id} - x_{jd})^2} \tag{4}$$

The position update equation of firefly  $i$  moving toward firefly  $j$  is:

$$x_{i+1}(t+1) = x_i(t) + \beta(x_j(t) - x_i(t)) + \alpha \left( rand - \frac{1}{2} \right) \tag{5}$$

Where  $x_{i+1}(t+1)$  denotes the position of firefly  $i$  at time  $t+1$ ,  $\alpha \in [0,1]$ , which indicates the step factor, where  $\alpha \left( rand - \frac{1}{2} \right)$  is a random disturbance to avoid falling into the local optimal value. When the decision variables change greatly, they can be transformed into  $\alpha \left( rand - \frac{1}{2} \right) \times scale$  in the back, where  $scale$  represents the difference between the maximum value and the minimum value of the variables. This situation applies to the larger parameters in the process. Otherwise firefly algorithm optimization speed is very slow.

#### 4. CONSTRUCTION OF BAYESIAN NETWORKS FOR MECHANICAL EQUIPMENT FAILURE

Mechanical equipment fault diagnosis process consists of collecting equipment testing data. Bayesian Network implementation diagnosis, diagnosis conclusion and so on. Mechanical equipment troubleshooting detailed flowchart shown in Figure 1.

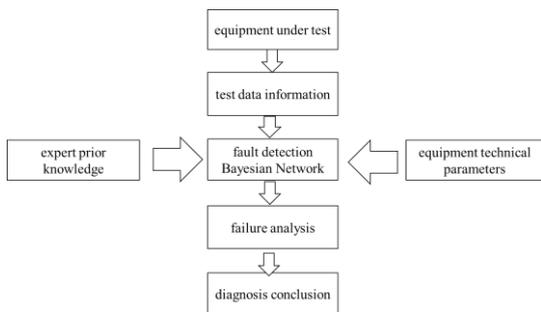


Figure 1: Mechanical equipment diagnostic flowchart

In the process of mechanical equipment fault diagnosis, the value of the fault state variable indicates the set of fault data samples. Therefore, mechanical equipment failure Bayesian Network construction process is that according to the collected fault sample set  $X$  to establish a network with the best matching fault data set. We introduce the  $K2$  evaluation function, measure the matching degree of the network structure and the fault sample data set by the value of  $K2$  evaluation function, and use the improved Firefly Algorithm as the heuristic optimization algorithm. The method needs prior knowledge. The fault information data collected by a given sensor and knowledge provided by experts in the field, and then calculates the score by the  $K2$  evaluation function to obtain the matching degree between the current network structure and the data sample set. Then, the improved Firefly Algorithm Search for the best network structure in all network structures and output the result.

#### 4.2 Evaluation Function

Let  $B$  is a mechanical failure Bayesian Network,  $X_i$  be a Bayesian Network node, its parent node set is  $Pa(X_i)$ ,  $X$  is a collection of collected mechanical fault samples, and  $N_{x_i, Pa(x_i)}$  indicates that the number of instanced records for variable  $X_i$  and its parent  $Pa(X_i)$  in the failure sample data set  $X$ . The evaluation function is summation of the subgraphs for all nodes and edges in the sample collection.

Suppose the data sample set  $X$  contains  $n$  variables, the variables  $X_i$  may have  $r_i$  values,  $E_{ij}$  is the  $j$  instance of  $Pa(X_i)$  related to the sample data set  $X$ , and there are  $q_i$  such instances in the sample set. When  $Pa(X_i)$  is instantiated into  $E_{ij}$ ,  $N_{ijk}$  is the number of  $X_i$  instantiated as  $X_{r_i}$  in the data sample set  $X$ .

Let  $N_{ij} = \sum_{k=1}^{r_i} N_{ijk}$ , then:

$$P(B; X) = P(B) \prod_{i=1}^n f_{K2}[x_i, Pa(x_i)] = P(B) f_{K2}(B; X) \tag{6}$$

among them:

$$f_{K2}(B; X) = \prod_{i=1}^n f_{K2}[x_i, Pa(x_i)] = \prod_{j=1}^{q_i} \left[ \frac{(r_i - 1)!}{(N_{ij} + r_i - 1)!} \prod_{k=1}^{r_i} N_{ijk}! \right] \tag{7}$$

In the above formula:  $f_{K2}$  represents  $K2$  evaluation function,  $P(B)$  is the prior probability. The value of  $P(B; X)$  is used to represent the fitting degree of the formed Bayesian Network  $B$  and the mechanical faulty sample set  $X$ . The value of  $f_{K2}$  directly reflects the evaluation value of the faulty Bayesian Network structure. Therefore, using the above network construction method for a known set of mechanical failure data  $X$  must be able to find an optimal mechanical failure Bayesian Network structure.

#### 4.3 Mechanical failure Bayesian Network construction process

Mechanical failure Bayesian Network construction begins with an initial network. The initial network is a collection of nodes represented by each mechanical fault state variable. Add one directional edge per search. The addition of directed edges is a directed edge that maximizes the value of the evaluation function. The algorithm terminates when the directed edge in the graph continues to increase and the score no longer changes.

When starting to construct the network, an initial network  $B_{K2}$  is established by the  $K2$  scoring function according to the mechanical failure sample data set  $X$ . And initializes the brightness  $I$  and the attraction degree  $\beta$ . Search for Optimal Bayesian Network Structure by Improved Firefly Algorithm. After several times of searching, it is assumed that the current network obtained is  $B_r$  and the node is  $X_i$ . After the evaluation function scores, a new node  $X_j$  is added to the network to form a new directed edge  $\{X_i - X_j\}$  network  $B_{r+1} = B_r \cup (X_i - X_j)$ , the new directional edges added in the network can maximize the added value of the scoring function  $f_{K2}$ . When the directed edge in the graph continues to increase and the value of the scoring function  $f_{K2}$  does not change, the optimal Bayesian Network structure  $B^*$  is obtained.

By the improved Firefly Algorithm combined with the  $K2$  evaluation function, we define the light absorption coefficient  $\gamma$  of the directed edge  $\{X_i - X_j\}$  medium of a single firefly in search of the optimal Bayesian Network as follows:

$$\gamma_{ij} = f_{K2}[X_i, Pa(X_i) \cup \{X_j\}] - f_{K2}[X_i, Pa(X_i)] \tag{8}$$

Initialize brightness  $I_0$ :

$$I_0 = \frac{1}{n |f_{K2}(B_{K2}; X)|} \tag{9}$$

When  $B^*$  is the current optimal Bayesian Network structure, the directed edge  $\{X_i - X_j\} \in B^*$ , so the increment of the brightness  $I$  after adding the directed edge to the Bayesian Network is:

$$\Delta I = \frac{1}{f_{K2}(B^*; X)} \tag{10}$$

During each search, the increase of directed edges is assessed by the grading function. The  $K2$  function to select the largest directed edge to join the current network. Firefly Algorithm is a population-based biomimetic optimization algorithm that requires multiple searches by fireflies to achieve optimal results.

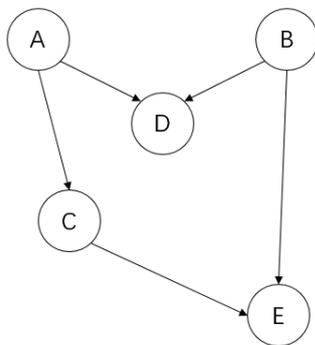
#### 4.4 Experiment

In order to test the validity of the model construction, applicability. Verify that a simple example of a vehicle cannot be started. Vehicles cannot start the fault set by the power, oil, starter, meters, switches and related test data. For the sake of simplicity, the value status of each fault node is represented by yes or no respectively. Mechanical Failure of Vehicles Table 1 shows the state of failure in Bayesian Network and prior knowledge provided by field experts.

**Table 1:** Bayesian Networks node meaning, value and probability distribution

node	node meaning	value	probability distribution
A	electricity failure	y/n	$P(A)$
B	Oil fault	y/n	$P(B)$
C	Engine fault	y/n	$P(C A)$
D	Instrument failure	y/n	$P(D A,B)$
E	Switch failure	y/n	$P(E C,D)$

Gradual iteration by the algorithm of this paper, the vehicle mechanical failure Bayesian Network, shown in Figure 1.



**Figure 2:** Vehicle mechanical failure Bayesian Network

## 5. CONCLUSION

Mechanical equipment troubleshooting is a complex process. This paper focuses on the fault diagnosis model of mechanical equipment based on Bayesian Network, and introduces the score function and Firefly Algorithm to optimize the model. Self-learning for a given prior knowledge during model building. Reduce the uncertainties caused by the detection object, detection environment, detection means and other factors. Improve the credibility of the test.

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