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Reliability Evaluation of a Disaster Airflow Emergency Control System Based on Bayesian Networks

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ABSTRACT

This study proposed a novel method for system failure reasoning based on Bayesian networks to solve emergency airflow control system reliability problems. A system fault tree model was established to identify the logical relationship between the units, which was then transformed into a Bayesian network fault analysis model to determine network node states and the conditional probability table, as well as to carry out diagnostic reasoning on the system node branches. The reliability analysis of the model based on Netica Bayesian tool shows that the probability of system failure caused by substation communication node is the highest under normal conditions, and data monitoring and central station communication nodes have a greater impact on intelligent control. By predicting and diagnosing system faults, the optimization of system design is realized on the framework of Bayesian network to improve the reliability, and there by establishing a theoretical foundation for future disaster prevention research.

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NOMENCLATURE

CPT	Conditional probability table	FMEA	Failure mode and effect analysis
FTA	Fault tree analysis	BN	Bayesian networks

1. INTRODUCTION

The diffusion of smoke flow along the roadway after a mine fire is critical to ensure mine disaster prevention. By adjusting the damper switch in the disaster area, the air volume can be modulated to ensure the safety of underground personnel during disasters [1, 2]. This emergency control system has been greatly popularized and applied. It is of great significance to improve disaster relief efficiency and reduce system failure rate through reliability evaluation.

Commonly used reliability analysis methods include failure mode and effect analysis (FMEA), fault tree analysis (FTA), and others. Lo and liou [3] proposed a new FMEA risk assessment method based on multi-criteria decision making. Hyun et al. [4] used fault tree analysis (FTA) and analytic hierarchy processes (AHP) to conduct risk assessment during tunnel construction. Peeters et al. [5] improved the efficiency of fault analysis by combining FTA and FMEA through recursion. However, these methods do not account for the connection between various failure modes and are not suitable to characterize uncertain casual relationships. Current equipment failure diagnosis strategies do not meet the requirements for failure diagnosis under complex catastrophe scenarios. Therefore, it is the direction of current scientific research to establish a judgment model through artificial intelligence for independent evaluation. Dynamic process fault detection and diagnosis based on a combined approach of hidden Markov and Bayesian network model [6]. It presents a novel technique using artificial neural network learning for automated diagnosis of localized faults in rolling element bearings [7]. Predictions of tool wear in hard turning of AISI4140 steel through artificial neural network, fuzzy logic and regression models，the results

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reveal that the artificial neural network (ANN)provides better accuracy when compared to regression analysis [8]. A new hybrid decision tree (DT) technique based on two artificial neural networks (ANN), namely multilayer perceptron (MLP) and radial basis function (RBF), is proposed to predict sediment transport in clean pipes [9].

Bayesian networks were developed to address uncertainty in artificial intelligence research, and have been widely used in artificial intelligence, pattern recognition, and other fields. In fact, learning structures of interval-based Bayesian networks in probabilistic generative model for human complex activity recognition is discussed in literature [10]. A new stability-based dynamic Bayesian network method for dynamic systems represented by their time series [11]. Given that Bayesian networks have a solid theoretical foundation, analysis ability, and a capacity to describe uncertainty, this approach has begun to be applied in recent years in medical diagnosis, risk and safety assessment, fault diagnosis, reliability analysis and assessment, among other fields. Comparison of automatic and guided learning for Bayesian networks to analyze pipe failures in the water distribution system [12]. A comparative study between discrete and continuous time Bayesian networks demonstrates clinical time series data with irregularity [13]. A novel scoring function based on family transfer entropy for Bayesian networks learning and its application to industrial alarm systems is discussed [14]. Copula-based Bayesian network model for process system risk assessment is discussed [15]. Bayesian networks are supported by mathematical theory and can be implemented through a variety of reasoning models and algorithms with good learning performance.

The FMEA method has a comprehensive analysis of failure modes, but it has insufficient analysis of the causes of failures and cannot reflect the logical relationship between various factors. FTA analyzes the causes of failures comprehensively and can reflect simple logical relationships, but it is easy to miss failure modes. It can be seen that these two methods have a certain degree of complementarity. Bayesian networks can reflect the characteristics of complex systems such as polymorphism, failure correlation, and uncertainty in logical relations. It has the ability to deal with uncertainties that FMEA and FTA do not have, and it can conduct bidirectional analysis, which is stronger reasoning and analysis ability. However, the disadvantage of Bayesian networks is that modeling is difficult. Especially when there is a lack of data, it is difficult to build Bayesian networks using data learning methods. Therefore, it is an effective method to use the information provided by FMEA and FTA to build a Bayesian network model to solve the problem of lack of data.

Aiming at the reliability problem of disaster airflow emergency control system, the reliability model of Bayesian network is constructed by integrating the reliability related information of FMEA and FTA. Determine the fault nodes of the entire control system, apply the fault data to the autonomous learning of the Bayesian network, and propose a reliability evaluation method for the disaster airflow emergency control system based on the Bayesian network. Carry out precise reasoning on the cause and result of the failure, determine the main failure factors, and provide reliability guidance for the disaster airflow emergency control system.

To address emergency control system reliability problems, Bayesian networks can be employed in conjunction with fault diagnosis models to determine the fault node of the entire control system, after which the fault data can be used for Bayesian network autonomous learning, thereby determining the main failure factors for disaster emergency control.

2. MODEL

2. 1. Bayesian Network Bayesian networks, also known as directed acyclic graphs (DAG), were first proposed by Pearl in 1986. Bayesian networks are composed of individual nodes, and the conditional probability between each node constitutes the conditional probability table (CPT) of the Bayesian network, which connects the whole network for reasoning diagnosis through the causal relationship between nodes and conditional dependence.

The reasoning of Bayesian network is to use the Bayesian network structure and its conditional probability table to calculate the posterior probability distribution of some non-evidence nodes under the value state of the set of known evidence nodes. Bayesian network reasoning algorithms are divided into exact reasoning and approximate reasoning, both of which are NP-hardness [16].

Bayesian networks can be represented as $B=<G, P>=<<V, E>, P>$, which includes two parts: $G=<V, E>$ represents the directed acyclic graph (DAG), where the elements in node set V represent variables, the directed edge E between nodes represents the association between variables, and P represents the conditional probability table (CPT). An example of a Bayesian network is shown in Figure 1. Node A is the parent of node B, and the prior probabilities of nodes B and C depend on the distribution probability of A.

According to Bayes theorem, the conditional probability formula is obtained as Equation (1):

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{1}$$

Suppose a directed acyclic graph of a Bayesian network $G=<V, E>$, where the elements in node set V represents variables $X_1, X_2, X_3..., X_n$, the directed edge E

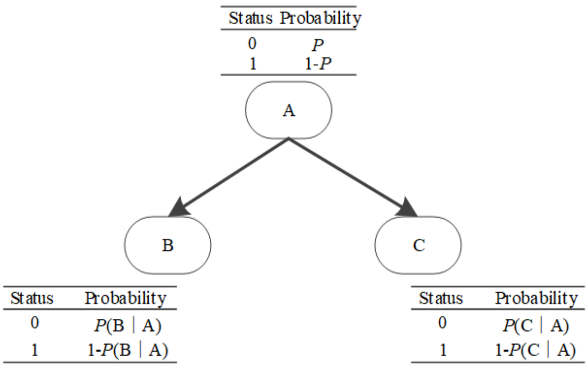


Figure 1. Basic framework of a Bayesian network

between nodes represents the correlation between variables, and the multiplication of conditional distributions of each node is the joint probability distribution such as Equation (2):

$$P(X_1, X_2, \ldots, X_i) = \prod_{i=1}^{n} P\left(X_i \middle| X_{\pi(i)}\right) \qquad (2)$$

When performing system reliability analysis, a Bayesian network model can be established. Suppose the model has n nodes X_0, X_1,..., X_{n-1}. X_0 represents a system failure node, X_1-X_{n-1} represents other failure causes and failure mode nodes. The actual state value of node X_i ($0 \leq i \leq n-1$) is represented by x_i, which can take two state values of 0 and 1. 0 means no occurrence, and 1 means occurrence. Afterward, the probability of failure of the whole system can be directly calculated by using the joint probability distribution such as Equation (3):

$$P(X_0 = 1) = \sum_{x_1 \ldots x_{n-1}} P(X_0 = 1, X_1 = x_1, \ldots X_{n-1} = x_{n-1}) \qquad (3)$$

Taking the failure cause event as the root node, the failure mode event as the intermediate node, and the failure impact event of the entire system failure as the leaf node, a Bayesian network model is constructed. Suppose that after the occurrence of a node X_j, the previous probability of other events can be expressed as Equation (4):

$$P\left(X_i = 1 \middle| X_j = 1\right) = \frac{P(X_j=1|X_i=1)P(X_i=1)}{P(X_j=1)} \qquad (4)$$

2. 2. Reliability Model In the event of system data imperfections, the study of system failure effect analysis can effectively determine system failure mode and failure cause, after which failure effect analysis of the fault tree structure can determine the logical relationship between various influencing factors. Finally, the fault tree can be converted into Bayesian networks, and the uncertainty of using Bayesian network problems to handle capacity reliability of the system can be analyzed. The block diagram of this method is shown in Figure 2.

First, make the system definition. Clarify the working principle of the system, analyze the function of the system, and determine the content and scope of the research object.

The second step starts with the basic unit of the system, analyzes the possible causes of the failure of each unit, the failure mode and the influence of the failure mode on the unit, and compiles the FMEA table.

The third step is to convert the FMEA form into FTA. Taking the fault effect of the basic unit as the top event, the fault mode as the middle event, and the fault cause as the basic event, the logical relationship between each event is analyzed, and the fault subtree is formed by connecting logic gates. Connect the fault subtree corresponding to each basic unit to the upper level system with appropriate logic gates to form a complete FTA.

The fourth step is to transform FTA into Bayesian network. Take the top event of the fault tree as the root node of the Bayesian network, the intermediate event of the fault tree as the intermediate node of the Bayesian network, and the basic event of the fault tree as the leaf node of the Bayesian network. Convert the logical relationship of the fault tree into the corresponding conditional probability table, and use statistical data or expert opinions to obtain the basic probability information of the root node.

Finally, reliability analysis is carried out. The reliability analysis work such as fault diagnosis reasoning is carried out by using the bidirectional analysis ability of Bayesian network.

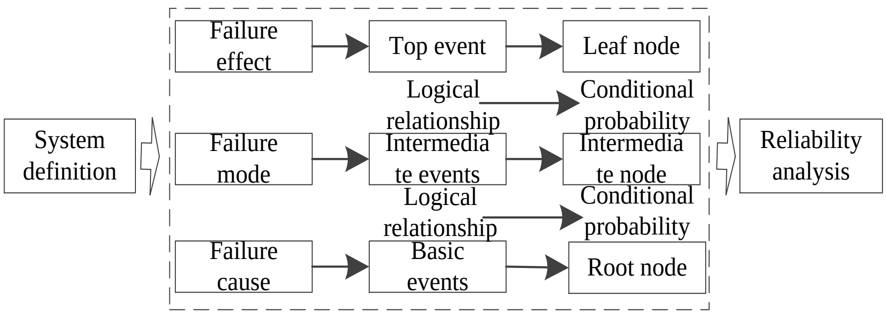


Figure 2. Reliability analysis block diagram

3. BAYESIAN NETWORK DETERMINATION

3. 1. Disaster Wind Emergency Control System According to the characteristics of the mine ventilation system and the law of smoke flow after a fire, a multi-channel electronically controlled pneumatic disaster relief damper was preset in each ventilation connection lane and its switching state was remotely controlled from the ground monitoring center, forming the disaster emergency rescue system. After a fire occurs in a mine, emergency control of remote airflow is carried out to adjust the air volume by adjusting the damper switch in the disaster area so that the polluted airflow enters the return air lane and is discharged, while fresh airflow is maintained in the densely populated area. The flow chart of a disaster airflow emergency control system is shown in Figure 3.

3. 2. System Failure Impact Analysis According to the definition of a disaster airflow emergency control system, failure mode influence analysis was carried out from three perspectives: fault cause, fault mode, and fault influence. The results are summarized in Table 1.

3. 3 System Fault Tree Analysis According to failure impact analyses, the system fault tree diagram was drawn with the catastrophic control fault as the top event

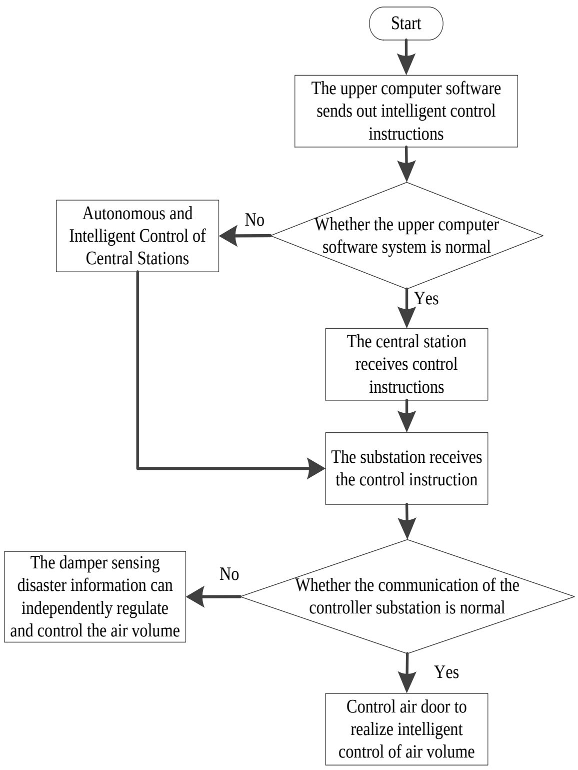


Figure 3. Flow chart of a disaster airflow emergency control system

TABLE 1. System failure impact analysis

Unit (U)	Failure cause (C)	Failure model (M)	Fault effect (E)
Upper machine	C1 data troubleshooting failure C2 disaster monitoring failure	M1 upper computer software control failure	E1 intelligent control fault
Ground central base station	C3 communication system failure C4 control system failure	M2 center station hardware control failure	
Controller station	C5 control system failure C6 communication system failure C7 data acquisition failure	M3 controller substation failure	E2 remote control failure
Damper	C8 starter failure C9 power system failure C10 mechanical system failure	M4 damper failure	

of the fault tree. Afterward, each fault subtree was connected, and the logical relationship between each event was determined, as shown in Figure 4. Any failure of the remote control and intelligent control will result in the failure of the top catastrophic control event, the failure of upper computer software control and center station hardware control will affect intelligent control fault, and any failure of the controller sub-station and damper will result in remote control fault. The control of upper computer software is affected by data solution and disaster monitoring; the control of central station hardware is affected by the communication system and control system of the central station; the fault of the controller sub-station is affected by the control system, communication system, and data acquisition of the sub-station; the failure of the damper is affected by the damper start-up device, power system, and mechanical system.

3. 4. Bayesian Network Construction

3. 4. 1. Bayesian Node Determination According to the system fault tree model, 17 Bayesian network nodes were determined to represent the fault of the remote control system from cause to effect. The classification of all nodes and states was described as follows:

Data solution (state: normal/abnormal): this node indicates that the upper computer software reads the disaster information of each sub-station underground, studies and analyzes the ventilation parameters and environmental parameters during the disaster period, and

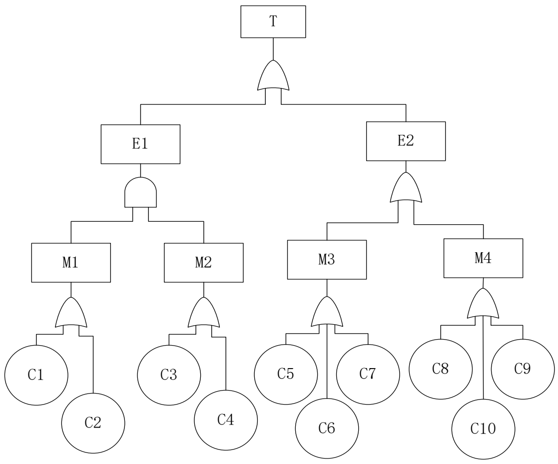


Figure 4. System fault tree analysis

generates the intelligent control scheme during the disaster period.

Disaster monitoring (status: normal/abnormal): this node represents the real-time acquisition of monitoring data of each sensor in the controller sub-station by the host computer and the ground central station.

Communication system of ground central station (state: normal/abnormal): this node represents the communication equipment between the ground center station and the host computer and the controller sub-station, which is composed of optical fiber and a communication interface.

Ground central station control system (state: normal/abnormal): this node indicates that the ground central station receives the instructions from the host computer or the autonomic control instructions and performs intelligent control of underground sub-stations through a programmable logic controller (PLC).

Communication system of the controller sub-station (state: normal/abnormal): this node represents the communication equipment between each sub-station and the central station and is composed of optical fiber and a communication interface.

Controller sub-station control system (state: normal/abnormal): this node represents that each branch station receives control instructions from the central station or directly reads control instructions from the upper computer and conducts intelligent control of the damper through a PLC.

Data collection of controller station (state: normal/abnormal): this node represents the real-time acquisition of downhole disaster monitoring data by each sub-station and the feedback to the upper computer and the ground central station.

Damper start device (state: normal/abnormal): this node represents the start switch of the damper power system after the damper receives the sub-station control command.

Damper power system (state: normal/abnormal): this node represents the high-pressure gas transported from the ground to the underground and the standby high-pressure gas cylinder as the power source of the damper, driving the cylinder to drive the active door.

Damper mechanical system (state: normal/abnormal): this node represents the mechanical structure of the damper; a steel wire rope is used to bypass the pulley to connect the driven door so that the two doors can be opened synchronously.

Control failure of upper computer software (state: normal/abnormal): the failure of any node in data calculation and disaster monitoring can cause the control failure of upper computer software.

Center station hardware control failure (state: normal/abnormal): the failure of any disaster monitoring node in the central station control system and communication system causes the failure of central station hardware control.

Control fault of the controller sub-station (state: normal/abnormal): any sub-station control system node failure of the communication system and data acquisition will cause control failure of the controller sub-station.

Damper failure (state: normal/abnormal): damper failure occurs at any node of the damper starter, power system, and mechanical system.

Intelligent control fault (state: normal/abnormal): the upper computer software control and the center station hardware control implement double insurance intelligent control, and accept the underground sub-station to collect the information for intelligent solutions. When both of them fail at the same time, an intelligent control fault will occur.

Remote control fault (state: normal/abnormal): remote control failure occurs when the downhole controller sub-station and damper malfunction, and the sub-station starts the automatic induction disaster relief mode.

Catastrophic control fault (state: intelligent fault/Remote fault) Catastrophic control faults include intelligent control faults and remote control faults.

3. 4. 2. Conditional Probability Table for Bayesian Nodes

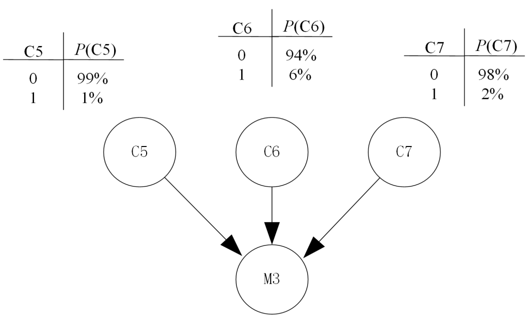
Historical data is typically used in Bayesian network learning algorithms as the prior probability of each node, and some comprehensive decision-making methods, such as the Delphi method [17] and fuzzy analytic hierarchy process [18] are adopted to consult expert opinions. The prior probability table and conditional probability table of the Bayesian network can be determined through systematic test statistics and expert advice, providing data support for Bayesian network process learning. Due to the subjectivity of human decision making, multiple groups of learning should be carried out based on debugging sample data to minimize error. The conditional probability table (CPT) is the core foundation of Bayesian reasoning, which can be obtained through parametric learning of historical records and statistics, as well as the experience of industry experts themselves. In this section, Bayesian network reasoning is performed for the "controller station fault" node branch. The fault tree bottom events "substation control system failure," "substation communication system failure," and "Data acquisition failure" root nodes are converted into the Bayesian network C5 "substation control system," C6 "substation communication system," C7 "data acquisition," and the top event "controller substation fault" leaf node is converted into the Bayesian network M3 "controller substation." Figure 5 shows the branches of the Bayesian network corresponding to the nodes of the "controller substation failure."

According to Table 1, if the controller station node M3 fails, the probability of failure caused by C5 node is P(C5=1 ∣ M3=1)=11.4%, the probability of failure caused by C6 node is P(C6=1 ∣ M3=1)=68.2%, and the probability of failure caused by C7 is P(C7=1 ∣ M3=1)=22.7%. The failure rate of C6 after calculating node M3 is P(C6=1 ∣ M3=1, C5=0)=76.1.6%. Similarly, P(C5=1 ∣ M3=1,C6=0)=33.6%.

3. 4. 3. Emergency Control System Bayesian Network

Based on the equipment downhole test statistics and fault information in the accident database, the root node historical information is obtained, as shown in Table 2.

The probabilistic inference was based on the Netica Bayesian network analysis tools. Each node of the system includes two states, "Y" means normal and "N" means failure. Through the prior probability of the root node and the conditional probability of each node, the initial Bayesian network of the disaster airflow emergency control system was established, as shown in Figure 6.



(a) Bayesian network branch

C5	*C6*	*C7*	*P(M3)*
0	0	0	0
0	0	1	1
0	1	0	1
1	0	0	1
0	1	1	1
1	0	1	1
1	1	0	1
1	1	1	1

(b) Conditional probability table

Figure 5. Bayesian network analysis

TABLE 2. Prior information of the root node

Node name	Node state	Transcendental probability
data decoding	normal	0.99
	failure	0.01
disaster monitoring	normal	0.95
	failure	0.05
Central station communication	normal	0.92
	failure	0.08
Central station control	normal	0.98
	failure	0.02
Substation communication	normal	0.99
	failure	0.01
Substation control	normal	0.94
	failure	0.06
data collection	normal	0.98
	failure	0.02
start device	normal	0.99
	failure	0.01
Power system	normal	0.96
	failure	0.04
Mechanical systems	normal	0.95
	failure	0.05

4. RELIABILITY ASSESSMENT

Air volume adjustment has a vital role in normal system operation during emergencies and disaster periods, the regulation process and control system structure are complex, especially the unit logical relationships.

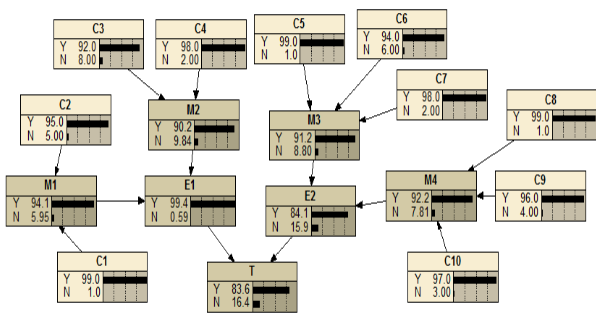
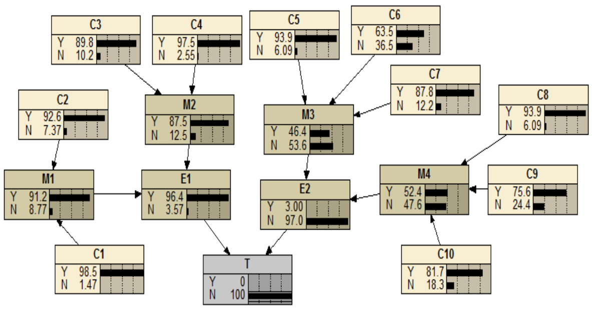


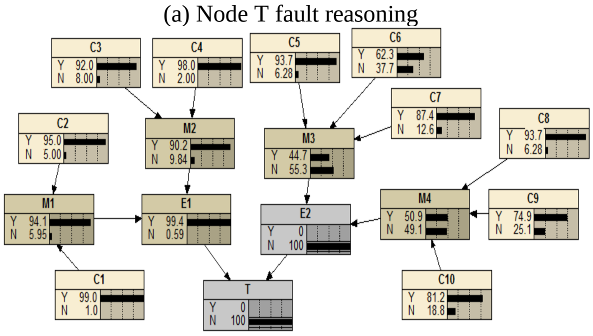
Figure 6. Bayesian network of a disaster airflow emergency control system

Regulation failure mechanisms can often be unclear, however, through the construction of a Bayesian network, reliable system evaluation can be performed based on the causal relationship between all nodes, allowing for the use of causal reasoning mechanisms to determine the system failure probability via the collaborative relationship between the units of the system. All of this in conjunction provides a theoretical basis for system reliability assessment.

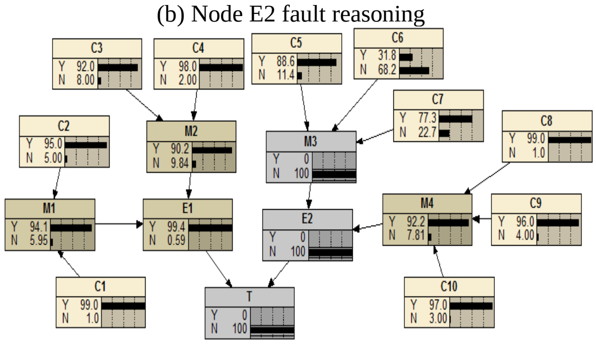
4. 1. Emergency Control Fault Analysis The reliability analysis was conducted according to the initial emergency control system Bayesian network. If the system failed, node T was assumed to be 100% in the N state, as shown in Figure 7(a). The intelligent control of node E1 failure probability was 3.6%, the remote control node E2 failure probability was 97%, the visible intelligent control in double insurance was under the action of high reliability; therefore, the analysis of the remote control node E2 to the next level node, as shown in Figure 7(b), determined that the controller sub-station node M3 failure rate was 55.3% and the damper node M4 failure rate was 49.1%. After comparison, the lower level analysis of the controller substation node M3 was conducted, as shown in Figure 7(c), and the communication node C6 failure rate of the sub-station was 68.2%, the control node C7 failure rate of the sub-station was 11.4%, and the data acquisition node C5 failure rate was 22.7%. The analysis shows that the probability of fault caused by sub-station communication was the highest under normal fault condition.



(a) Node T fault reasoning



(b) Node E2 fault reasoning



(c) Node M3 fault reasoning

Figure 7. Node M3 fault reasoning

4. 2. Intelligent Control Fault Analysis The emergency control system of catastrophic wind flow obtains the airflow control parameters of each branch through intelligent calculation of underground data collection, thus realizing intelligent control of fire smoke flow, which is the key of the emergency control system. The intelligent control system examined herein was made up of upper machine and ground centers in parallel, which could simultaneously read intelligent control commands sent to relief sub-station data information and conduct intelligent double insurance control. When the emergency air control system fails, assuming that the remote control node E2 is in a normal state, the intelligent control node E1 will fail, so as to conduct reliability reasoning on each cause node.

At this point, as shown in Figure 8, both the upper computer node M1 and the ground central station node M2 fail simultaneously. The failure rate of node C1 is 16.8%, the failure rate of node C2 is 84%, the failure rate of node C3 is 81.3%, and the failure rate of node C4 is 20.3%. Analysis shows that the data monitoring node C2 and the communication node C3 of the central station are more likely to cause intelligent control faults, so as to conduct troubleshooting.

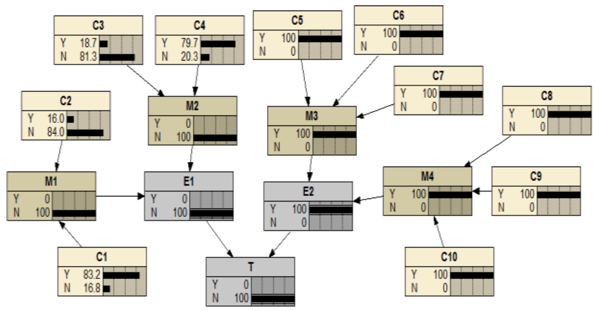


Figure 8. Fault analysis of intelligent control

5. CONCLUSION

Given the lack of perfect system data, a reliability evaluation model from failure impact analysis and fault impact analysis to Bayesian network was established to analyze the reliability of the system by using the uncertainty processing ability of Bayesian networks.

The structural process of the emergency control system was analyzed, the system reliability analysis model was established, and 17 Bayesian network nodes and states were determined. Based on the prior probability of the root node and the conditional probability of each node, the initial Bayesian network of a disaster airflow emergency control system was established.

Based on the Netica Bayesian learning software, the reliable diagnosis of the disaster airflow emergency control system was carried out, and the diagnosis results showed that the probability of failure caused by sub-station communication node was the highest under normal circumstances. Through the analysis of the intelligent control of the system, it was concluded that the data monitoring node and the central station communication node have a greater impact on the intelligent control and are prone to failure. Predict and diagnose system failures, analyze the weak links of the system, guide operation and maintenance, and realize the optimization of system design.

6. ACKNOWLEDGEMENTS

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Persian Abstract

چکیده

این مطالعه یک روش جدید برای استدلال خرابی سیستم مبتنی بر شبکه‌های بیزی برای حل مشکلات قابلیت اطمینان سیستم کنترل جریان هوای اضطراری ارائه داده است. یک مدل درخت خطای سیستم برای شناسایی رابطه منطقی بین واحدها ایجاد شد که سپس به مدل تجزیه و تحلیل خطای شبکه بیزی برای تعیین حالت‌های گره شبکه و جدول احتمال شرطی و همچنین انجام استدلال‌های تشخیصی در شاخه‌های گره سیستم تبدیل شد. تجزیه و تحلیل قابلیت اطمینان مدل مبتنی بر ابزار Netica Bayesian نشان می‌دهد که احتمال خرابی سیستم ناشی از گره ارتباطی پست در شرایط عادی بیشترین است و نظارت بر داده و گره‌های ارتباطی ایستگاه مرکزی تأثیر بیشتری در کنترل هوشمند دارند. با پیش‌بینی و تشخیص خطاهای سیستم، بهینه‌سازی طراحی سیستم در چارچوب شبکه بیزی برای بهبود قابلیت اطمینان و در آنجا با ایجاد یک بنیان نظری برای تحقیقات پیشگیری از بلایای آتی تحقق می‌یابد.