

Article

Fault Tracking Method for Relay Protection Devices

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Abstract: A method of fault tracking for relay protection devices is presented in this paper. Fault tracking means that after the failure of relay protection devices, the anomalies and warning information are obtained through data-mining technology, and then, the fault tracking algorithm is used to find the cause of failure. Let us take microcomputer protection as an example: Firstly, the common failure symptoms and the prior probability of failure causes can be collected through empirical field data. Then, the concept of an event set is proposed; thus, the causes set and the symptoms set of failure can be created. According to the causal relationship between the causes set of failure and symptoms set of failure, the reasoning chain and the corresponding Bayesian network model are built. Then, the probability of failure causes can be obtained through backward reasoning to continue the tracking analysis of failure causes for relay protection devices. Since the data used in modeling are all from statistics, this method has strong applicability and represents a simple and reliable method for the timely determination and elimination of failure in a power system.

Keywords: reasoning chain; Bayesian network; fault tracking; relay protection device

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1. Introduction

When a power system fails, the corresponding circuit breaker should be tripped to cut off the fault, to reduce power outages. However, if the protection or circuit breaker itself fails, the result is a refuse-operation or maloperation, which is likely to expand the failure range. At present, the mainstream ideas of fault diagnosis of power systems are concerned with the accuracy of protection and circuit breakers. Some fault diagnosis methods can further determine whether the failure is caused by refuse-operation or maloperation, but these methods are unable to identify the internal causes of failure. Therefore, in order to rapidly find the cause and promptly eliminate it when failure occurs, this paper puts forward a concept of fault tracking to solve the problem. Fault tracking [1] refers to the process of using data-mining technology to classify and extract the alarm data inside substations, so as to determine the internal causes of failures. That is, after failure of the known device, the warning information can be used to traceback and find internal causes of its failure. Logically, this method is contrary to the traditional fault diagnosis methods. This method aims at making full use of various information sources in a power system to extend the function of the fault diagnosis algorithm. At the same time, this idea improves the concept of fault diagnosis. The notion of fault tracking means that fault diagnosis is no longer restricted to condition monitoring or fault feature recognition and enables it to go deeper into the device to determine the causes of failure. Through fault tracking, the internal causes of power system failure can be diagnosed, from shallow to deep levels. This method is based on alarm data inside substations, so it can provide a reference for what monitoring information needs to be added. In this paper, the analysis of various fault types of relay protection devices also provides an important guidance for the maintenance, design and improvement of devices.

In this study, the failure of a relay protection device was taken as an example to construct a fault tracking model. The algorithm of fault tracking for relay protection devices was utilized on the basis of the model. Relay protection devices provide a guarantee for proper operation of an entire power system. This is essential for the reliable, stable and economic operation of a power system to ensure its consistent operation and function. At present, most of the research on the failure of relay protection devices focuses on condition-based maintenance [2,3], failure detection [4–6] and the diagnosis of hidden failures [7]. There are still few studies on the failures caused by internal faults of relay protection devices. Some only focus on one or two specific cases, such as separate research and analysis of the secondary circuit problem [8,9]. Others include too few fault types with insufficiently detailed analysis [10,11].

In view of the above analysis, this paper puts forward a fault tracking method for relay protection devices. By utilizing the received abnormal and warning signals, a fault tracking model for relay protection devices can be constructed on the basis of the combination of reasoning chain and Bayesian theory. The reverse reasoning ability of the Bayesian network is used to find causes of failure. This model contains the vast majority of fault types of relay protection devices. Based on related alarm and monitoring information, this method determines which monitoring information should be included. At the same time, the analysis of various fault types and their causes in this paper provides an important reference for the maintenance, design and improvement of relay protection devices.

2. Microcomputer Protection

2.1. Composition of Microcomputer Relay Protection

The microcomputer relay protection of a power system refers to a relay protection device based on digital signal processing technology with a microcomputer and microcontroller as the core components. With the progress of computer science, microcomputer relay protection has become a mainstream aspect of relay protection, which is mainly achieved through hardware and software [3,12].

1. **Hardware:** The hardware of a microcomputer protection device mainly includes the analog input (AI), digital input (DI), central processing unit main system (CPU), digital output (DO), man-machine conversation interface (MMI), communication interface (CI) and power supplement unit (PSU). Among them, analog input is responsible for voltage and current analog acquisition and signal discretization. The digital input is responsible for collecting the contact information from the switchblade, the protection plate and other devices. The CPU main system includes the microprocessor CPU, data memory, program memory, timer, parallel interface and serial interface, which is responsible for the measurement, logic and control functions of relay protection. The digital output is composed of a photoelectric coupler and relay, which is responsible for protection against tripping and warning signal output. The power supply circuit provides DC regulated power for the whole device to ensure reliable power supply.
2. **Software:** The software of a microcomputer protection device mainly includes the data acquisition, digital signal processing, protection discrimination logic, human-computer interaction program, self-checking program, communication interface program and operating system.

2.2. Fault Analysis of Microcomputer Protection Device

The failure of a relay protection device is mainly divided into two categories: refuse-operation and maloperation. Refuse-operation refers to the failure of the protection function module in the relay device to detect the fault, or the failure of the transmission or execution of the tripping signal issued by the relay in the tripping circuit and the breaker control circuit and operation mechanism. When the protection device sends out

the tripping signal, if there is no short circuit in the protected range, or if there is a short circuit in the adjacent lower-level equipment and its protection device does not refuse to operate, then this is referred to as protection maloperation [4].

We mainly studied the causes of refuse-operation or maloperation due to the problems of the protection device itself and its secondary circuit. Firstly, the reasons were divided into two categories caused by software settings and hardware problems. The main reasons for refuse-operation and maloperation due to software problems include setting errors or setting value errors. The fault causes in the hardware can be classified by modules, such as the failure of components in the CPU main system and the loss or distortion of analog acquisition data in the data acquisition system. Among them, most of failures in the man-machine conversation interface are caused by human errors and so are not taken into account. Through the analysis of the accident causes of the protection device and consulting the relevant literature [6,10,13,14], common causes that may directly lead to refuse-operation or maloperation of the protection device were obtained. All the failure causes were put into the causes set of failure and named M , $M = \{m1, m2 \dots m22\}$, as shown in Table 1. The prior probability p is the probability of the occurrence of the causes, that is, the ratio of the occurrence times of the corresponding failure cause to the total fault times of the protection device, obtained based on References [13,15].

Table 1. Causes set of failure.

Failure Location	Number	Failure Causes	Prior Probability $p/\%$
Software parts	m1	Setting value area change	1.98
	m2	TA ratio compensation coefficient change	2.40
	m3	Resistance values of distance protection change	2.70
	m4	Fixed-value-setting error	1.21
	m5	Software setting problem	0.56
CPU main system	m6	CPU component faults	2.26
Data acquisition system	m7	Multi-point grounding in the secondary circuit of TA	14.22
	m8	Poor contact or abrupton of secondary circuit of TA	8.25
	m9	TA saturation	7.33
	m10	Multipoint grounding in the secondary circuit of TV	12.63
	m11	Poor contact or abrupton of secondary circuit of TV	7.74
	m12	Voltage transformer wiring error	3.93
Digital input	m13	Virtual connection or abrupton in digital input	4.47
	m14	Short circuit faults in digital input	3.59
	m15	Protection plate fault in digital input	3.85
Digital output	m16	Virtual connection or abrupton in digital output	4.10
	m17	Short circuit faults in digital output	3.33
	m18	Relay fault of digital output	5.26
Power supplement unit	m19	Power supply cannot work properly	3.21
	m20	Poor performance of voltage regulator circuit components	1.68
	m21	Excessive starting current of power supply	1.33
Communication interface	m22	Communication interface fault	2.23

Before and after the failure occurs, the substation receives a large number of abnormal and warning signals. These data are recorded by the fault oscillograph. Through data-mining technology, the useful information related to protection can be sorted and screened out, and then the symptoms of failure related to causes are obtained. Let all the

selected symptoms of failure constitute the symptoms set of failure, named S , $S = \{s1, s2, \dots, s35\}$, as shown in Table 2. When there are enough failure samples, the corresponding relationship between causes and symptoms of failure can be found. We can describe it using probability statistics in order to qualitatively and quantitatively conduct fault diagnosis or fault tracking. Tables 1 and 2 cover the common causes and symptoms of failure in the current microcomputer protection devices. If other causes or symptoms of failure not in the table appear in practical applications, they can also be added into the table according to the category. With the completion of Table 2, the accuracy of fault tracking is improved. Assuming that the required information was obtained through data-mining technology, this study did not involve specific methods of data mining.

Table 2. Symptoms set of failure.

Number	Failure Symptoms	Number	Failure Symptoms
s1	Setting value check inconsistency	s19	Voltage waveform distortion
s2	Current differential setting value verification inaccuracy	s20	A function plate cannot input
s3	Distance protection setting value verification inaccuracy	s21	Protection device cannot reset
s4	Fixed value error alarm	s22	Unable to reclose breaker
s5	Protective soft-clamp not put into operation or control word set zero	s23	Inputting another protection plate when inputting a hard plate
s6	RAM fault alarm	s24	Switch indicator light is not on
s7	A/D protection fault alarm	s25	Protection output fault warning
s8	Digital signal processor fault alarm	s26	Unable to manually switch
s9	Content damage alarm of fixed value area	s27	Switch jumps off soon after switch closing
s10	AB/BC/AC phase diffuent of current sampling	s28	Protection-switching relay power failure
s11	Abnormal data/invalid warning of current sampling	s29	Protection-switching relay switch on at the same time
s12	TA protection break line warning	s30	DC power supply fault warning
s13	Current sampling is zero	s31	DC protection disappears
s14	Current waveform distortion	s32	Abnormal output power of power supply
s15	Voltage sampling is zero	s33	Power overload alarm
s16	Abnormal data/invalid warning of voltage sampling	s34	Communication interruption
s17	TV protection break-line warning	s35	Communication channel anomaly
s18	Three-phase voltage ripple		

3. Reasoning Chain and Bayesian Network

3.1. Reasoning Chain

A chain is a dynamic data structure. It consists of nodes that contain event information and points to relationships between nodes. The chain organizes and manages these nodes to form a new data structure that can achieve specific functions while avoiding a ring network. The reasoning chain shows the causality between events clearly and visually. Reason nodes at the front of the reasoning chain are used to characterize causes of the event [16,17]. The reasoning chain also meets the principle of reverse reasoning, the reason node information can be inferred according to the subsequent nodes. The simplest form of reasoning chain is denoted by $A \rightarrow B$, meaning ‘if A , then B ’.

For the failure of a relay protection device, these nodes can be divided into causes of failure nodes and symptoms of failure nodes according to the causal relationship. Then, the reasoning chain from the causes set of failure to symptoms set of failure can be constructed. For example, if the current transformer is saturated, then the distorted current waveform is obtained, that is $m9 \rightarrow s14$.

3.2. Bayesian Network

A Bayesian network is a probabilistic network that combines the Bayesian probability method with graph theory. At the qualitative level, it uses a directed acyclic graph to show the relationship between the nodes more intuitively. At the quantitative level, the Bayesian network better expresses the correlation between symptom nodes and cause nodes through conditional probability distribution. Prior probability and posterior probability are two key factors of Bayes' theorem. The prior probability can be obtained from existing data statistics and calculations. The posterior probability is calculated by prior information and sample data.

In the fault tracking of a relay protection device, ' m ' represents the suspected failure causes, namely the hypothesis in Bayesian theory; ' s ' represents failure symptoms, that is, the argument supporting the assumption. The Bayesian formula [18] is shown in (1):

$$p(m_i|s_j) = \frac{p(s_j|m_i) * p(m_i)}{\sum_{k=1}^l p(s_j|m_k) * p(m_k)} \quad (1)$$

In Formula (1):

In this paper, $l = 22$, namely, the total number of failure causes in Table 1;

$p(m_i)$: The prior probability of suspected failure causes m_i is true;

$p(s_j|m_i)$: The probability of inducing failure symptom s_j when m_i occurs, which is conditional probability;

$p(m_i|s_j)$: The probability that the failure causes m_i is true when the failure symptom s_j is true, which is posterior probability.

Through the analysis of the Bayesian formula, it can be seen that, when predicting an uncertainty phenomenon, it is necessary to generate a prior probability by combining the existing information and statistical data systematically. The adjustment of the probability prediction of unknown events in the process of collecting new information and accumulating experience must also be realized, so as to improve the accuracy of the prediction results. When dealing with failure of relay protection devices, the internal faults of the protection device are causes, and the failure symptoms are results. Fault tracking in this paper refers to the process of finding causes by reverse reasoning when the result of the event is known. To be specific, the purpose is to track the causes of failure according to the known symptom information. When the symptoms of failure occur, the probability of each suspected failure cause is calculated, and then the most likely cause of relay protection device rejection or maloperation can be inferred. Since there are often multiple symptoms in a failure, Formula (2) can be used to calculate the Bayesian suspicion $B(m_i)$ of possible causes corresponding to multiple symptoms [19]. Usually, the cause with the largest Bayesian suspicion is the most likely cause of failure. ' S_x ' represents the possible symptoms set corresponding to the cause of failure.

$$B(m_i) = \frac{\sum_{s \in S_x} p(m_i|s_j)}{\sum_{k=1}^l \sum_{s \in S_x} p(m_k|s_j)} \quad (2)$$

The prior probability of failure causes of relay protection devices is given in Table 1. By consulting a large number of data and actual failure cases, the incidence relation of causes and symptoms of failure can be obtained through analysis and calculation, as shown in Table in the Appendix A. The values in the table represent the conditional probability $p(s_j|m_i)$ of the failure symptom s_j when the cause m_i occurs, that is, the ratio between the frequency of the failure symptom s_j and the total number of the failure cause m_i .

4. Construction of Fault Tracking Model

4.1. Construction of Reasoning Chain

According to the connection relationship shown in Table in Appendix A, the reasoning chain model can be established as shown in Figure in the Appendix B. In practice, after incorrect action of the protection device, only part of the failure symptoms in Table 2 can be obtained by data-mining technology. For example, the failure of a relay protection device caused by TV secondary circuit multipoint grounding can be seen from four possible failure symptoms: (1) voltage sampling being zero, (2) the abnormal/invalid alarm of voltage sampling data, (3) three-phase voltage drift and (4) voltage waveform distortion. Therefore, the failure cause is m_{10} , and the failure symptoms are s_{15} , s_{16} , s_{18} and s_{19} . A smaller reasoning chain can be obtained, as shown in Figure 1a.

Since different causes may lead to the same symptom of failure, all the obtained symptom information is classified as a symptoms subset of failure in this paper, named S_x , and all the causes (suspected causes of failure) related to the elements in this subset are classified as a causes subset of failure, named M_x . Taking the TV secondary circuit multipoint grounding failure m_{10} as an example, when the symptoms are s_{15} , s_{16} , s_{18} and s_{19} , the corresponding causes subset of failure $M_x = \{m_{10}, m_{11}, m_{12}\}$. According to Table in Appendix A, there are still failure symptoms s_{17} connected to the causes in M_x . In order to prevent the error of fault tracking results caused by data loss, the symptoms subset of failure $S_x = \{s_{15}, s_{16}, s_{17}, s_{18}, s_{19}\}$ is set. The reasoning chain is shown in Figure 1b. Therefore, in the actual fault tracking calculation, we can establish a simplified reasoning chain model based on the obtained failure symptoms, which helps to reduce the complexity of the network and simplify the calculation.

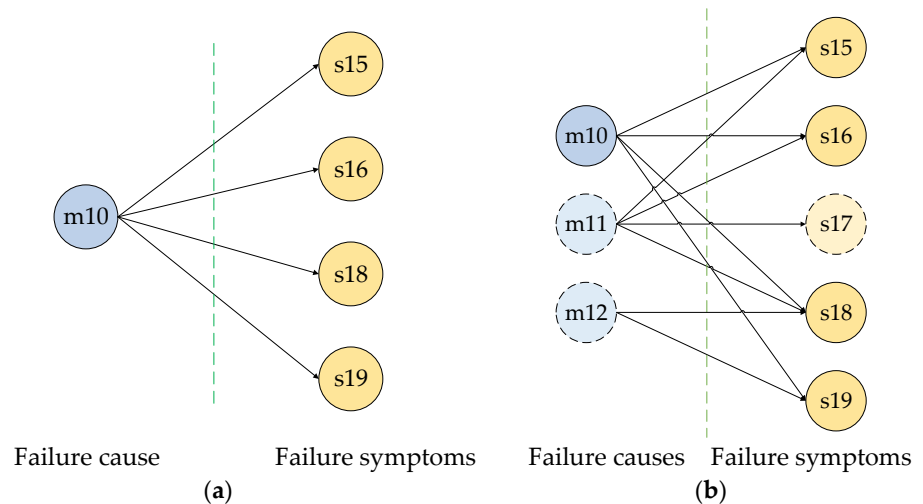


Figure 1. Schematic diagram of reasoning chain for relay protection device TV secondary circuit multipoint grounding fault tracing.

4.2. Construction of Bayesian Networks

From the complete reasoning chain model diagram, it can be seen that a cause may have multiple failure symptoms, and the same symptom also corresponds to more than one failure cause. Therefore, the next step is to use the Bayesian network to conduct reverse reasoning according to the known failure symptoms to determine the most likely failure cause. According to the reasoning chain in Figure 1b, a Bayesian network model can be constructed, as shown in Figure 2.

The Bayesian network model is conducive to obtaining fault tracking results conveniently and quickly. In addition, the model takes into account the partial loss of data during transmission. For example, if the s_{19} data are lost during the transmission, only s_{15} , s_{16} and s_{18} are obtained at the station, and the simplified reasoning chain model and

the Bayesian network model can still be obtained according to the above three failure symptoms, which contain both the lost data s_{19} and the unrealized failure symptom s_{17} . In the calculation of Bayesian suspicion, it is unknown whether the failure symptoms s_{17} and s_{19} do not occur, or the data of these two symptoms are lost. Therefore, it is necessary to consider the possibility of data loss and also reduce the interference of unrealized failure symptoms on the results. In this paper, the corresponding posterior probabilities of the failure symptoms (s_{17} and s_{19}) not obtained in the model are multiplied by 0.1 and then substituted into Formula (2) for calculation. They are therefore taken into account in the calculation, but their influence on the results is reduced.

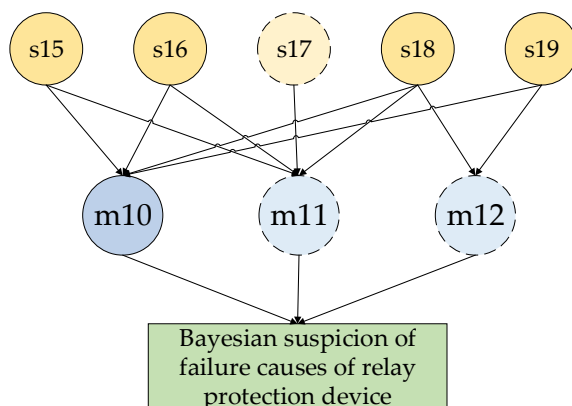


Figure 2. Schematic diagram of Bayesian network for relay protection device fault tracing.

In addition, for a complex situation where multiple parts have faults at the same time, multiple simple reasoning chains and Bayesian network diagrams can be constructed after the obtained symptoms of failure are classified. Different diagrams do not affect each other, and they are calculated individually to obtain multiple possible causes at the same time. If a certain part of the equipment has multiple failures, maintenance work can also be carried out in accordance with the size of Bayesian suspicion in order to make the maintenance content clearer.

4.3. Fault Tracking Process

The fault tracking process of a relay protection device is as follows:

After the relevant warning information of relay protection device failure is obtained by using data-mining technology, the symptoms subset of failure is established, and the corresponding causes subset of failure is also obtained according to the causal relationship in Figure in Appendix B.

If all the events in the two subsets are connected by causality in a graph, that is, only a connected graph is formed, then only a reasoning chain model is constructed. On the contrary, if the causes and symptoms of failure belong to various modules, then various independent reasoning chain models are constructed, and the causes subset and symptoms subset of failure are also be split into several corresponding groups.

The next step is to build a corresponding Bayesian network model according to the reasoning chain. The probability of each suspected failure cause is calculated by Bayesian reverse reasoning and output in order of size. The probability of all possible causes is listed in the results, and the cause with the maximum probability is the most likely cause. Multiple models can obtain multiple causes. The on-site maintenance of relay protection devices can be used in combination with this approach. In case of time emergency, the field personnel can firstly check the most likely cause of failure, which can decrease maintenance time significantly and improve the efficiency of the on-site staff.

5. Case Studies

5.1. Fault Case 1 (Simple Fault)

When an AC double phase-to-ground metal fault occurs at the outlet of a 110 kV incoming line (No.151) in a 110 kV substation, the protection device returns after starting and refuses to operate [9]. After the accident, the substation shows that it has received abnormal voltage sampling data warning signals. When viewing the wave recording file, it can be seen that the AC phase voltage is not zero, the amplitude and phase of the three-phase voltage are offset and the input voltage of the protection device is distorted. During the insulation inspection of the voltage circuit, it can be found that there are still earthing points after switching off the earthing point in the control room. After inspection, the secondary circuit of TV secondary winding in the 110 kV TV terminal box is grounded by a zinc oxide arrester, which has been broken down and has caused two-point grounding of TV secondary circuit. Therefore, when the grounding short-circuit fault occurs in the primary system, the electric potential difference between the two points is formed, which causes the measurement voltage value of the detection circuit of the protection device to be incorrect and waveform distortion, leading to the incorrect action of the directional element and causing the protection to refuse to operate.

Through postaccident inspection, we can obtain the symptoms of failure: s_{16} (abnormal data/invalid warning of voltage sampling), s_{18} (three-phase voltage ripple) and s_{19} (voltage waveform distortion). The associated causes subset of failure is $M_x = \{m_{10}, m_{11}, m_{12}\}$; that is, one of the most likely causes of protection device failure is m_{10} (multipoint grounding in the secondary circuit of TV), m_{11} (poor contact or the abrupture of the secondary circuit of TV) or m_{12} (a voltage transformer wiring error). It can be seen from Figure in Appendix B that the symptoms subset of failure connected with the causes subset M_x is $S_x = \{s_{15}, s_{16}, s_{17}, s_{18}, s_{19}\}$. Symptoms s_{15} and s_{17} do not appear in the postaccident inspection, possibly because data are lost or these two symptoms do not occur. Therefore, the reasoning chain model can be established, as shown in Figure 1b. Due to the lack of the two failure symptoms s_{15} and s_{17} , it is impossible to determine whether the data are lost, meaning in the Bayesian network model, s_{15} and s_{17} in Figure 3 are represented by virtual lines.

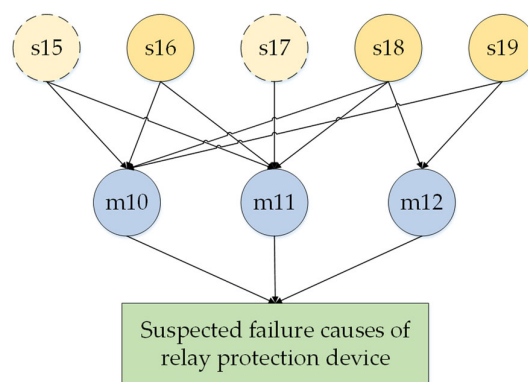


Figure 3. Bayesian network of simple fault case study.

Through Table 1 and Table in Appendix A, the prior probability of elements in the causes subset M_x and the conditional probability between symptoms and possible causes of failure are obtained, as shown in Table 3.

Table 3. The prior probability and conditional probability in the simple fault case.

Failure Cause	Prior Probability	Conditional Probability				
		s15	s16	s17	s18	s19
m10	12.63	0.05	0.5	—	0.55	0.7
m11	7.74	0.95	0.5	1	0.2	—
m12	3.93	—	—	—	0.4	0.3

The posterior probabilities can be obtained by substituting the data in Table 3 to Formula (1), as shown in Table 4.

Table 4. The posterior probability in the simple fault case.

Failure Cause	Posterior Probability				
	s15	s16	s17	s18	s19
m10	0.079	0.69	—	0.69	0.882
m11	0.921	0.31	1	0.154	—
m12	—	—	—	0.156	0.118

Substituting the posterior probability into Formula (2), since the symptoms s_{15} and s_{17} are not received, the posterior probabilities $p(m_{10}|s_{15})$, $p(m_{11}|s_{15})$ and $p(m_{11}|s_{17})$ of s_{15} and s_{17} are multiplied by 0.1 in substitution. The purpose of taking s_{15} and s_{17} into account in the calculation is to consider the possibility of data loss and reduce error. Multiplying 0.1 can reduce its proportion in the results and prevent the unrealized failure symptoms from having a great impact on the results. Through calculation, the results of Bayesian suspicion of each suspected failure cause are as follows: $B(m_{10}) = 0.709$, $B(m_{11}) = 0.205$ and $B(m_{12}) = 0.086$. Therefore, it can be concluded that the most likely cause of the failure is m_{10} (multipoint grounding in the secondary circuit of TV), which is consistent with the actual situation. A small amount of data loss does not affect the accuracy of the results, so this method can achieve a certain degree of resistance to data loss.

5.2. Fault Case 2 (Complex Faults)

If the alarm and abnormal information of other modules are found simultaneously in the former case, it indicates that the relay protection device is likely to be responsible for more than one part of the problem. In addition to the failure symptoms listed in the previous example, there are still s_{24} (switch indicator light is not on), s_{28} (protection-switching relay power failure), s_{30} (DC power supply fault warning) and s_{31} (DC protection disappears). Therefore, the symptoms subset S_x of failure is $S_x = \{s_{24}, s_{25}, s_{26}, s_{28}, s_{29}, s_{30}, s_{31}, s_{32}, s_{33}\}$, and the causes subset M_x of failure is $M_x = \{m_{16}, m_{18}, m_{19}, m_{20}\}$. Another Bayesian network model was created as shown in Figure 4.

The prior and conditional probabilities in Tables 1 and 3 were substituted to Formulas (1) and (2) to obtain Bayesian suspicions for each possible cause of failure as follows: $B(m_{19}) = 0.612$, $B(m_{18}) = 0.199$, $B(m_{16}) = 0.114$ and $B(m_{20}) = 0.075$. It can be inferred that the most possible causes of failure are m_{19} (the power supply cannot work properly) and m_{10} (multipoint grounding in the secondary circuit of TV) calculated from the previous case. In other words, for a complex situation where multiple parts of the device fail at the same time, multiple causes can be obtained by establishing multiple reasoning chains and Bayesian models for calculation, which proves that this method is still effective for complex failure cases.

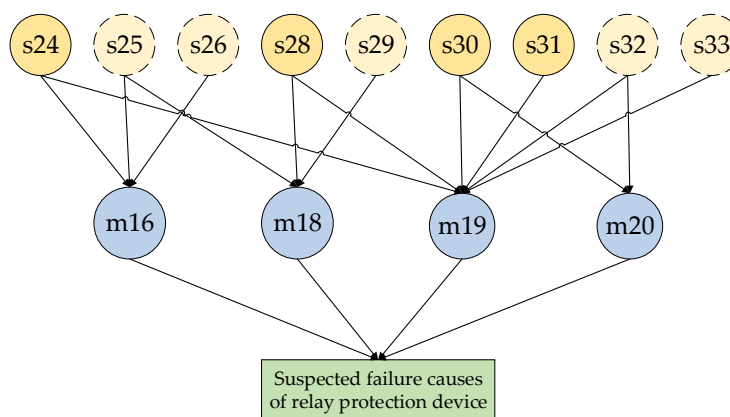


Figure 4. Bayesian network of complex fault case study.

6. Conclusions

Taking the relay protection devices as an example, this paper puts forward a fault tracking method, which proposes a new approach to the identification of the causes of equipment failure. Firstly, based on obtaining failure symptom information, the possible causes subset of failure can be constructed. According to the relationship between the two subsets from the statistics, the corresponding reasoning chain is constructed. Then, the Bayesian network is used for reverse reasoning, and the Bayesian suspicion of possible failure causes can be calculated so as to obtain the reason for the failure of the relay protection device. The functions of the reasoning chain and Bayesian network are complementary. On the one hand, the reasoning chain is used to realize the reduction of knowledge and the simplification of failure characteristics to establish the minimum event sets, which can simplify the network structure and contribute to the establishment of a more optimized and intuitive Bayesian network model. On the other hand, using the Bayesian network to deal with causal reasoning can give consideration to the error or lack of alarm signals in the transmission process and has higher accuracy for dealing with uncertainty problems. This method combines a Bayesian network with a reasoning chain to achieve efficient and rapid fault tracking and diagnosis. It is simple, effective and easy to implement.

This method is based on empirical data and probability theory. The key to this method is the construction of Tables 1 and 2, which can be obtained through practice accumulation and related experiments. This is also a limitation of the method. The integrity of the two tables has a significant impact on the accuracy of this method. When failure occurs, accurate and complete records of symptoms and causes are needed. With the continuous progress of monitoring and detection methods, the failure information contained in Tables 1 and 2 is more abundant and accurate, which provides a more solid foundation for the realization of this method and the accuracy of device fault tracking and diagnosis. On the contrary, if there are only a few statistics to refer to, or if there are omissions in recording the data, it seriously affects the accuracy of the results. With sufficient data, the effectiveness and accuracy are proven by example analysis. In view of the fact that there are almost no existing studies on fault tracking at present, this method creatively deduces the fault cause from fault symptoms. Therefore, this method has strong application value and can be used to determine failure causes quickly, conveniently and accurately. In addition to relay protection devices, this method can also be applied to fault tracking of circuit breakers, communication interfaces and other equipment.

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Appendix A

Table A1. The incidence relation of failure causes and failure symptoms.

Number	s1	s2	s3	s4	s5	s6	s7	s8	s9	s10	s11	s12	s13	s14	s15	s16	s17	s18	s19
m1	1																		
m2		1																	
m3			1																
m4				0.9															
m5					0.9														
m6						0.1	0.35	0.4	0.15										
m7										0.75	0.75				0.5				
m8											0.55	1	0.95						
m9														0.95					
m10															0.05	0.75		0.55	0.7
m11															0.95	0.55	1	0.2	
m12																		0.4	0.3
Number	s20	s21	s22	s23	s24	s25	s26	s27	s28	s29	s30	s31	s32	s33	s34	s35			
m13	0.6	0.85	0.15																
m14				0.75	0.1														
m15	0.5			0.15	0.9														
m16						0.9	0.55	0.5											
m17							0.45	0.5	0.95										
m18							0.45			0.9	0.4								
m19						0.75				0.55		0.9	0.6	0.4	0.15				
m20												0.65		0.9					
m21																0.95			
m22																	0.7	0.95	

Appendix B

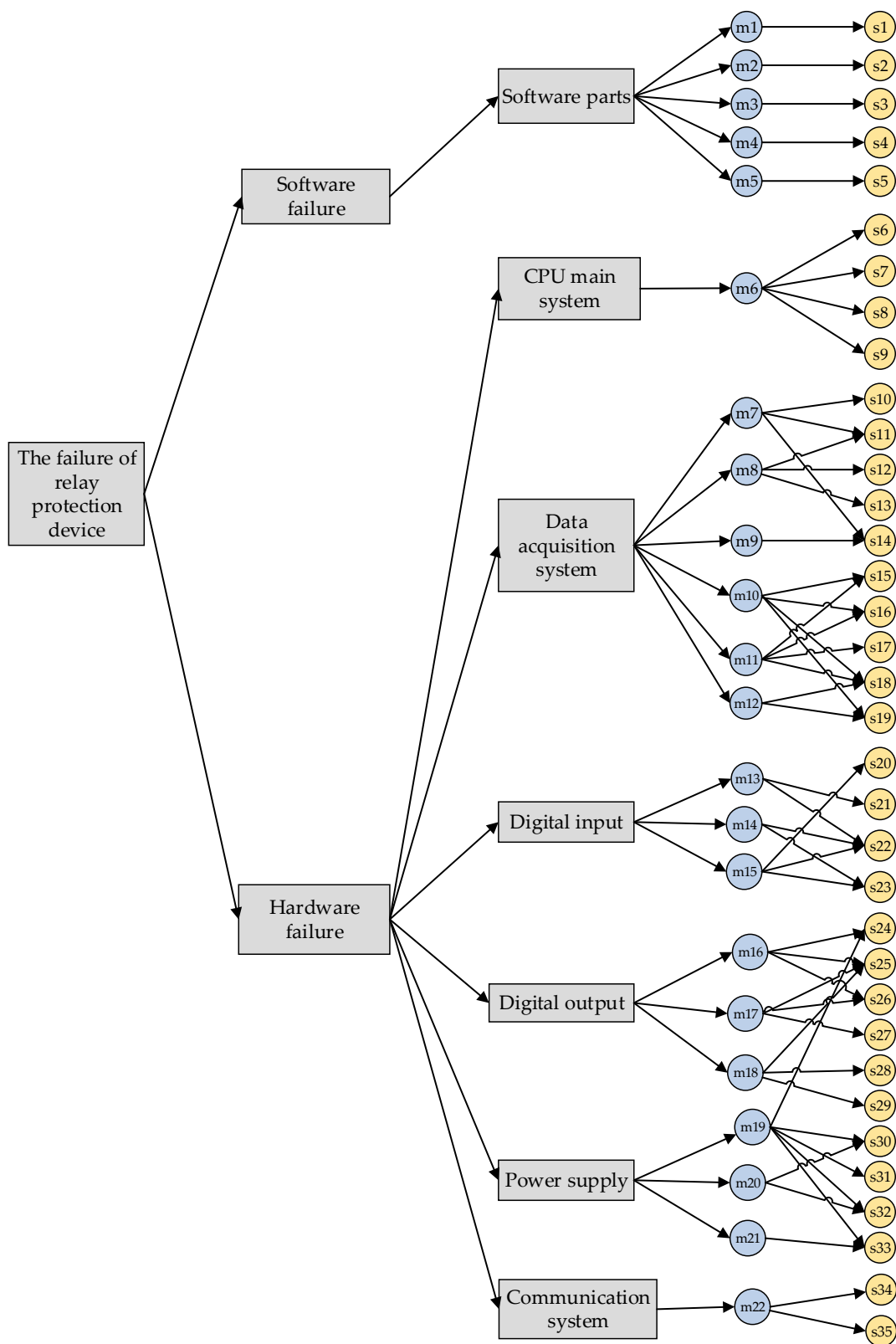


Figure A1 Complete schematic diagram of reasoning chain for relay protection device fault tracing.

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