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Fault Diagnosis Research of Submarine Casing Cutting Robot for Abandoned Oil Wellhead

Xiaojie Tian, Yonghong Liu, Yunwei Zhang, Rongju Lin and Yuanyuan Xi

College of Mechanical and Electronic Engineering, China University of Petroleum, Qingdao, Shandong, 266550, China
Tianxj20050101@163.com; liuyh@upc.edu.cn; zhangyw1989@163.com; 1440644797@qq.com; 250088857@qq.com

Abstract

The effectiveness of a submarine casing cutting robot is mainly influenced not only by its operational but also by its reliability and safety. In this paper, fault diagnosis research of this cutting robot is evaluated using the Bayesian network. A methodology of transforming the fault tree model into Bayesian network model is used. The fault tree model is established simply and conveniently. Bayesian network can address interesting questions allowing both forward and backward analysis. Combining the merits of two methods, the causes of failures, the occurrence probabilities and the importance of various components are analyzed based on the Netica software. The results show that the robot has high reliability and should be paid attentions to the research of feeding mechanism and the discharge gap detection circuits.

Keywords: *Casing cutting robot; Bayesian network; Fault diagnosis; Submarine abandoned oil wells*

1. Introduction

As the exploitation of ocean resources continue to increase, more and more oil production facilities were built in the area of operation. A 20 year plan for a platform is usual, but it is common to have a life cycle between 30 and 40 years. According to the related regulations and laws, the platform must be decommissioned when it reaches its production [1]. A pipe cutting robot is used to dismantle the abandoned oil wellhead during platform decommission. It is operated at surface by work on the oil platform and should have high operability and reliability. The robot consists of many subsystems and devices, which is mainly influenced not by its capability but also by its reliability and safety [2]. Due to its complex structure and the exacting work conditions on the seafloor, it is inevitable that faults in a robot often occur. As faults cannot be prevented entirely, it is essential to minimize both their probability of occurrence and impact when they do occur. Through diagnosis, the reliability level and failure law of the robot can be clarified. Thus appropriate measures can be taken to improve its reliability, safety and capability.

Fault location has therefore become a first objective in engineering applications. Several techniques have focused on identifying faults. Obviously, effective diagnostic approaches can decrease downtime and consequently enhance operational functionality [3, 4]. In Fault diagnosis, there are many traditional methods, such as fault tree, neural networks, and expert systems. They are proved to be inflexible, incomplete, and required comprehensive a prior knowledge of the fault characteristics, rather than actually deducing the fault themselves. The growing demand for safety and reliability of modern engineering systems motivate the development of robust fault diagnosis algorithm. Bayesian network is a method developed in

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recent years to deal with uncertain information and probabilistic reasoning, which is more and more used for fault diagnosis and applied to the representation and reasoning of uncertainties and probabilistic knowledge. Accordingly, it can be well used for the robot's fault diagnosis.

Bayesian network have successfully applied in a variety of practical tasks. Sun *et al.*, [5] introduces a Bayesian network approach for quick detection and localization of assembly fixture faults based on the complete measurement data set. Lo *et al.*, [6] proposed the Bayesian network structure on the basis of a bond graph model. The specification of prior and CPDs were completed by expert knowledge and historical data. Simulation studies on the single tank and coupled tank systems show that the proposed fault diagnosis based on Bayesian network is feasible. Faulty components can be localized correctly without extensive computation which is a major criterion of on line diagnosis. Duan and Zhou [7] presented the method for diagnosing faults using fault tree analysis and Bayesian networks (BN) to optimize system diagnosis. They employed the use of both fault tree for modeling and BN for the inference ability and tested the methodology on a real system. Raquel *et al.*, [8] established a model based on discrete Bayesian networks for diagnosis of radio access networks of cellular systems. The smooth Bayesian networks are used to decrease the sensitivity of diagnosis accuracy to imprecision in the definition of the model parameters. Bayesian network model can be attained through the transformation of some traditional reliability model. Bobbio *et al.*, [9] proposed an algorithm that transform fault tree into static Bayesian network, or transform dynamic fault trees into dynamic Bayesian network. Torres-Toledano *et al.*, [10] transformed reliability block diagram into static Bayesian networks.

As the robot's work environment is the ocean abandoned oil well, direct intervention of human is very limited and combined with very little prior knowledge, which makes the fault diagnosis very difficult. This paper makes fault diagnosis of the cutting robot by the method of Bayesian network, which is modeled by transforming the fault tree model. Then, the fault diagnosis is researched based on this model. Finally, the model-based fault diagnosis is to detect and localize faulty components in the cutting robot.

2. Submarine Casing Cutting Robot

The casing cutting robot is mainly composed of two parts, mechanical system and control system. The mechanical system is located in the abandoned oil well, which contains wellhead hanger, upper centralizer, lower centralizer, rotation motor, guiding mechanism, feeding mechanism and other components, as shown in Figure 1. The wellhead hanger can connect the cutting robot with the wellhead, which is on the topside. The upper and lower centralizers can ensure the cutting robot centralizing and stabilizing during work. The rotation motor provides the rotating power for the whole system. The feeding mechanism is a core component, which is in charge of cutting the casing. A guiding mechanism has the guiding effect during tripping in the oil well. Thus it can be seen that each component plays an important role in the cutting robot and high reliability can ensure the whole system operational and safety.

The control system is located on the platform, which is composed of the hardware and software as shown in Figure 2. The control system commands the signals to the cutting robot and monitors the whole cutting process. The hardware unit mainly consists of the following parts part: control PC, the PMAC card, A/D convertor, interface board, discharge gap detection circuit, data acquisition system and amplifier. The software unit includes the online control software of experimental prototype based on VB6.0, the control and motion programs of PMAC, and various control logics.

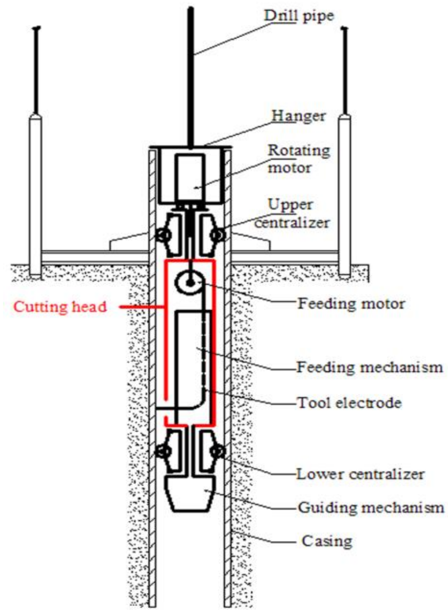

Figure 1. Schematics of the Submarine Casing Cutting Robot

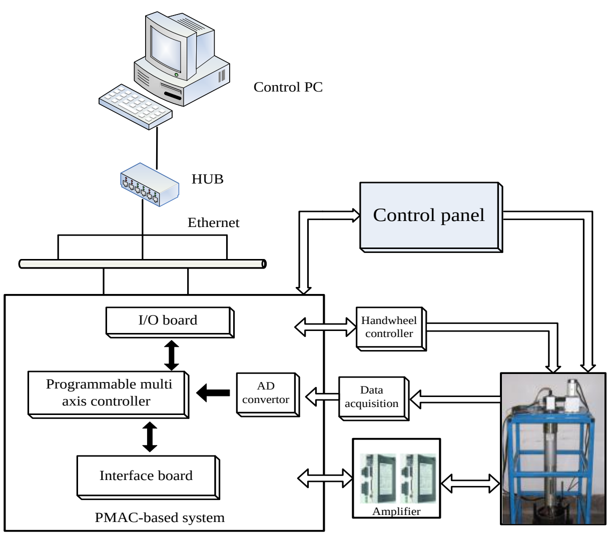

Figure 2. Architecture of the Control System

3. Fault Diagnosis System Based on Bayesian Network

The Bayesian network is also called the belief network or causal network. It is represented as a Directed Acyclic Graph (DAG). A set of random variables makes up the nodes of the network. The directed arrows connect pairs of nodes. The intuitive meaning of an arrow in the network is that one node has a direct influence on the other. Here the nodes are called the parent node and child node [11]. For each node in the Bayesian network, there is a conditional probability table (CPT), which depicts the dependent relationship between each node and its parent node.

$$U = \{X_1, ..., X_n\} \tag{1}$$

$$P = \{p(X_1|\pi_1), ..., p(X_n|\pi_n)\} \tag{2}$$

$$P(U) = \prod_{i=1}^{n} p(X_i|\pi_i) \tag{3}$$

There is a pair (D, P) that allows efficient representation of a joint probability distribution. U is a set of random variables, as shown in Equ. (1). P is a set of conditional probability functions as shown in Equ. (2), where π_i is the parent set of X_i in U. If there is a link from X_i to X_j, X_j is a child of X_i and X_i is a parent of X_j. The set P defines a unique joint probability distribution over U given by Equ. (3)

Bayesian network is consisted of qualitative and quantitative parts. The qualitative part is a DAG, in which the nodes represent the system variables and the arcs symbolize the dependencies or the cause-effect relationships among the variables. The quantitative part is the CPT, which depicts the dependent relationship between each node and its parent node. In quantitative fault diagnosis, precise mathematical model is used to monitor system states, detect abnormal behaviors and diagnose the failures. The main problems with such methodologies are the intricacy and overheads of obtaining precise numerical models and the sensitivity of the diagnostic system to modeling error. Usually, the effects of modeling errors obscure the effects of faults and cause false alarms.

Constructing a Bayesian network from data needs to learn the network structure and the parameters. The structure is expressed as directed arcs that indicate what depends in what. The parameters present the strength of these dependencies. For the discrete variables, the parameters are encoded by CPT of each node in the network. The CPT learning is to estimate the probabilities for a given structure according to a database. In fault diagnosis, when given a series values of observation variables, the posterior probability of a particular variable can be calculated by different reasoning algorithms, such as cliques algorithms and variable elimination based on Bayesian theorem. Bayesian networks can perform forward or predictive analyses as well as backward or diagnostic analyses. Given the evidence variable with known states, the updated belief of some fixture node can be stated as follows.

$$P(C_i = f|e) = \frac{P(e|C_i = f)\cdot P(C_i = f)}{P(e)} \tag{4}$$

Where $P(Ci{=}f|e)$ is the posterior probability given the evidence e, $P(e|C_i{=}f)$ is the conditional probability of e being true when C_i is in the fault state, and $P(C_i{=}f)$ is the prior probability of the ith fixture with the fault state. Because the prior probability and the conditional probability could be derived from the network, the posterior will be accessed easily.

4. Model Methodology

4.1. The Establishment of Fault Tree Model

The common establish methods of fault tree are main two types: deduction method and synthesis method. Deduction method is also known as manually model method, which analyzes the occurrence reasons of top event thinking. And then, it finds all the direct possible causes of each floor events gradually from the top event until it reaches to the basic events. This method is time consuming. The synthesis method makes some distributed fault trees into a fault tree according to the analysis' requirements through computer programs. In this paper, the synthesis method is used to establish the fault tree of the cutting robot.

4.2. Translate the Fault Tree Model into Bayesian Network

The translation between the fault tree model and Bayesian network is straightforward, following the five steps:

(1) For the basic events in the fault tree, a corresponding root node in the Bayesian network is created. If the same basic event occurs more than once in the fault tree, only one root node is needed in the Bayesian network.

(2) For the priori probability of the basic events in the fault tree, it is assigned to the corresponding root node in the Bayesian network.

(3) For each pair in the fault tree, a corresponding node is created in the Bayesian network.

(4) Nodes are connected in the Bayesian network as that in the fault tree.

(5) The CPT is created for each node in the Bayesian network from a pair.

4.3. Validation of the Model

Validation is an important aspect of a proposed model because it provides a reasonable amount of confidence to the results of the model. For this model, carrying out a full validation of the model is an impractical exercise. At present, partial validation has been developed and the following three axioms should be satisfied [12]:

(1) A slight increase/decrease in the prior subjective probability of each parent node should certainly result in the effect of a relative increase/decrease of the posterior probabilities of child nodes.

(2) Given the variation in subjective probability distributions of each parent node, its influence magnitude to child node values should be kept consistent.

(3) The total influence magnitudes of the combination of the probability variations from x attributes on the values should always be greater than that from the set of x-y ($y \in x$) attributes.

5. Fault Diagnosis of Submarine Casing Cutting Robot

5.1. Establishing the Bayesian Network Model for Submarine Casing Cutting Robot

As the cutting robot works in the casing of subsea abandoned oil wells, surrounding environment is relatively stable and the main causes of failure is components' failures. This paper establish the fault tree of this robot according to the experts' experience and test data collected from samples of parts for the process, as shown in Figure 3. Specification of prior and conditional probability distributions (CPDs) for the Bayesian network can be completed by expert knowledge and learning from historical data, as shown in Table 1. After the structure and the conditional probabilities have been determined, the network is ready for application.

As the fault tree model is established, it can be transformed into the corresponding Bayesian network according to the method that mentioned in Section 3.2. The Bayesian network model is established by using the Netica software [13], as shown in Figure 4.

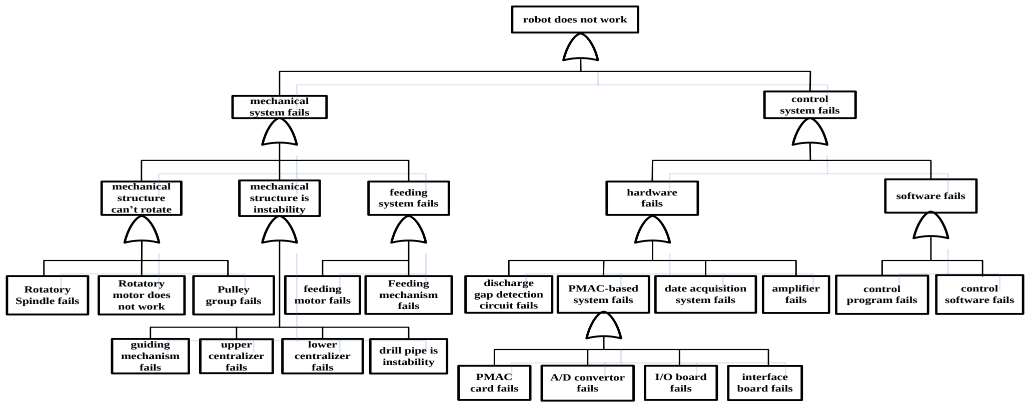

Figure 3. Fault Tree of the Submarine Casing Cutting Robot

Table 1. Fault Tree's Nodal Parameter of the Submarine Electro Discharge Cutting Robot

	Node event	Symbol indicates	Priori probability	Posterior probability
Basic events	rotatory Spindle fails	R1	0.004	0.038462
	rotatory motor does not work	R2	0.002	0.019231
	pulley group fails	R3	0.009	0.08654
	guiding mechanism fails	I1	0.003	0.028847
	upper centralizer fails	I2	0.005	0.048078
	lower centralizer fails	I3	0.005	0.048078
	drill pipe is instability	I4	0.007	0.067309
	feeding motor fails	F1	0.002	0.019231
	feeding mechanism fails	F2	0.03	0.28847
	PMAC card fails	P1	0.001	0.0096155
	A/D convertor fails	P2	0.001	0.0096155
	I/O board fails	P3	0.001	0.0096155
	interface board fails	P4	0.002	0.019231
	discharge gap detection circuit fails	H1	0.02	0.19231
	date acquisition system fails	H2	0.006	0.057693
	amplifier fails	H3	0.002	0.019231
	control program fails	S1	0.004	0.038462
	control software fails	S2	0.005	0.048078
Intermediate events	mechanical structure can't rotate	R		
	mechanical structure is instability	I		
	feeding system fails	F		
	PMAC-based system fails	P		
	hardware fails	H		
	software fails	S		
	mechanical system fails	M		
	control system fails	C		
Top event	robot does not work	W		

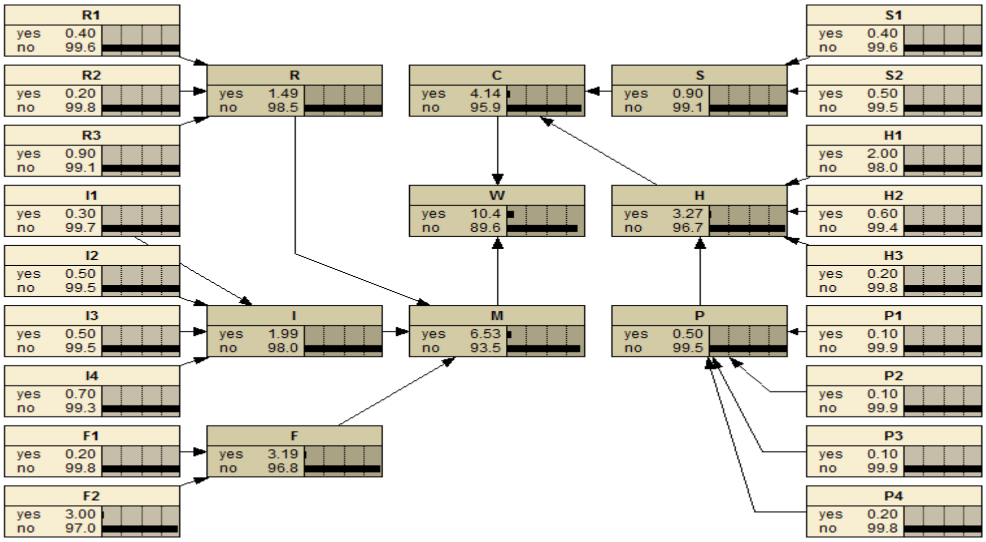

Figure 4. Bayesian Network of the Submarine Casing Cutting Robot

5.2. Validation of the Model

A sensitivity analysis has been carried out in order to give a validation of the model. The established model should satisfy the three axioms described in Section 3.3. The priori probability of R1, R2 and R3 increase by 50% respectively, as shown in Figure 5. It is revealed that the failure probability increases from 10.4% to 11.075%. Then, the priori probability of I1, I2, I3 and I3 increase by 50% respectively, as shown in Figure 6. It can be seen that the failure probability increases from 11.075% to 11.966%. The exercise of increasing each influencing node satisfies the axioms in Section 3.3. Thus it gives a partial validation of the model.

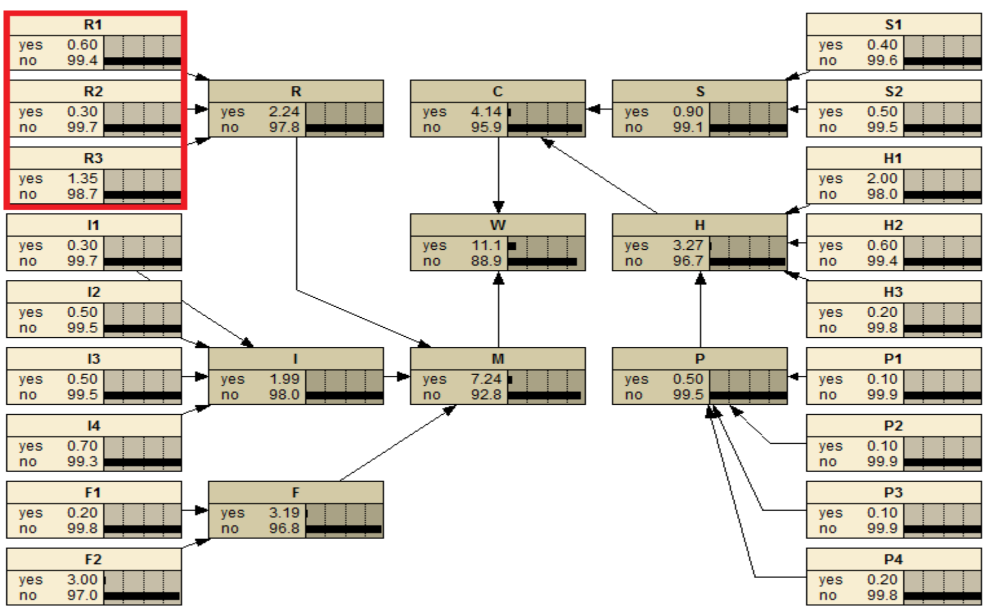

Figure 5. Bayesian Network of the Submarine Casing Cutting Robot when the Priori Probability of R1, R2 and R3 Increase by 50%

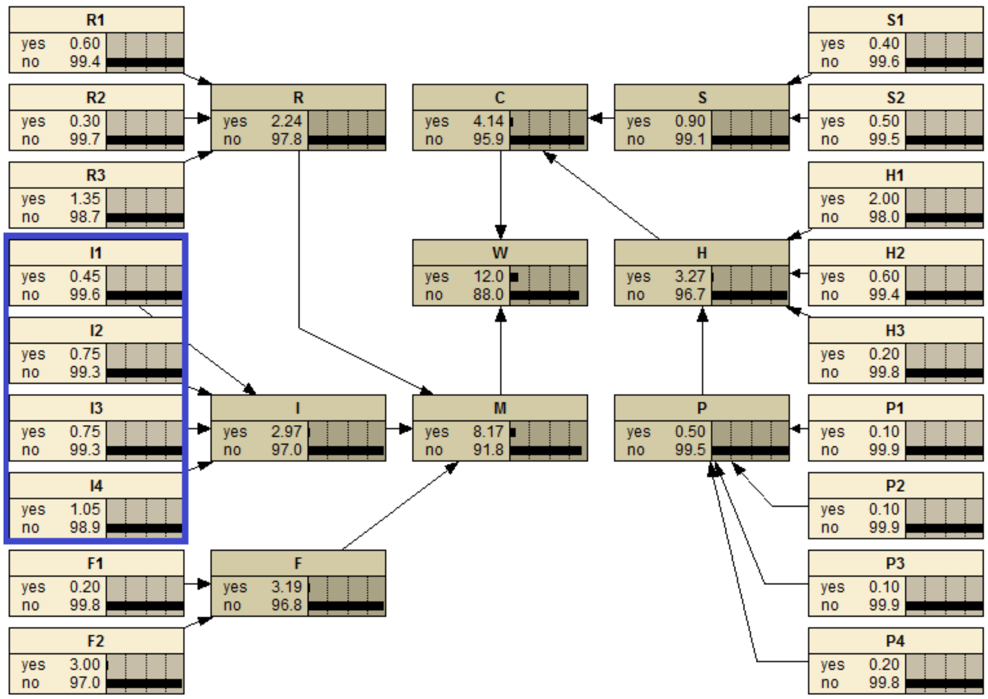

Figure 6. Bayesian Network of the Submarine Casing Cutting Robot when the Priori Probability of I1, I2, I3 and I3 Increase by 50%

5.3. Fault Diagnosis of the Submarine Casing Cutting Robot

Supposing that the robot cannot work properly, it is placed in this state. The corresponding diagnosis result can be attained through the Netica software, as shown in Figure 7. Meanwhile, the posterior probability of each basic event can be attained, as shown in Table 1. From the diagnosis result, it can be seen that the posterior probability of each basic event is changed, compared to their prior probability, as shown in Figure 8.

As can be seen from Figure 4, the probability of the robot working normal is 89.6%, which has high reliability. As can be seen from Figure 8, the most likely cause is feeding mechanism fails with the probability of 28.847% when the robot does not work. Therefore, the feeding mechanism should be paid more attention. The feeding mechanism is the core component of the mechanical system and in charge of feeding the tool electrode. It can ensure the feeding process stable, no creeping, and low frictional resistance.

The failure probability of discharge gap detection circuit fails is the second with the probability of 19.231%. In electric discharge process, the electrode and the workpiece must keep a certain discharge gap. Due to the workpiece and electrode materials constantly being removed, the gap will continue to expand. If the electrode feeding velocity cannot compensate the removed materials in time, discharge process will stop because the gap is too large. Conversely, if the gap is too small, a short circuit will happen. The discharge gap detection circuit is very important. We should improve the design of the circuit in order to maintain a certain discharge gap better.

The failure probability of pulley group is also quite large with the probability of 8.654%. The problem of pulley group is the key issues, which determines the rotation of the electrode feed mechanism in the casing unlimitedly and continuously. Thus, the design of the pulley group is important and it can improve the whole mechanism stability.

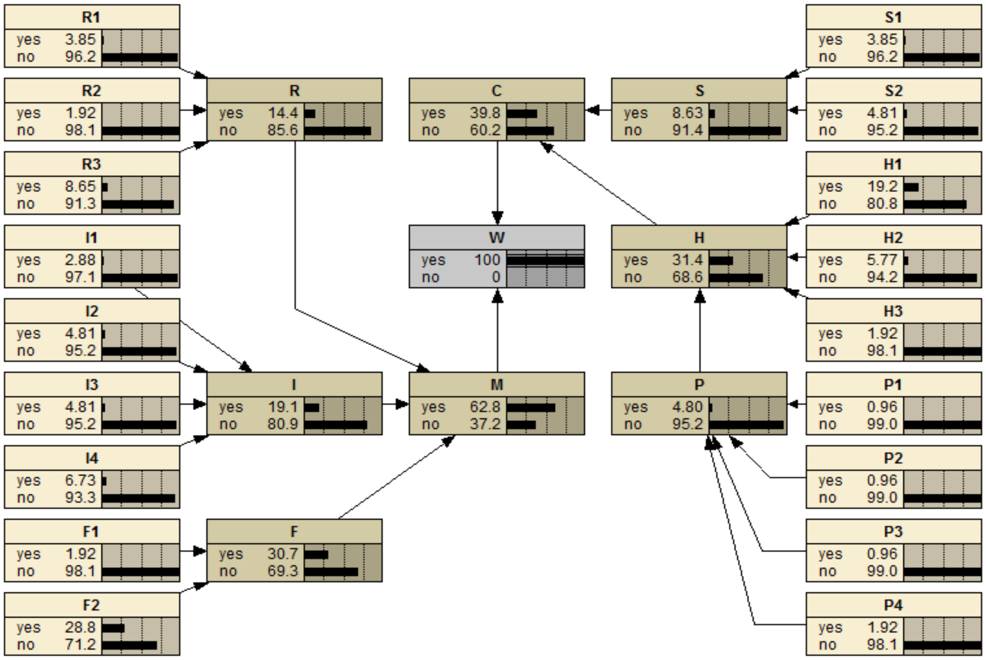

Figure 7. Diagnosis Result of Submarine Casing Cutting Robot

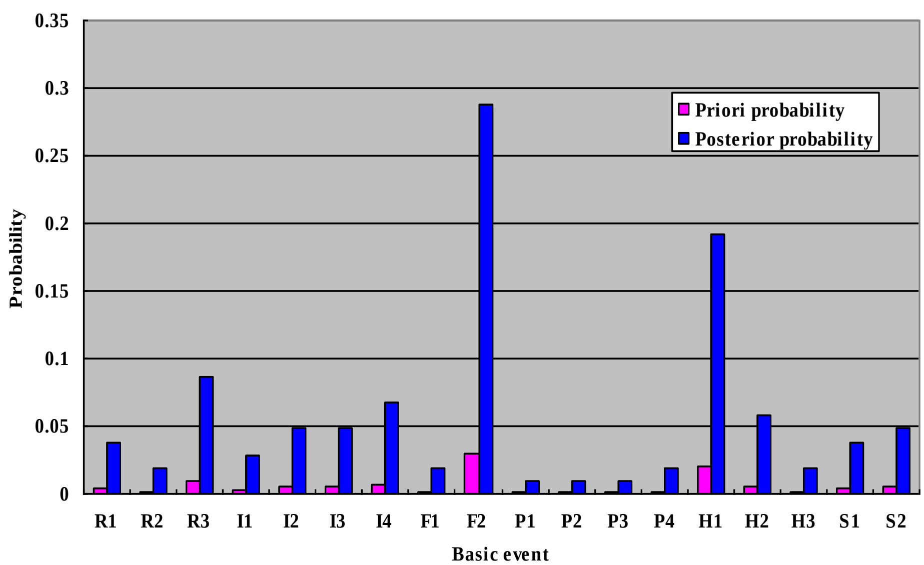

Figure 8. Prior Probability and Posterior Probability of Basic Event

6. Conclusions

This paper has applied the Bayesian network to the diagnosis of a submarine casing cutting robot. The Bayesian network model is established by transforming from a fault tree model. It has been shown that this method of diagnosis model is closer to the reasoning logic of a human expert. Based on the model, fault diagnosis research is executed by using the Netica software. Thus the posterior probabilities of the causes are obtained and the conclusions are as follows.

(1) The submarine casing cutting robot has high reliability of 89.6%.

(2) Feeding mechanism failure is a critical problem of mechanical system design, which should be paid first attention to the study of this respect.

(3) Discharge gap detection circuit is very important. So the design of circuits should be improved in order to keep a better discharge gap.

(4) Pulley group is the key problem of whether the feed mechanism can rotate continuously and unlimitedly, so the design of this part should be improved or use other transmission mechanisms.

(5) A future scope of the fault diagnosis of the cutting robot can be directed toward Bayesian networks based on the availability of research on the operation procedure and human factors.

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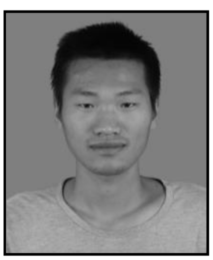
Authors

Xiaojie Tian, **s**he was born in Shandong, China, in 1985. She received her B. S. and M. S. degree in Mechanical Engineering from China University of Petroleum in 2008 and 2010 respectively. Currently, she is a Ph.D. candidate in Electromechanics Engineering in China University of Petroleum, China. Her recent research interest is the casing cutting robot system.

Yonghong Liu, he was born in Anhui, China, in 1965. He received his Ph.D. degree in Mechanical Manufacture from Harbin Institute of Technology, Harbin, China, in 1996. He is currently a professor and doctoral supervisor in College of Mechanical and Electronic, China University of Petroleum, China. His current research interests include EDM of ceramics, expansion sand screen for sand control and control system of subsea drilling equipments. He is a member of China Nontraditional Machining Committee and Nontraditional Machining Association of Shandong Province. He is Prominent Young and Middle-aged Specialist of Shandong Province and selected in New Century National Hundred, Thousand and Ten Thousand Talent Project.



Yunwei Zhang, he was born in Shandong, China, in 1990. He received his B. S. degree in Machinery Design and Manufacturing and its Automation from China University of Petroleum in 2011. Currently, he is a postgraduate student in Mechanical Engineering in China University of Petroleum, China. His recent research interest is fault diagnosis research of casing cutting tool.

Rongju Lin, he was born in Fujian, China, in 1988. He received his B. S. degree in Machinery Design and Manufacturing and its Automation from China University of Petroleum in 2010. Currently, he is a postgraduate student in Mechanical Engineering in China University of Petroleum, China. His recent research interest is numerical control system of casing cutting tool.

Yuanyuan Xi, he was born was born in Anhui, China, in 1981. He received his B. S. degree in Computer Science and Technology from Zhengzhou University in 2004. Currently, he is a postgraduate student in Mechanical Engineering in China University of Petroleum. His recent research interest is the design of casing cutting tool.