

Available online at www.sciencedirect.com**SciVerse ScienceDirect**

Procedia Environmental Sciences 16 (2012) 192 – 201

Procedia

Environmental Sciences

The 7th International Conference on Waste Management and Technology

Research on method of health assessment about the destruction equipment for high-risk hazardous chemical waste

Hongyuan Zhang^{a,b}, Jing Zhang^{b,*}, Xuecheng Liu^b, Guohui Yan^b, Yanzhao Liu^b^a*School of Automation Science and Electrical Engineerin BUAA, Beijing, 100083, China*^b*Institute of Chemical Defense of CPLA, Beijing, 102205, China*

Abstract

The destroying tasks of high-risk hazardous chemical waste have a strict request to the health status of destruction equipment. The paper proposes the health status classification method based on time between failures for the destruction of equipment, set up health status assessment model based on Time-varying Bayesian Networks and the time slice, which can take advantage of history fault information and health status monitoring indicator information to health status assessment for the destruction equipment, and which provides a reliable and safe evaluation method.

© 2012 Selection and/or peer-review under responsibility of Basel Convention Coordinating Centre for Asia and the Pacific and National Center of Solid Waste Management, Ministry of Environmental Protection of China.

Open access under [CC BY-NC-ND license](https://creativecommons.org/licenses/by-nc-nd/4.0/).

Keywords: health status; destruction equipment; high-risk hazardous chemical wastes; Bayesian Networks; health assessment

1. Instruction

The high-risk hazardous chemical waste is a kind of flammable, easily explosive, high toxicity and easy pollution material. And it needs special equipment for destroying. This kind of destroying equipment needs to be reliable and highly automatic, which has complicated structure and too much operation parameters. And it is difficult to manage the entire equipment status. With time going, many parts of the equipment aging, and the health status degrades, which consumedly increase the possibility of accident. Therefore, according to the equipment's operation parameter and its system model, how to evaluate the health status of the equipment is an important problem at present.

2. Health status classification of destruction equipment

* Corresponding author.

E-mail address: zhybeijing@sina.com

Equipment health status is defined as the ability extent of keeping the equipment definite performance under currently operational environment, and the character parameters which exhibit the performance can make as the index of equipment health status [1]. So as to use the quantitative health index, we can assess the systematic health status. The health status judgment of the destruction equipment refers to the judgment of performance degradation or deviation degree of the current state and the desired state of normal operating performance. In the destruction operation, the object is a special high-risk waste, demanding security reliability equipment. Therefore, destruction equipment operating status cannot be simply failure and normal two states, and it should be more detailed descriptions of equipment current status. Health status is a more detailed description of a system state.

We have a number of sensor modules installed in the special high-risk waste destruction equipment, which can real-time acquire device status data. However, on the one hand the installation of the sensors is limited, on the other the basis of real-time status data composed of the components and some subsystems of equipment are difficult to grasp. We can only collect some important data to the device during operation, for the various components of the device subsystem and element component level cannot fully take into account. Therefore, we finally get the device status data with small sample size, overall, real-time characteristics.

The destruction operation of the special high-risk waste is only about two months annually, the rest of the equipment in a sealed state. Therefore, we should pay more attention to the health status of the equipment during operation. Here, we have the equipment mean time between failures (MTBF) as the main basis of the division of equipment health status rating, divided into four levels: health, sub-health, worthy of use, disabled. If the device is no failure in the subsystem of the operating period of 2 months per year, as well as components, which means that the device does not require any maintenance during operation, then the device in a healthy state. Similarly, the failure of equipment, the average interval of less than one working day, that is not normal equipment operation, must be down for maintenance, and then the device is in fault condition. Specific health status classification is in Table 1.

Table 1 Destruction of equipment health status classification

<i>Device Status levels</i>	<i>MTBF</i>	<i>Description of health status</i>
Health	greater than the annual operating time (61 days)	no failure at the subsystems and components at the component level
Sub-health	less than the annual operating time (61 days) . greater than the preventive maintenance interval	Subsystem failure does not occur, the Ministry of components does not affect the operation performance, but also to complete the work; the need for the maintenance and strengthening of monitoring
Worthy of use	more than one working day less than the preventive maintenance interval	Subsystem is a minor fault, but does not affect the operation and safety of the equipment; in need of repair and focus on
Disabled	less than one working day	a serious failure has affected the safety of operations; requiring immediate repair or replacement.

3. Idea of health status assessment for destruction equipment

There are many health status assessment methods, such as modeling, analytic hierarchy process, fuzzy evaluation method, artificial neural network, Bayesian network-based method, gray theory, the extension theory [2]. Bayesian network is a very important tool; it has advantages for dealing with small sample data, learning and feedback in real time on the network, and thus in real time to determine a range of state

parameters of the equipment, which is suitable for assessment of health status of special high-risk waste destruction equipment. However, destruction equipment has complex structure, and the relationship between the various subsystems and components is difficult to clear, direct application of Bayesian networks for destruction equipment modeling is quite difficult. To Take into account, the device has a large number of historical fault information, we can construct a static fault tree, then the static fault tree is converted to dynamic Bayesian network model, so as to equipment history information can be taken full advantage of, which is easier to achieve in the operation, close to the actual operation, but also easy to avoid build errors. The main steps of health status assessment for destruction equipment are as follows:

(1) History failure information combined with the destruction of the equipment structure is used to build up a static fault tree model for the destruction of equipment.

(2) Through the transformation algorithm for static fault tree model to dynamic Bayesian networks, a dynamic Bayesian network model of the destroyed equipment is built.

(3) According to the dynamic Bayesian network model for destruction equipment and the failure rate of component parts, we can calculate the initial failure rate of the destruction equipment,

(4) Through the last failure information of destruction equipment and Bayes' theorem to update the failure rate of various components and parts, we can come to the posterior probability of component parts failure rate. For serviceable parts, the posterior probability of its failure rate should be higher than the prior probability.

(5) The fragment of time and the time of acquisition. Every three minutes in accordance with the equipment feeding, defined time slice T per unit length as three minutes. Define acquisition time ct for from the discovery of the failure to equipment downtime of destruction equipment subsystems. The number of destroyed equipment to collect state data cn , $cn = ct / T$.

(6) Through the acquisition of the operational status data of the destruction equipment, and the posterior probability of individual component failure rate, and the equipment failure rate formula based on multiple time slices, we can calculate the current failure rate of the equipment.

(7) Through the relationship between the MTBF and failure rate, we can obtain the mean time between failures of the corresponding part of the equipment.

(8) According to the mean time between failures of the corresponding part, we can determine the health level of the corresponding part of the destruction equipment from the health state classification table.

4. Dynamic Bayesian network model of destruction equipment

4.1. Static fault tree model of destruction equipment

Destruction of equipment can be divided as the subsystem level, component level, and part level three levels. Subsystem-level includes loading system, incineration system, exhaust gas treatment system and control system. Also a number of components are included in each subsystem level. The specific structure is shown in Fig 1.

Selecting the health status of the destruction equipment as the top event, according to fault information on the history, combined with the relationship between the various levels of the equipment, in accordance with the principles of constructing fault tree can be drawn from the static fault tree model of the destruction equipment, as shown in Fig 2.

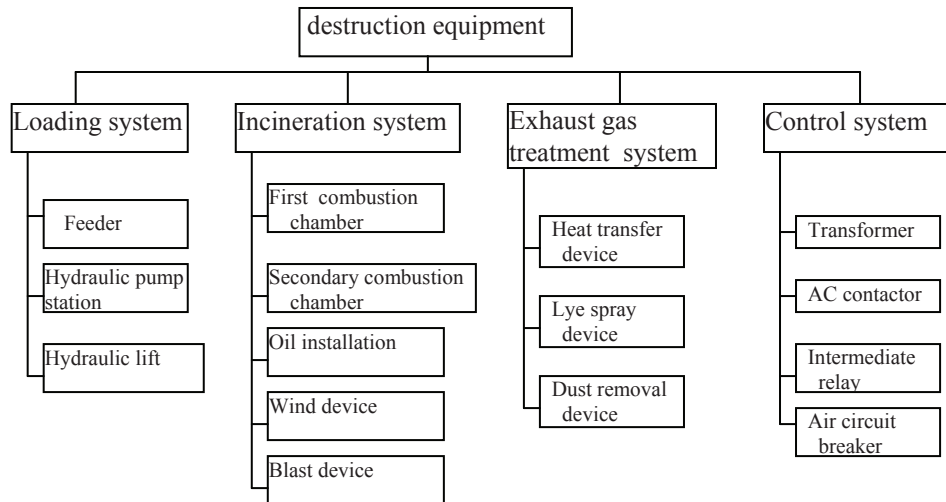


Fig 1 Structure of incineration destruction equipment

4.2. Conversion arithmetic of the dynamic Bayesian networks model and model building

Static fault tree conversion to dynamic Bayesian networks has been a lot of related algorithms at home and abroad [3-4]. By comparing the various algorithms, combined with the actual special high-risk chemical waste destruction operations, improvement of the static fault tree algorithm to dynamic Bayesian networks are as follows:

- (1) All the basic events in fault tree express for the corresponded root node in the Bayesian network. If the basic affairs of the fault appear many times, it express only one root node in the Bayesian network.
- (2) The prior probability of the fault tree basic event directly assign to the corresponding root node of Bayesian network as its priori probability.
- (3) Each logic gate in the fault tree is expressed as a node in the Bayesian network, the node marks and the status value is consistent with the fault tree gate output event.
- (4) Connect nodes in the Bayesian network nodes in accordance with the relationship between expression in the fault tree logic gates and basic events, and connect the input-output relationship of the direction of the fault tree logic gates corresponding.
- (5) Express the logical relationship of the fault tree logic gate corresponding to the node's conditional probability tables for Bayesian network.

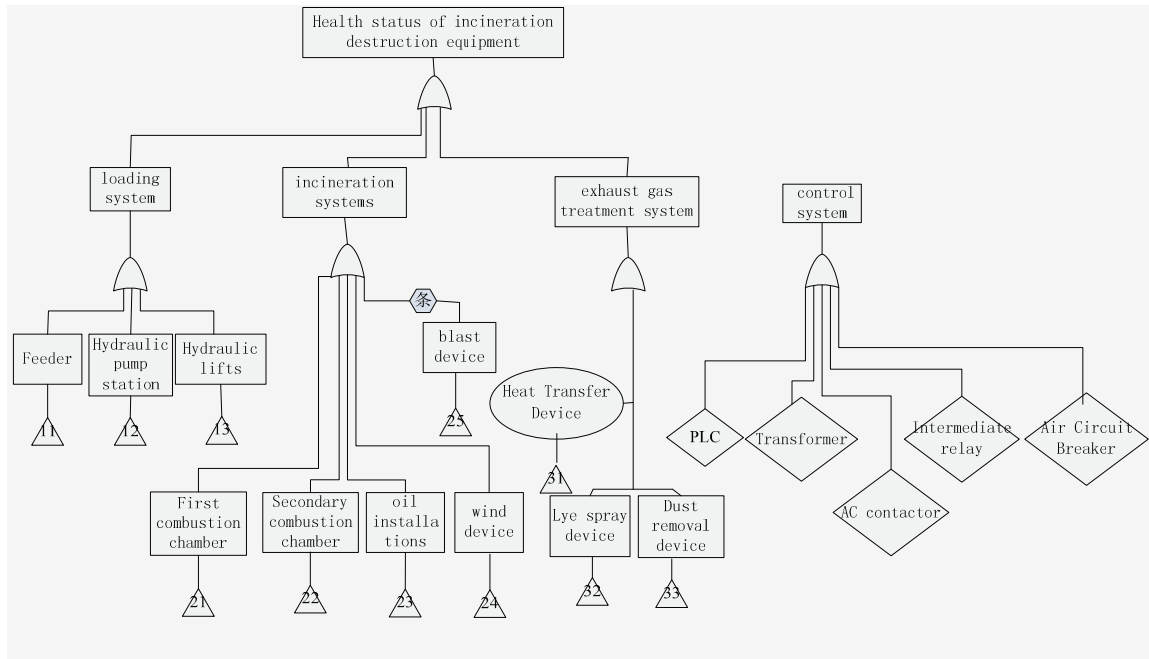


Fig 2 Static fault tree model of destruction equipment

Static fault tree conversion algorithms to dynamic Bayesian networks of the destruction equipment are shown in Fig 3.

In the figure, “Outcome” stands for health status of the system; A for the feeding system failure; A1, A2, A3, respectively, for the failure of the feeder, hydraulic lift failure and pump station failure; B for incineration system failure; B1, B2, B3, B4, B5, for a combustion chamber failure, failure of the secondary combustion chamber, fuel supply device failure, the failure of the device failure of the wind and blowing devices; C for exhaust gas treatment system failure; C1, C2, C3, respectively, for the heat exchanger device failure, lye spray device failure, the dust removal device failures; D control system failure; D1, D2, D3, and D4 respectively for the PLC failure, transformer failure, the failure of AC contactor, the failure of intermediate relay and air circuit breaker failure. Due to space limitations, the prior probability table of the various components of Bayesian networks and conditional probability is not listed, which will illustrate as example through the application of the dynamic Bayesian network.

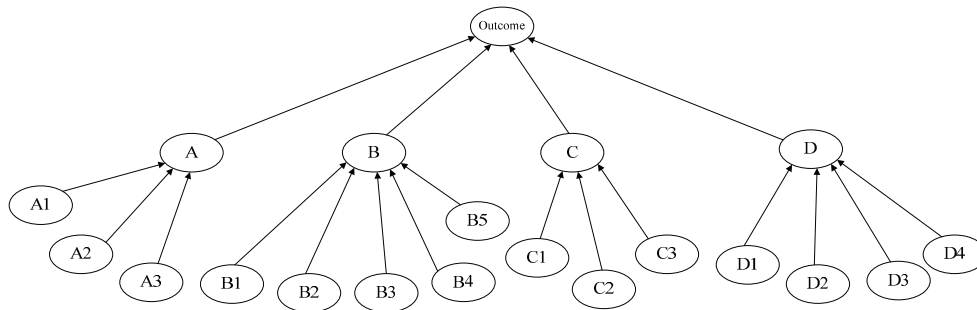


Fig 3 Static fault tree conversion algorithms to dynamic Bayesian networks

5. Failure rate calculation at each stage and health status level judgment for the equipment

5.1. Failure rate calculation at each stage based on the Bayesian for the destruction equipment

(1) The initial failure rate of the destruction equipment

Application of the priori distribution of the basic components, according to the dynamic Bayesian network model of destruction equipment, based on the independent features [5-6], the probability of the initial failure rate of the destruction equipment can be obtained:

$$p(x_1, x_2, \dots, x_n | y_1, y_2, \dots, y_m) = \frac{\prod_j p(y_j | pa(Y_j)) \prod_i p(x_i | pa(X_i))}{\sum_{x_1, x_2, \dots, x_n} \prod_j p(y_j | pa(Y_j)) \prod_i p(x_i | pa(X_i))} \tag{1}$$

$i \in [1, n], j \in [1, m]$

Where: x_i , a value X_i state; y_i , Y_i values of the observed variables; $pa(Y_i)$, y_i of the collection of the parent node; n is the hidden nodes in the network, m is the observation nodes in the network.

(2) Failure rate based multiple time slice of destruction equipment

By Equation (1), we can draw the initial health status of the destruction equipment based on dynamic Bayesian networks. But clearly, with the extension of the destruction equipment operating time, the health status of the equipment will change constantly, which is increasingly not consistent with our theoretical initial health status calculated. Thus we need to collect real-time status data of destruction equipment, through the learning of dynamic Bayesian networks, to amend the prior distribution of the various subsystems, as well as components and parts, to arrive at the subsequent posterior distribution, and eventually come to real-time dynamic Bayesian networks of the destruction equipment.

Equipment real-time status data got, assume that node x_i corresponding event y_j occur, x_i corresponding posterior probability of failure rate:

$$P(x_i = 1 | y_j = 1) = \frac{\sum_{x_1, x_2, \dots, x_n} P(X_k = x_k, x_i = 1, 1 \leq k \leq n, k \neq i, k \neq j)}{P(y_j = 1)} \tag{2}$$

$i \in [1, n], j \in [1, m]$ Where parameters are coincident with (1).

It should be noted that real-time data acquisition and selected data process should focus on selected sample of device status parameters, in order to make a dynamic Bayesian network model established closer to the destruction equipment operating status reality. In this paper, we select the state parameters of equipment failure when the first three minutes, each time slice 3, where the fault is the last fault history of equipment occurred. Three minutes selected as fault condition parameter is due to special high-risk waste destruction feeding once every three minutes. In this way, the representative device parameters make the model closer to the actual operation, the error is smaller.

Combination the length of time from the discovery of the health status “disabled” of the equipment to its completely shut down, we can calculate the required number of time slice, thus to get a set of observed values of device status.

T time slice going with dynamic Bayesian networks, due to the observed value is only a combination of state, so this observation equipment health status is as follows:

$$p(x_1, x_2, \dots, x_n | y_{11}, y_{12}, \dots, y_{1m}, \dots, y_{T1}, y_{T2}, \dots, y_{Ym}) = \frac{\prod_{i,j} p(y_{ij} | pa(y_{ij})) \prod_i p(x_i | pa(x_i))}{\sum_{x_1 x_2 \dots x_n} \prod_{i,j} p(y_{i,j} | pa(y_{i,j})) \prod_i p(x_i | pa(x_i))} \tag{3}$$

$$i \in [1, n], j \in [1, m]$$

Where: x_i represents the posterior probability of the failure rate of various components. y_{ij} for conditional probability of the j time slices of component parts, n is the component number, m is the network nodes, i, j , the number of conditional probability.

How can obtain the conditional probability of each node from the observed values of the device parameters? In this paper, the fuzzy membership function is used. Through the use of triangular membership function, observations of the device status parameter can be converted into the conditional probability of each node.

$$f(x) = \begin{cases} 0 & x \leq a, x \geq c \\ \frac{x-a}{b-a} & a \leq x \leq b \\ \frac{c-x}{c-b} & b \leq x \leq c \end{cases} \tag{4}$$

Where: x for the observations of device status parameters; $f(x)$ for the probability of the initial conditions, $[a, c]$ for the fluctuation range of the device normal operation parameters, b for the optimal value of the device status parameter.

5.2. Health status level judgment for the destruction equipment

The conversion formula of MTBF and failure rate of various stages is as flows:

$$MTBF = \int_0^{\infty} R(t)dt ; MTBF = \int_0^{\infty} \exp(-\int_0^t \lambda(t)dt)dt = 1/\lambda \tag{5}$$

Where: λ is the failure rate and MTBF is mean time between failure (hours), $R(t)$ stands for the probability of the normal operation from its run ($t = 0$) to a time t .

According to MTBF of the corresponding part, we can determine the health level of the corresponding part of the destruction equipment from the health state classification table 1.

6. Example

We illustrate the above decision algorithm from the subsystem of destruction equipment - the incineration system.

6.1. Judgment of the initial health status of the incineration system

According to the above dynamic Bayesian network model of incineration system, we can get its failure prior probability of all its integral parts and component. We selected the failure rate data of each part of component from some of the products the factory manual, and references[7-10]. Since most of the components and parts are electronic devices, the rest belong to the machinery or machine equipment, the failure rate distribution can be viewed as the exponential distribution. Various infrastructure components of the initial failure rate are in Table 2.

Table 2 The initial failure rate of the basic components of the incineration system

Parts	component	failure rate parameter λ (/ h)	parts	component	failure rate parameter λ (/ h)
First combustion chamber	combustion	1.401×10^{-4}	oil installations	1st pump	54.136×10^{-6}
	Door	26.3×10^{-5}		2nd pump	54.136×10^{-6}
	Motorized Faders	38.2×10^{-5}	wind device	induced draft fan	0.307×10^{-5}
Secondary combustion chamber	combustion	1.401×10^{-4}	blast device	Fan motor	20.798×10^{-6}
	Thermocouple	3.4×10^{-6}		Dampers	38.10322×10^{-6}
	pressure sensors	77.778×10^{-6}		Impeller components	12.5×10^{-6}
				Throttle controller	45.35923×10^{-6}

The various components of the incineration system are exponential distribution, so the burning system failure rate distribution is the exponential distribution. By the formula (1),and Microsoft MSBNX software, we can conclude that the initial incineration system failure rate: $\lambda = 2.361 \times 10^{-4}$.

The MTBF of the incineration system shall be obtained by the formula (4):

MTBF of = $1 / \lambda = 4235.49h$, and about 176 days.

According to Table 1, we can conclude the initial health status is health.

6.2. Judgment of the operation health status of the incineration system

We set all kinds of sensors for operation condition monitoring of incineration system, and the dynamic data acquisition was real-time deposited in Oracel database. We choose one history failure data of incineration system in Table 3.

Table 3 the last burning of the various components of the system failure

component	Failure time	component	Failure time
1st pump	2011-7-1 8:53:57	2nd pump	2011-7-1 8:53:59
Door	2011-7-1 8:54:07	blast device	2011-7-1 8:54:59

In the case of the incineration system has failed, by the formula (2), and Microsoft MSBNX software, the various components failure rate updates, see Table 4. Failure rate changes in the three parts of a combustion chamber, the four components of the two components of the oil installations and blowing devices.

Table 4 Posteriori failure rate of various infrastructure components of the incineration system

Parts	component	failure rate parameter λ (/ h)	parts	component	failure rate parameter λ (/ h)
First combustion chamber	combustion	1.625×10^{-4}	oil installations	1st pump	2.783×10^{-4}
	Door	7.83×10^{-4}		2nd pump	2.783×10^{-4}
	Motorized Faders	4.19×10^{-4}	wind device	induced draft fan	0.307×10^{-5}
Secondary combustion chamber	combustion	1.401×10^{-4}	blast device	Fan motor	41.251×10^{-6}
	Thermocouple	3.4×10^{-6}		Dampers	80.94172×10^{-6}
	pressure sensors	77.778×10^{-6}		Impeller components	27.4×10^{-6}
				Throttle controller	93.72335×10^{-6}

In the process of burning subsystem operation, from the discovery of the burning subsystem fails to equipment downtime takes about 15 minutes, ie, $ct = 15$. In the case of once every 3 minutes acquisition incineration system state data, the time fragment length $T = 3$ minutes, $cn = ct / T$, that is, $cn = 5$. Therefore, we collected 5 fragment real-time deposits of the incineration system operation state data, in Table 5.

Table 5 Observational data in a run of the incineration system

Fragment of time (three minutes)	First combustion chamber temperature ($^{\circ}\text{C}$)	Secondary combustion chamber temperature ($^{\circ}\text{C}$)	Furnace negative pressure (pa)
1	1263	1456	-31
2	1322	1516	-23
3	1298	1482	-27
4	1275	1473	-28
5	1281	1476	-26
Remarks	First combustion chamber temperature fluctuation range: [1100,1300], The temperature of the best condition:1200 $^{\circ}\text{C}$ Secondary combustion chamber temperature fluctuation range: [1200,1600], The temperature of the best condition:1400 $^{\circ}\text{C}$ Furnace negative pressure fluctuation range: [-10,-40], The negative pressure of the best condition: -25 pa		

According to Table 4, Table 5, the formula (3), (4),(5), and Microsoft MSBNX software, we can draw at this time the burning system $\text{MTBF} = 1301\text{h}$, about 54 days.

The preventive maintenance intervals of incineration system are usually half of the operating cycle, which is 30 days. According to table 1, the incineration system at this time is the sub-health state.

7. Conclusion

Due to high demand for reliability, security of special high-risk chemical waste destruction equipment operation, real-time control of the health status of the equipment is required. On the basis of clear concept of health status, combined with the actual operation of destruction equipment, destruction equipment health status classification method based on the mean time between failures is set up. Bayesian networks suitable for handling small sample data, real-time network for learning and feedback in real time to determine the characteristics of a series of the device state parameters, based on failure tree and the use of the improved conversion algorithm, this paper establish dynamic Bayesian network model of health status for the destruction equipment. Combination of operating conditions, through the acquisition of T time

fragments of the destroyed equipment status data, the posterior probability of the composition of components to be updated, and come to the destruction of equipment, real-time health status, eventual realization of a dynamic monitoring of the health status of the destruction equipment, which provides a more secure and reliable assessment method for special high-risk chemical waste destruction operations.

References

- [1] Bing Guangfu, Li Xuejun, DHILLON Balbir-S, Chu Wanwen. New system quantitative evaluation method for device status based on fuzzy analytic hierarchy process[J]. *Theory and Practice of Systems Engineering*.China:2010,30(4).
- [2] Bo Wu: Research on Methods and Application of Health Assessment; *Computer Measurement&Control*.2009.17(12): 2345-2347 .
- [3] Bobbio A, Portinale L, Minichino M, Ciancamerla E.Comparing Fault Trees and Bayesian Networks for Dependability Analysis[A].The 18th International Conference on Computer Safety,Reliability and Security[C].Toulouse,France: 1999,310-322.
- [4] Wang Guangyan, Ma Zhijun, Hu Qiwei. Fault tree analysis based on Bayesian network[J]. *Theory and Practice of Systems Engineering*.China:2004,(6):76-83.
- [5] Wang Guoping, Rui Youting, Chen Weidong. Multi-barrel weapon system-intensive simulation technology [J]. *Journal of System Simulation*, 2004,16(5):963-966.
- [6] C S Shukla,F F Chen.An Intelligent Decision Support System for Part Launching in a Flexible Manufacturing System[J].*Int J Adv Manuf Technol*(S0268- 3768),2001,18:422-433.
- [7] Rekec Software Co.&Intellect Writing. Chen Xiaotong, Zhao Yandi, Wang Yufen Translation. *Reliability Practical Guide* [M], Aeronautics and Astronautics University of Beijing Press: 2005.7.
- [8] Jia Yunxian. *Reliability-based maintenance manual*, Ordnance Engineering College.
- [9] People's Liberation Army General Armament Department. GJB/Z108 Non-working status expected reliability manual of electronic equipment [S].1999.
- [10] People's Liberation Army General Armament Department. GJB/Z 299B-98 Expected Reliability Manual of electronic equipment[S].1999