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SYSTEM RELIABILITY MODELING AND ASSESSMENT FOR SOLAR ARRAY DRIVE ASSEMBLY BASED ON BAYESIAN NETWORKS

MODELOWANIE I OCENA NIEZAWODNOŚCI SYSTEMU W OPARCIU O SIECI BAYESOWSKIE NA PRZYKŁADZIE UKŁADU NAPĘDU PANELI SŁONECZNYCH

Along with the increase of complexity in engineering systems, there exist many dynamic characteristics within the system failure process, such as sequence dependency, functional dependency and spares. Markov-based dynamic fault trees can figure out the modeling of systems with these characteristics. However, when confronted with the issue of state space explosion resulted from the growth of system complexity, the Markov-based approach is no longer efficient. In this paper, we combine the Bayesian networks with the dynamic fault trees to model the reliability of such types of systems. The inference technique of Bayesian network is utilized for reliability assessment and fault probability estimation. The solar array drive assembly is used to demonstrate the effectiveness of this method.

Keywords: *fault tree, dynamic fault tree, Bayesian network, system reliability, solar array drive assembly.*

Wraz ze wzrostem złożoności w systemach technicznych, pojawia się wiele charakterystyk dynamicznych w ramach procesu awarii systemu, takich jak zależność sekwencyjna, zależność funkcjonalna czy zabezpieczające elementy zapasowe. Oparte na koncepcjach Markowa dynamiczne drzewa uszkodzeń mogą posłużyć do modelowania systemów z powyższymi charakterystykami. Jednak w konfrontacji z problemem eksplozji stanów wynikającym ze wzrostu złożoności systemu, podejście oparte na teoriach Markowa nie jest już skuteczne. W niniejszej pracy łączymy sieci bayesowskie z dynamicznymi drzewami uszkodzeń w celu modelowania niezawodności tego typu systemów. Technikę wnioskowania sieci bayesowskiej wykorzystano do oceny niezawodności i prawdopodobieństwa wystąpienia uszkodzenia. Skuteczność niniejszej metody wykazano na przykładzie układu napędu paneli słonecznych.

Słowa kluczowe: *drzewo uszkodzeń, dynamiczne drzewo uszkodzeń, sieć bayesowska, niezawodność systemu, układ napędu paneli słonecznych.*

1. Introduction

Along with the increasing complexity of the structure and function of modern military satellites, meteorological satellites, commercial broadcasting and telecommunication satellites, there have been many new requirements for their reliability that have been put forward. The system is anticipated to achieve the required function and the high reliability while operating in a harsh environment. Modern satellites generally utilize solar power, a kind of sustainable energy, to meet the energy requirements and to sustain a long service lifetime. A array of solar batteries is installed in the satellite to produce electric energy. To generate enough energy, a drive assembly is utilized to rotate the solar array that directly faces the solar beam to receive the maximum solar irradiance. Therefore, a comprehensive and rigorous reliability analysis for solar array drive assembly is of great importance.

The traditional fault tree analysis method is a system reliability analysis methodology that is based on two states and static fault logic. It has been widely used for reliability and safety analysis in complex engineering systems. However, for many systems, there exist many complex dynamic characteristics during the failure process of modern engineering systems, such as sequence dependency and functional dependency. Static fault trees are not capable of modeling these failure processes.

Dugan presented a dynamic fault tree (DFT) method for analyzing reliability of systems with these aforementioned dynamic characteristics [2]. In this method, sets of dynamic gates are defined first for modeling these dynamic failure mechanisms. Then, the DFT model is decomposed into independent static modules and dynamic modules by functional decomposition, where Binary Decision Diagram (BDD) is employed to solve the static module and Markov Chain resolves the dynamic module issue.

As system dimensions increase, the number of components and the failure logic between them are become extremely large and complex. As the result, the determination and quantification of an appropriate Markov model increase exponentially. Thus, the efficiency of a Markov model has led to various concerns by many reliability analysts and experts. Amari presented a numerical integration based method for calculating the probability of dynamic gates [8]. It can alleviate the state space explosion issue encountered by Markov models. However, it fails to calculate the importance of basic components as well as the reverse inference. Rao proposed a Monte Carlo simulation based DFT method [1]. Yuge presented an inclusion-exclusion principle based method for solving DFT [3]. It can precisely calculate the probability of occurrence of the top event of fault trees with Priority-AND gate and repeated basic events given the minimal cut sets. However, they also cannot calculate the importance measure of basic events.

Bayesian networks (BN) captures the nodal relationships using a graphic approach [9]. By utilizing the conditional independency between nodes, it reduces the dimensions of the conditional probability table of non-root nodes as well as the complexity of all corresponding calculations. By adding different kinds of evidence into the BN, we can perform the forward reliability assessment, conduct the backward fault diagnosis, and further calculate the importance of individual components. Boudali proposed a discrete time BN based methodology for system reliability modeling and assessment [4].

The remainder of the paper is organized as follows. Section 2 provides a brief introduction on BN and its inference capability. In Section 3, we present the discrete time BN model, and outline the quantification of conditional probability table of static and dynamic logic gates. Section 4 presents an application example. We summarize our work and conclusion in Section 5.

2. BN model

2.1. Review of BN and conditional independency

A BN is a directed acyclic graph comprised of nodes and arcs. Nodes represent random variables (RVs) and the arcs between pairs of nodes capture the dependency information between the RVs [5]. Each root node has a prior probability table (PPT) representing the probability distribution of the nodes in its state space. A non-root node has a conditional probability table (CPT) representing its conditional probability distribution under the state combination of its father nodes [5,7].

Consider a system with 5 components, denoted as A, B, C, D, and E. We further assume that components and the system have two states. Without considering the conditional independency, the expression of joint probability distribution of these 5 variables can be given as:

$$P(A,B,C,D,E) = P(A)P(B \mid A)P(C \mid A,B)P(D \mid A,B,C)P(E \mid A,B,C,D) \tag{1}$$

The number of independent parameters is $31(2^5-1)$.

Suppose that A is independent of B, D is independent of A and B given C, and E is independent of A, B, and D conditional on C. The decomposition of the joint probability distribution of these variables is:

$$P(A,B,C,D,E) = P(A)P(B)P(C \mid A,B)P(D \mid C)P(E \mid C) \tag{2}$$

From Eq. (2), the number of independent parameters is reduced to 10, which significantly reduces the dimensions and complexity of calculation.

2.2. An example of BN and its bidirectional reasoning

In order to explain the principles of BN fully, an example of BN is shown in Fig. 1. It contains four root nodes, one intermediate node and one leaf node. As mentioned above, each node has a PPT or CPT to quantify its probability distribution given the state combination of its parent nodes. Utilizing the inference algorithm of BN, we can implement the probability inference between these variables. The probability distribution of root nodes is given in Fig. 1.

Utilizing the joint tree inference algorithm of BN, the probability distribution of node T without evidence can be calculated:

$$P(T=0)=0.9793,\ P(T=1)=0.0207$$

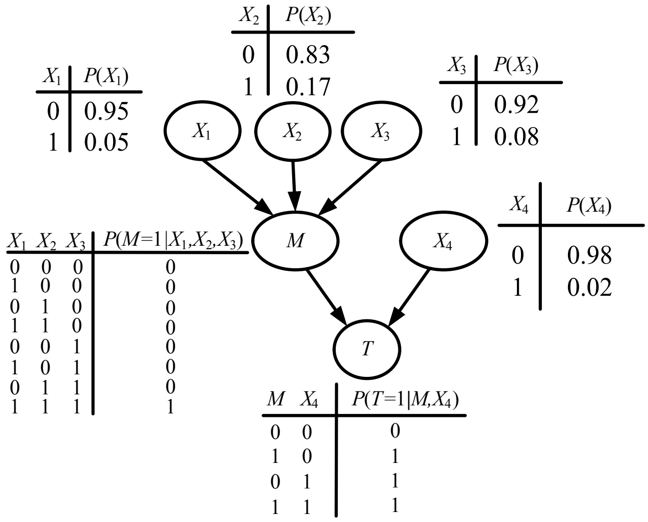


Fig. 1. An example of BN

Supposing each root node is in state 1 respectively, the conditional probability distribution of leaf node T is shown in Table 1.

Table 1. Conditional probability distribution of leaf node T

X_i	X_1	X_2	X_3	X_4
$P(T=0 \mid X_i=1)$	0.9667	0.9761	0.9717	0.0000
$P(T=1 \mid X_i=1)$	0.0333	0.0239	0.0283	1.0000

Supposing the leaf node is in state 1, the posterior probability distribution of root nodes is shown in Table 2.

Table 2. The posterior probability distribution of root nodes

X_i	X_1	X_2	X_3	X_4
$P(X_i=0 \mid T=1)$	0.9194	0.8032	0.8903	0.0322
$P(X_i=1 \mid T=1)$	0.0806	0.1968	0.1097	0.9678

By utilizing the bidirectional inference, we can implement probability inference between nodes within the BN and perform the reliability analysis and probability inference of each potential fault in engineering systems.

3. Reliability assessment model based on DFT and discrete time BN

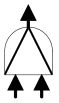
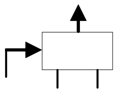
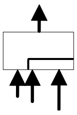
3.1. DFT

DFT methodology extends traditional fault tree method by defining a set of dynamic logic gates to represent the time dependency and functional dependency among component failure mechanisms. Priority-AND gate (PAND), Functional Dependent Gate (FDEP) and Spare are most commonly used dynamic gates. Their notation and failure mechanism are listed in Table 3.

3.2. Discrete time BN model for system reliability modeling and assessment

Consider the reliability of a system at mission time t. The time interval $(0,t]$ is evenly divided into n equal intervals, the length of each interval is $\Delta=T/n$. Let the interval $(t, +\infty)$ be the $(n+1)$th interval. So the time line is divided into $n+1$ intervals. We define the $n+1$ intervals

Table 3. Dynamic gates and failure mechanism

Dynamic gate	Notation	Failure mechanism
PAND		If and only if both A and B occur, and A occurs before B, the output occurs
FDEP		If the trigger event occur, all the dependent events occur
Spare		The primary input is initially powered on, and all spares are standby. While primary input fail, the defective items are replaced one by one. If all inputs fail, the output event occurs.

as the state space of nodes in BN, and marked as $1,2,\cdots,n+1$, respectively. Then, if a node is in state i, it means that it will fail in time interval $((i-1)\Delta, i\Delta]$. The failure time of components and the system corresponds to the state of node in BN. If a node or component is in state n+1, it means that it will not fail at mission time t. The probability of the system being in state n+1 represents the reliability of the system at time t. The CPT of non-root node will be discussed in the next section.

3.3. Determination of CPT in BN corresponding to various gates in DFT

Before the quantification of system reliability, the DFT model is needed to transform into a BN model. For a given BN, the graphic structure represents the qualitative relationship between an individual node and its parent and child nodes. Meanwhile the CPT with each non-root node represents the quantitative relationship between the same nodes. Generally, it is quite easy to acquire the graphic structure of the BN according to the structure of DFT. Next, we will discuss the CPD of various kinds of gates, which could be transferred to CPT in its corresponding BN models.

(1) AND Gate

Let $X=[X_1,X_2,\cdots,X_m]$, where $X_i, i=1,2,\cdots,m$ denote the state variable of input events and m is the number of input events to the gate. Let Y be the state variable of the output event. The state space of each variable is $\{1,2,\cdots,n+1\}$. Let $k=\max(X_1,X_2,\cdots,X_m)$. The conditional probability distribution of Y under a certain state combination of input events can be given by

$$P(Y=j\mid X)=\begin{cases}1, & j=k\\ 0, & j\neq k\end{cases} \tag{3}$$

(2) OR Gate

The notation and meanings of all variables and their corresponding state spaces are the same as aforementioned AND Gate. Let $r=\min(X_1,X_2,\cdots,X_m)$. The conditional probability distribution of output of OR Gate is

$$P(Y=j\mid X)=\begin{cases}1, & j=r\\ 0, & j\neq r\end{cases} \tag{4}$$

(3) Priority-AND Gate

Let A and B be the input events of the Priority-AND gate, Y is the output event, and a, b, y are their values, respectively. The conditional probability distribution of Y is

$$\text{While } a<b\leq n+1,\ P(Y=i)=\begin{cases}1, & i=b\\ 0, & \text{else}\end{cases} \tag{5}$$

$$\text{While } a\geq b,\ P(Y=i)=\begin{cases}1, & i=n+1\\ 0, & \text{else}\end{cases} \tag{6}$$

(4) Functional Dependent Gate

For the case that the functional dependent gate has only one trigger event A, the CPT of the output B dependent of A on condition that A has happened will be an identity matrix. Its CPD is

$$P(B=j\mid A=i)=\begin{cases}1 & j=i\\ 0 & j\neq i\end{cases}\qquad i,j=1,2,\cdots,n+1 \tag{7}$$

Meanwhile the FDEP has two or more trigger events, and an intermediate node is inserted between the output node and all the trigger nodes. The CPT of the intermediate node depends on the relationship between the intermediate node and all the trigger nodes. The CPT of the output node will also be an identity matrix as it is only dependent on the intermediate node.

(5) Cold Spares

According to the failure mechanism of Cold Spare (CSP), the failure distribution of the spare is related to its failure rate and the failure time of the primary component. Let x, y be the state of primary input A and spare B, and λ is the failure rate of A and B. Thus, the conditional probability distribution of B is

$$P(B=y\mid A=x)=\begin{cases}\dfrac{\int_{(x-1)\Delta}^{x\Delta}\int_{(y-1)\Delta}^{y\Delta}\lambda e^{-\lambda(t-\tau)}\lambda e^{-\lambda\tau}\,d\tau\,dt}{\int_{(x-1)\Delta}^{x\Delta}\lambda e^{-\lambda\tau}\,d\tau}=\lambda\Delta e^{\lambda x\Delta}e^{-\lambda y\Delta} & ,x<y<n+1\\ 1-\sum_{i=x+1}^{n}P(B=i\mid A=x) & ,x<y=n+1\\ 0 & ,x\geq y\end{cases} \tag{8}$$

(6) Hot Spares

In spite of the difference in failure mechanisms between AND Gate and Hot Spare Gate (HSP), the conditional probability distribution of the output nodes for hot spares are identical, so they are not repeated again.

4. Reliability modeling and assessment of solar array drive assembly of satellite based on BN

The solar array drive assembly (SADA) plays a vital role in the orientation function of a satellite solar array. Therefore, it is significant to perform reliability analysis and assessment on the drive assembly to ensure that the high reliability performance of the solar array and the entire satellite system. This paper presents a reliability analysis and assessment method based on the DFT and BN methodology.

The SADA provides the linkage between the solar array and the satellite body, with the function of driving the array to rotate to parallel with the solar beam to get as more solar energy as possible. The studied SADA is comprised of solar array sensitive apparatus, on-

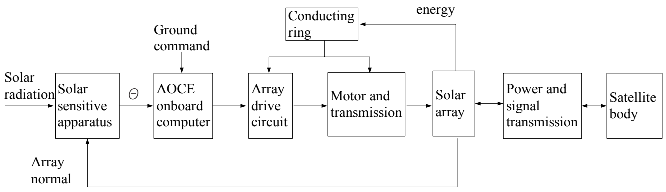


Fig. 2. Working principle diagram of orientation system of SADA

board computer, conducting ring, drive circuit, and motor transmission and so on. Its working principle diagram is shown in Fig. 2 [6].

In the paper, the event 'Failure of SADA' is defined as the top event. Let A, B, C, D, E, F, G, H, I, S, and K represent failure events of solar sensitivity apparatus, on-board computer, harmonic reducer, drive motor, human factor, electrical system, transmission, conducting ring, position sensor, windings and electric brush, respectively. Let A_1 and A_2, B_1 and B_2, S_1 and S_2, F_1 and F_2, I_1 and I_2, K_1 and K_2 be the primary and spare of solar sensitivity apparatus, on-board computer, windings, electrical system, position sensor and brush, respectively.

The solar sensitivity apparatus, on-board computer, stator windings of motor and position sensor can be modeled by the CSP gate. The electrical system can be modeled using FDEP gate as it has components with functional dependency characteristics. The conducting ring is modeled using HSP gate.

Suppose that all other failures between components are independent apart from aforementioned dependent failures. Finally, we get the DFT of SADA shown in Fig. 3. After mapping all the events of the DFT into the nodes of BN, the BN model of SADA could be obtained as shown in Fig. 4.

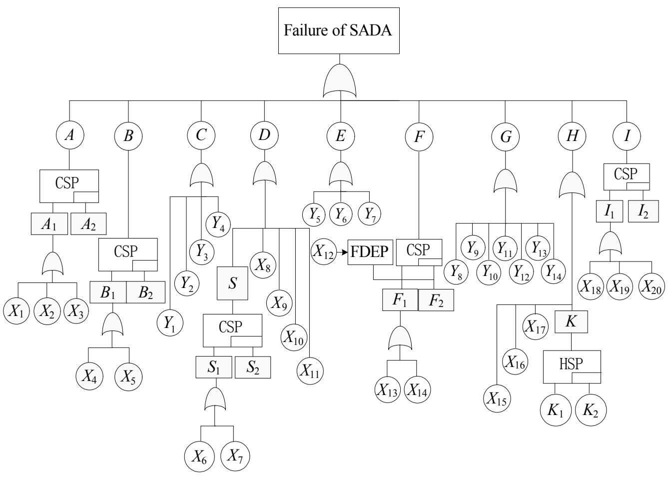


Fig. 3. DFT of SADA

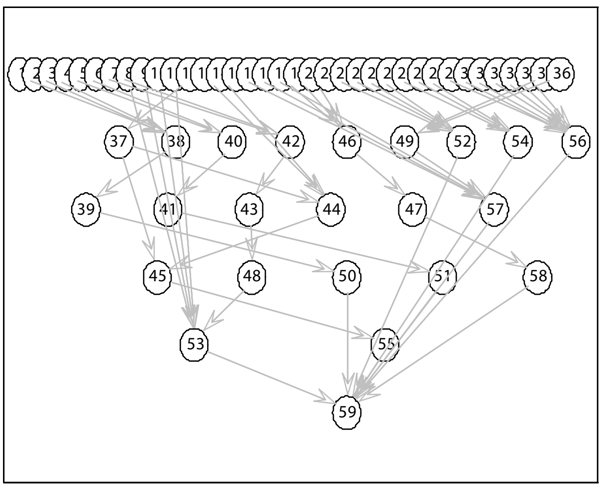


Fig. 4. BN model of SADA

The code, name, and failure rate of all basic events are listed in Table 4. The system reliability curve for mission time 50000 hours when n was taken 2, 3, and 4 is shown in Fig. 5. The system reliability for every 100 hours when n were taken 2, 3, 4 under [45000, 50000] hour mission time is shown in Fig. 6. From the statistical analysis based on the calculated data, we know that the maximum error of reliability between the second set data and the first set data is 0.0606%, meanwhile the maximum error between the third set data and the second set data is 0.0305%. Taking into account the existence of the other uncertainties in the system, n can be taken to be 4 in order to meet the error requirements for reliability.

Table 4. Code, name and failure rate of basic events (10-6failure/hour)

Code	Event name	Failure rate (λ)	Code	Event name	Failure rate (λ)
X_1	Failure of optical head	0.5	X_{19}	Failure of LEDs	0.5
X_2	Censer failure	0.6	X_{20}	Failure of detection circuit	0.5
X_3	Failure of signal processing circuit	0.12	Y_1	Failure of flexible gear	0.1
X_4	Hardware failure of on-board computer	0.5	Y_2	Gear wear	0.6
X_5	Software failure of on-board computer	0.25	Y_3	Failure of solid lubricant film	0.55
X_6	Fatigue failure of windings	0.25	Y_4	Failure of lubricating grease	0.5
X_7	Windings are burned down	0.1	Y_5	Go fly of instruction	0.5
X_8	Failure of drive circuit	0.12	Y_6	Mistakes in hardware design	0.2
X_9	Locked rotor	0.12	Y_7	Mistakes in software design	0.2
X_{10}	Friction increases	0.1	Y_8	Clutch failure	0.6
X_{11}	Fatigue failure	0.1	Y_9	The bearing is jammed	0.5
X_{12}	Interface fault	0.6	Y_{10}	Bond breakage	0.1
X_{13}	Circuit failure	0.125	Y_{11}	Failure of Rotation axis of potentiometer	0.5
X_{14}	Transistor failure	0.5	Y_{12}	Gear failure	0.1
X_{15}	The circuit is burned down by discharge	0.1	Y_{13}	External failure	0.5
X_{16}	Failure of bearing lubricant	0.1	Y_{14}	Comprehensive failure	0.5
X_{17}	Failure of insulation	0.15	K_1	Primary failure of electric brush	0.5
X_{18}	Failure of image censer	0.5	K_2	Spare failure of electric brush	0.5

The probability distributions of the top event T for 5 time interval under t=50000, n=4 are shown in Table 5. That is, the system probability of failure and reliability within the mission time are 0.2931 and 0.7069, respectively.

When the system in the failure state (the state of leaf node T is 5), the probabilities of failure for every bottom event can be calculated by using the reverse inference of the BN as shown in Table 6. From

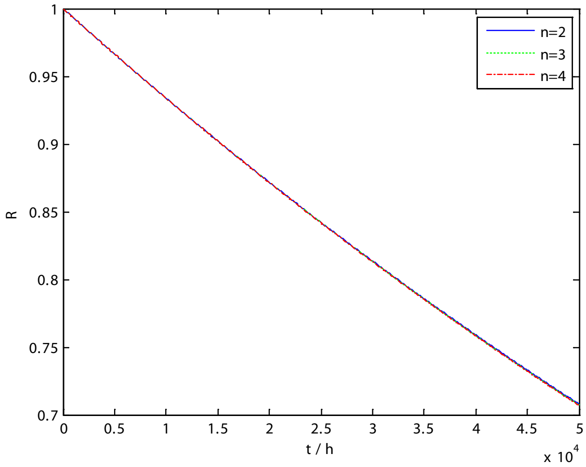


Fig. 5. System reliability curve for mission time 50000 hours

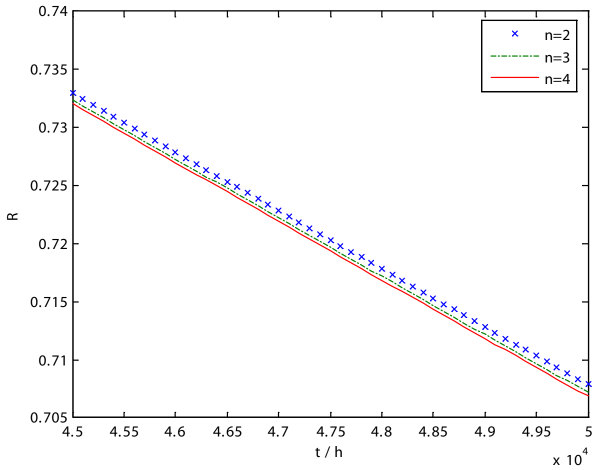


Fig. 6. Reliability comparisons for n at a given value 2, 3 and 4, respectively

Table 5. Probability distributions of top event under n=4

T=i	1	2	3	4	5
$P(T=i)$	0.0820	0.0759	0.0703	0.0649	0.7069

Table 6 we can conclude that the minimum probability of failure is X_7. The maximum probability of failure is X_{28} , which is also the weakest part of the system.

Based on the reasoning algorithm of the BN, the failure conditional probabilities of the top event on condition that the bottom event is on failure state can be calculated as shown in Table 7.

5. Conclusions

This study proposed a hybrid reliability modeling and assessment method based on Bayesian network and dynamic fault tree. The method for determining the conditional probability of logic gates is investigated as well. The dynamic fault tree model and its corresponding Bayesian network are tested and applied to predict the lifetime of solar array drive assemblies. The junction tree inference algorithm is used for the proposed hybrid model. The results can be used for system failure diagnosis and is expected to identify and further remove the design weakness of the system. The results obtained from the satellite's solar power control system have shown that the proposed method is effective and accurate, showing its potential application for reliability assessment on large and complex engineering systems.

Table 6. Probability of failure for every component under system failure

X_i	$P(X_i=1\|T=1)$	X_i	$P(X_i=1\|T=1)$	X_i	$P(X_i=1\|T=1)$
X_1	0.0260	X_{13}	0.0064	Y_5	0.0842
X_2	0.0311	X_{14}	0.0254	Y_6	0.0339
X_3	0.0063	X_{15}	0.0170	Y_7	0.0339
X_4	0.0255	X_{16}	0.0170	Y_8	0.1008
X_5	0.0128	X_{17}	0.0255	Y_9	0.0842
X_6	0.0126	X_{18}	0.0262	Y_{10}	0.0170
X_7	0.0051	X_{19}	0.0262	Y_{11}	0.0842
X_8	0.0204	X_{20}	0.0262	Y_{12}	0.0170
X_9	0.0204	Y_1	0.0170	Y_{13}	0.0842
X_{10}	0.0170	Y_2	0.1008	Y_{14}	0.0842
X_{11}	0.0170	Y_3	0.0925	K_1	0.0261
X_{12}	0.1008	Y_4	0.0842	K_2	0.0261

Table 7. System probabilities of failure on condition that each bottom event is in failed state

X_i	$P(T=1\|X_i=1)$	X_i	$P(T=1\|X_i=1)$	X_i	$P(T=1\|X_i=1)$
X_1	0.3083	X_{13}	0.3012	Y_5	1.0000
X_2	0.3083	X_{14}	0.3011	Y_6	1.0000
X_3	0.3084	X_{15}	1.0000	Y_7	1.0000
X_4	0.3027	X_{16}	1.0000	Y_8	1.0000
X_5	0.3027	X_{17}	1.0000	Y_9	1.0000
X_6	0.2977	X_{18}	0.3115	Y_{10}	1.0000
X_7	0.2977	X_{19}	0.3115	Y_{11}	1.0000
X_8	1.0000	X_{20}	0.3115	Y_{12}	1.0000
X_9	1.0000	Y_1	1.0000	Y_{13}	1.0000
X_{10}	1.0000	Y_2	1.0000	Y_{14}	1.0000
X_{11}	1.0000	Y_3	1.0000	K_1	0.3102
X_{12}	1.0000	Y_4	1.0000	K_2	0.3102

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