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Failure Analysis for Hydraulic System of Heavy-Duty Machine Tool with Incomplete Failure Data

Shizheng Li [1,2], Zhaojun Yang [1,2], Hailong Tian [1,2,3,*], Chuanhai Chen [1,2,*], Yongfu Zhu [3], Fuqin Deng [4,5,*] and Song Lu [6,7]

1 Key Laboratory of CNC Equipment Reliability, Ministry of Education, Jilin University, Changchun 130025, China; lsz18@mails.jlu.edu.cn (S.L.); yjz@jlu.edu.cn (Z.Y.)
2 School of Mechanical and Aerospace Engineering, Jilin University, Changchun 130025, China
3 College of Materials Science and Engineering, Jilin University, Changchun 130025, China; yfzhu@jlu.edu.cn
4 Faculty of Intelligent Manufacturing, Wuyi University, Jiangmen 529000, China
5 The Shenzhen Institute of Artificial intelligence and Robotics for Society, Shenzhen 518101, China
6 Han's Laser, Shenzhen 518101, China; Lus118251@hanslaser.com
7 School of Mechanical Engineering, Dongguan University of Technology, Dongguan 523808, China
* Correspondence: tianhl@jlu.edu.cn (H.T.); cchchina@jlu.edu.cn (C.C.); dengfuqin@cuhk.edu.cn (F.D.)

Abstract: A hydraulic system is a key subsystem of heavy-duty machine tools with a high failure intensity, the failure of which often causes shutdown of production and economic loss in machining. Therefore, it is necessary to implement failure analysis to identify the weak links of system and improve the reliability. For hydraulic system, there is often an amount of failure data collected in field, which help to calculate the occurrence probability of basic events through fault tree analysis method. However, the data are incomplete and uncertain. To address this issue, this study presents a fault tree analysis methodology. Experts' opinions are utilized, combined with field data based on the Dempster–Shafer theory and rough set theory to fill the incompleteness and eliminate the uncertainty. For application in a case study, a fault tree of the hydraulic system of heavy-duty machine tools is firstly constructed. Then, the importance analysis is performed to help identify the weak links of hydraulic system. The results show the critical basic events affecting the safety and reliability of a hydraulic system.

Keywords: heavy-duty machine tools; hydraulic system; fault tree analysis; reliability; Dempster–Shafer theory; rough set theory

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1. Introduction

Heavy-duty CNC machine tools (HCMTs) are responsible for the manufacturing of parts related to major pillar industries and national key projects [1–3] in fields of aerospace, marine, hydraulic engineering, metallurgy, energy, rail transit, etc. Among subsystems of HCMT, the hydraulic system plays a key role in the power transmission and control of HCMT [4], the failure frequency of which also accounts for the largest proportion [5]. The parts scrap or production accidents caused by hydraulic failure from seals [6], pipes, valves, and so on will lead to enormous waste, because HCMTs are mainly used to process large-scale and expensive parts [7]. Therefore, to avoid unnecessary waste and maintain the machine manufacturing sustainably, it is necessary to analyze the failure of hydraulic systems to find their weaknesses for reliability growth or for creating a maintenance strategy of HCMT.

Fault Tree Analysis (FTA) is a systematic approach that identifies weaknesses, evaluates possible upgrades, and monitors and predicts behavior and has been used in various areas [8–11], such as nuclear, electric power, aerospace, oil and gas transmission, etc. Thus far, researchers have applied the FTA method for reliability analyses of machine tool products [12–16]. They constructed fault trees of different kinds of machine tool products and minimal cut sets were obtained. Analyses of these fault trees are only performed on a qualitative level. The importance measure of a basic event (BE) cannot be mathematically calculated on a quantitative level [17], which helps to determine which components or parts of the system are more critical for risk management and decision making.

As a complex system with mechanisms, electronics and hydraulics, the BEs in the fault tree of hydraulic system are generally described as failure modes, regardless of the components, due to its complexity and the large number of components [18]. In addition, the hydraulic system of HCMT manifests a high failure rate. This means a certain amount of failure data can be collected on field. This corresponds well to the failure modes and also provide useful information for measuring the importance of BEs. Shen [19] constructed a fault tree for tool storage of machining center on a quantitative level and obtained an importance measure of BEs using failure data. In [20,21], the failure rate and importance measure of BEs were obtained through quantitative analysis of hydraulic system of excavator; the weakest components were identified. However, the result of quantitative analysis using field data only is questionable in the application of an HCMT hydraulic system because the data are always incomplete in practice, which is reflected in the following two cases: (a) The causes of some failures are uncertain. There may be several BEs jointly causing one failure, but the contribution weight of each BE cannot be determined. We call this a Type I problem for convenience. (b) The occurrence probabilities of some BEs are too low so that there is a lack of observed data in some cases, in which it is difficult to determine the occurrence probability in an objective manner. We call this a Type II problem. To handle imprecise and insufficient failure information of a system, researchers have applied fuzzy theory with expert judgement to define the events' probabilities [22,23]. Mi [24] utilized fuzzy theory to qualify the uncertainty of basic events and applied it to a CNC hydraulic system. The application of fuzzy fault tree can also be found in the hydraulics of other machineries. Ren [25] obtained the importance degree of BEs for hydraulic system of A-frame launch and recovery system for the "Jiaolong" manned submersible from expert experiences by applying fuzzy theory, Li [26] proposed a fuzzy dynamic fault tree model to assess the probability of failure events in the absence of failure data. Li [27] used triangular fuzzy numbers to describe the probability of BEs in the fault tree of hydraulic system of Anchor Drilling Rigs. Zhang [28] performed quantitative analysis of hydraulic system based on a T-S fuzzy model. However, the selection of membership function in these researches is usually subjectively determined based on the engineers' experience and intuition, which is a challenge for a hydraulic system of HCMT due to its complex composition [29,30]. Moreover, the information contained in failure data is precious and should not be ignored. The fusion of failure information and experts' opinions is necessary.

This study aims at making the FTA results accurate for a hydraulic system of HCMT with incomplete failure data. Experts' opinions are utilized in combination with field data to address the above issue. First, the collected failure data are used to preliminarily calculate the frequency of BEs. Next, in dealing with a Type I problem, the weight of each possible BE, which commonly leads to one failure, is evaluated using the Dempster–Shafer evidence theory to correct the probability obtained in the first step. In dealing with a Type II problem, the probability interval of BEs that lacks data is also estimated by experts using the rough set theory. The rest of this paper is organized as follows. Section 2 proposes the method based on the Dempster–Shafer theory and rough set theory to combine failure data and experts' opinions. In Section 3, the proposed approach is applied in a case study to perform the final importance analysis of hydraulic system of HCMT. Finally, the results are summarized in Section 4.

2. Fault Tree Analysis Method Combining Incomplete Failure Data and Experts' Opinions

The procedures of hydraulic system FTA can be given as follows:

1. Model definition: System description, confirm the components of equipment, problem identification.
2. Hazard analysis: Obtain the failure mode for components of the system.
3. Fault tree construction: Identify the top event, Bes, and sub-events, then build up a fault tree according to the logical relationship.
4. Qualitative analysis: Obtain the minimal cut sets.
5. Quantitative analysis: Calculate the frequencies of BEs using failure data, then calculate the occurrence and importance measure of BEs.
6. Risk assessment and control: Make decisions based on the results of the analysis and improve the reliability of the system.

Due to Type I and Type II problems, the results of quantitative analysis just using field data are inaccurate using a conventional FTA method. Therefore, this study focuses on improving the quantitative analysis step; the framework of fault tree qualitative analysis is shown in Figure 1. The quantitative analysis, including the occurrence probability calculation of BEs and importance analysis, will be described in detail in the next body.

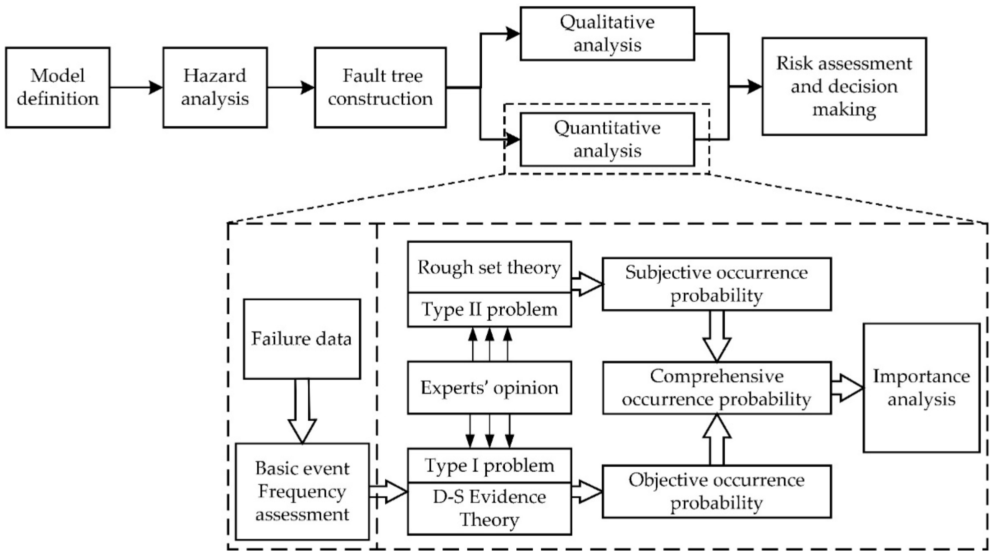


Figure 1. The framework of FTA for the hydraulic system of HCMT.

2.1. Occurrence Calculation

2.1.1. Objective Occurrence Calculation Based on the Dempster–Shafer Evidence Theory

Like conventional FTA, failure data are first preprocessed to calculated the frequencies of BEs. For data with Type I problem, experts' opinions are needed to assign probability weights to all BEs that may cause the failure. The results might vary depending on measurement precision or the uncertainty in statements of experts. The Dempster–Shafer evidence theory (D-S theory) [31] is a mathematical theory of evidence developed to combine information supplied by different experts or from other sources. It performs well in dealing with uncertain information. Therefore, an approach of processing a Type I problem based on the D-S theory is given as the following steps:

Let $\mathbf{X} = \{X_1, X_2, \ldots, X_q\}$ denote the BE set obtained through fault tree construction, where X_i ($i = 1, \ldots, q$) is the ith BE. Step 1 is a frequency assessment based on failure data: analyze the failure data with clear causes. Trace the source and find all possible BEs causing the failure, then calculate the frequencies.

Step 2: From this step, failure data with a Type I problem is processed: for a single failure with an uncertain cause, a group of experts ($E_1, \ldots, E_m$) determine all possible BEs that can cause the failure, which are expressed as ($D_1, \ldots, D_s$), to establish the frame of discernment, symbolized by $\mathbf{D} = (D_1, \ldots, D_s)$, with $D_i \in \mathbf{X}$ and $\mathbf{D} \subseteq \mathbf{X}$.

$P(D)$ is denoted as the power set composed of 2^D elements of $\mathbf{D}$; each element of 2^D represents a proposition. A mass assignment to each subset of $P(D)$ is known as the basic probability assignment (BPA) M. If $A_1, \ldots, A_n$ are the sets of interest with $A_j \in P(D)$, then a BPA is defined as:

$$M : P(D) \to [0,1], \sum_{j=1}^{n} M(A_j) = 1, \ M(\varnothing) = 0 \tag{1}$$

Step 3: Experts determine all possible combinations of $D_1, \ldots, D_s$, which are expressed as $A_1, \ldots, A_n$, as focal elements of the frame of discernment. It shows that $A_j \subseteq \mathbf{D}$ ($j = 1, \ldots, n$). Next, the assessment of each focal element is provided by each expert, as shown in Table 1, where $M_k(A_j)$ ($j = 1, \ldots, n$; $k = 1, \ldots, m$) is the BPA provided by expert E_k on the assessment of A_j.

Table 1. The BPA value assigned by experts.

Focal Element	Expert E_1	Expert E_2	...	Expert E_m
A_1	$M_1(A_1)$	$M_2(A_1)$	...	$M_m(A_1)$
A_2	$M_1(A_2)$	$M_2(A_2)$	...	$M_m(A_2)$
...	...	...	...	
A_n	$M_1(A_n)$	$M_2(A_n)$	...	$M_m(A_n)$

Step 4: Evidence combination: if the evidence shows agreement, combine it with Dempster's combination rule as follows:

$$\begin{cases} M(A) = \begin{cases} \dfrac{\sum\limits_{\cap A_j = A} \prod\limits_{k=1}^{m} M_k\left(A_j\right)}{1-K}, & A \neq \varnothing, A \subseteq D \\ 0, & A = \varnothing, A \subseteq D \end{cases} \\ K = \sum\limits_{\cap A_j = \varnothing} \prod\limits_{k=1}^{m} M_k\left(A_j\right) \end{cases} \tag{2}$$

When evidence highly conflicts with each other, the above combination rule is not efficient; thus, a new combination rule [32] for conflict evidence is introduced as Equation (3):

$$\begin{cases} M(A) = \begin{cases} \dfrac{\sum\limits_{A_i \cap A_j = A} \left(\sum\limits_{k=1}^{m} M_k(A_i)\right)\left(\sum\limits_{l=1}^{m} M_l\left(A_j\right)\right)}{m^2-K}, & A \neq \varnothing, A \subseteq D \\ 0, & A = \varnothing, A \subseteq D \end{cases} \\ K = \sum\limits_{A_i \cap A_j = \varnothing} \left(\sum\limits_{k=1}^{m} M_k(A_i)\right)\left(\sum\limits_{l=1}^{m} M_l\left(A_j\right)\right) \end{cases} \tag{3}$$

where K is the conflict coefficient and m is the amount of evidence in the frame of discernment D. Then, the aggregated assessment of focal elements with respect to each BPA can be calculated by the combination rule, a group assessment matrix M is constructed as $\mathbf{M} = [M(A_1), M(A_2), \ldots, M(A_t)]$.

Step 5: Calculate the belief and plausibility function of D_i, which are defined as follows:

$$\begin{cases} Bel(D_i) = \sum\limits_{A_j \subseteq D_i} M(A_j) \\ Pl(D_i) = \sum\limits_{A_j \cap D_i \neq \varnothing} M(A_j) \quad , D_i \subseteq D \end{cases} \tag{4}$$

The results of the belief and plausibility function of D_i compose the frequency interval, as shown in Table 2.

Table 2. Frequency interval of D_i.

Combination	D_1	D_2	...	D_s
Frequency interval	$[Bel(D_1), Pl(D_1)]$	$[Bel(D_2), Pl(D_2)]$	...	$[Bel(D_s), Pl(D_s)]$

Step 6: Merge the results in Table 2 with the frequency of corresponding BEs obtained in Step 1.

Repeat Step 2 to Step 6 until all data with Type I problem are processed. Additionally, the mass has to be normalized, because experts tend to ignore the restriction in Equation (1). The final result, $P^1_{X_i}$, is normalized by Equation (5) and defined as the objective occurrence probability of BE X_i, which represents the occurrence probability calculated by solving a Type I problem:

$$P^1_{X_i} = \frac{\left[N^-_{X_i}, N^+_{X_i}\right]}{N} \tag{5}$$

where N denotes the number of failures and $\left[N^-_{X_i}, N^+_{X_i}\right]$ is the merged frequency interval of X_i.

2.1.2. Subjective Occurrence Estimation Based on Rough Set Theory

For BEs with a Type II problem, human judgments become an essential requirement. Hence, experts' opinions are also introduced to estimate the occurrence probability. Unlike fuzzy set theory, which defines a set by a partial membership without a clear boundary, the rough set theory utilizes the boundary region of a set to express vagueness. Additionally, there is no need for it to require additional subjective information to analyze data [33], which remains objective. The steps of subjective occurrence estimation based on rough set theory are proposed as follows [34]:

Step 1: Define the problem. Find all possible BEs with insufficient failure data to form a set $\mathbf{T}$ as $\mathbf{T} = \{T_1, T_2, \ldots, T_p\}$, where T_i is the ith BE with Type II problem, $T_i \in \mathbf{X}$, $I = 1, \ldots, p$.

Assume there are three experts, including designers F_1, maintainers F_2, and users F_3, which give an estimation of the occurrence of each BE, which is expressed by the interval rough number, as shown in Table 3, where $\xi_{ij} = \left(\left[a_{ij}, b_{ij}\right], \left[c_{ij}, d_{ij}\right]\right)$, $c_{ij} < a_{ij} < b_{ij} < d_{ij}$, indicating the occurrence of T_i given by expert F_j, j = 1, 2, 3.

Table 3. Estimation of occurrence given by experts.

BE	Designers F_1	Maintainers F_2	Users F_3
T_1	ξ_{11}	ξ_{12}	ξ_{13}
T_2	ξ_{21}	ξ_{22}	ξ_{23}
...	...	...	...
T_p	ξ_{p1}	ξ_{p2}	ξ_{p3}

Step 2: Determine the expert weight.

When determining the weight of each expert, the influence of expert risk preferences is considered and reflected by the distance between the expert estimation and its positive and negative ideal point.

(1) Determine the positive and negative ideal point: For expert F_j, the positive ideal point is defined as the maximum estimation of the occurrence of all T_i by Equation (6), while the negative ideal point is defined as the minimum estimation of the occurrence of all T_i by Equation (7):

$$\xi^+_j = \left(\left[\max_i a_{ij}, \max_i b_{ij}\right], \left[\max_i c_{ij}, \max_i d_{ij}\right]\right) \tag{6}$$

$$\xi_j^- = \left(\left[\min_i a_{ij}, \min_i b_{ij}\right], \left[\min_i c_{ij}, \min_i d_{ij}\right]\right) \tag{7}$$

(2) Calculate the distance between the occurrence estimation and its positive and negative ideal point by Equations (8) and (9), respectively:

$$d_{ij}^+ = d\left(\xi_{ij}, \xi_j^+\right) \tag{8}$$

$$d_{ij}^- = d\left(\xi_{ij}, \xi_j^-\right) \tag{9}$$

where for interval rough number $\xi_1 = ([a_1, b_1], [c_1, d_1])$ and $\xi_2 = ([a_2, b_2], [c_2, d_2])$, the operator $d(\bullet)$ is defined as follows:

$$d(\xi_1, \xi_2) = \sqrt{\frac{(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2 + (d_1 - d_2)^2}{4}} \tag{10}$$

(3) The risk preference coefficient is fused into the above distances to produce a new distance, called the preference distance, which represents the difference in the subjective assessment of different types of experts. The preference distance is defined as follows:

$$d_{ij} = \tau d_{ij}^+ + (1 - \tau) d_{ij}^- \tag{11}$$

where τ is the risk preference coefficient. If the expert is a risk liker, then $\tau > 0.5$; if the expert is neutral, then $\tau = 0.5$; if the expert is a risk evader, then $\tau < 0.5$.

(4) The entropy weight method is adopted in determination of the expert weight by Equation (12):

$$\begin{cases} e_j = -\frac{1}{\ln p} \sum\limits_{i=1}^{p} \frac{d_{ij}}{\sum\limits_{i=1}^{p} d_{ij}} \cdot \ln \frac{d_{ij}}{\sum\limits_{i=1}^{p} d_{ij}} \\ w_j = \frac{1 - e_j}{\sum\limits_{j=1}^{3} \left(1 - e_j\right)} \end{cases} \tag{12}$$

where e_j is the distance entropy for expert F_j, w_j is the weight of expert F_j, with $j = 1, 2, 3$, $0 \leq w_j \leq 1$, and $\sum\limits_{j=1}^{3} w_j = 1$.

Step 3: Calculate the utility value of each interval rough number and its expectation:

$$u_i = \sum_{j=1}^{3} \xi_{ij} w_j, i = 1, 2, \cdots, p \tag{13}$$

$$P_{T_i}^2 = E[u_i] \tag{14}$$

where the expectation is calculated as $E[\xi] = \frac{1}{4}(a + b + c + d)$ for $\xi = ([a, b], [c, d])$.

The final result, $P_{T_i}^2$, is defined as the subjective occurrence of T_i, which represents the occurrence probability estimated by solving a Type II problem.

2.1.3. Fusion of the Objective Occurrence and Subjective Occurrence

After calculating the objective and subjective occurrence, the results need to be combined. Denote the objective occurrence vector as $P_{X_i}^1 = \left[P_{X_1}^1, P_{X_2}^1, \cdots, P_{X_q}^1\right]$ and the subjective occurrence vector as $P_{X_i}^2 = \left[P_{X_1}^2, P_{X_2}^2, \cdots, P_{X_q}^2\right]$, where $P_{X_i}^1 = 0$ for X_i that is not involved in a Type I problem, and $P_{X_i}^2 = 0$ for X_i that is not involved in a Type II problem.

Combine and normalize the two occurrences by Equation (15):

$$P_{X_i} = \frac{P^1_{X_i} + P^2_{X_i}}{\sum\limits_{i=1}^{q} \left(P^1_{X_i} + P^2_{X_i} \right)} \tag{15}$$

The final result, P_{X_i}, is defined as the comprehensive occurrence. Since the objective occurrence is in the form of an interval, the result after its fusion with subjective occurrence is still an interval, i.e., $P_{X_i} = \left[P^-_{X_i}, P^+_{X_i} \right]$, where:

$$P^-_{X_i} = \frac{P^{1-}_{X_i} + P^2_{X_i}}{\sum\limits_{i=1}^{q} \left(P^{1+}_{X_i} + P^2_{X_i} \right)}, P^+_{X_i} = \frac{P^{1+}_{X_i} + P^2_{X_i}}{\sum\limits_{i=1}^{q} \left(P^{1-}_{X_i} + P^2_{X_i} \right)} \tag{16}$$

2.2. Importance Analysis

An important analysis can help identify which BEs are critical and need to be improved; it is useful for decision making. In this study, the probability importance is employed to evaluate the contribution of each BE to the occurrence probability of top event, which is expressed as follow:

$$I^g_{X_i} = \prod_{j=1, i \neq j}^{n} \left(1 - P_{X_j} \right) \tag{17}$$

where $I^g_{X_i}$ is the probability importance of X_i.

For the comprehensive occurrence probability in the form of an interval, the corresponding probability importance is still an interval, which is $I^g_{X_i} = \left[I^{g-}_{X_i}, I^{g+}_{X_i} \right]$, where:

$$I^{g-}_{X_i} = \prod_{j=1, i \neq j}^{q} \left(1 - P^+_{X_j} \right), I^{g+}_{X_i} = \prod_{j=1, i \neq j}^{q} \left(1 - P^-_{X_j} \right) \tag{18}$$

Therefore, the ranking of importance is essentially the ranking of interval numbers. A ranking rule based on possibility degree matrix for interval numbers is introduced [35]; the steps are as follows:

Step 1: Establish the possibility matrix $P = \left(p_{ij} \right)_{q \times q}$ (i, j=1, . . . , q), using the possibility formula as follows:

$$I^g_{X_i} = \prod_{j=1, i \neq j}^{n} \left(1 - P_{X_j} \right) \tag{19}$$

Step 2: Construct a Boolean matrix $Q = \left(q_{ij} \right)_{q \times q}$, where:

$$q_{ij} = \begin{cases} 1, & p_{ij} \geq 0.5 \\ 0, & p_{ij} < 0.5 \end{cases} \tag{20}$$

Step 3: Sum the Boolean matrix in rows; the results are as follows:

$$R_i = \sum_{j=1}^{q} q_{ij} i = 1, 2, \cdots, q \tag{21}$$

Step 4: Order the probability importance according to the size of R_i.

After the above steps are completed, the probability importance ranking of each BE is obtained and used for subsequent safety assessment and decision making.

3. A Case Study

The proposed method is applied to fault tree analysis for the hydraulic system of heavy horizontal lathe and heavy gantry boring and milling machine in a factory, which are two typical HCMTs. After more than 12 months of field tracking (over 2000 h in total), a total of 143 hydraulic related failure data of heavy-duty horizontal lathe and 88 hydraulic related failure of heavy gantry boring and milling machines were collected, which were recorded according to the Chinese national standard GB/T 23567.1. Failure data contain information including failure time, failure position, failure symptoms, maintenance time, and maintenance mode. For the sake of convenience, the failure data were combined for analysis, because the hydraulic systems of the two types of HCMT are similar in structure and configuration.

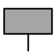
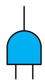
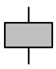
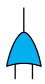
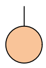
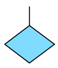
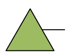
3.1. Fault Tree Construction

By analyzing the failure data, "The hydraulic system of HCMT cannot work" was considered as the top event. By reviewing previous hazard records [36] and using the experts' opinions, main sub-event failures were determined and given in Table 4. The fault tree is constructed and shown in Figures 2–10, where Figure 2 is the main tree and Figures 3–10 are the sub-trees. Table 5 shows the symbols used in fault trees and Table 6 lists all the sub-events and BEs in the tree; the basic event set is $\mathbf{X} = \{X_1, X_2, \ldots, X_{27}\}$. Through qualitative analysis, the minimal cut sets are obtained as: $\{X_1\}$, $\{X_2\}$, $\{X_3\}$, $\{X_4\}$, $\{X_5\}$, $\{X_6\}$, $\{X_7\}$, $\{X_8\}$, $\{X_9\}$, $\{X_{10}\}$, $\{X_{11}\}$, $\{X_{12}\}$, $\{X_{13}\}$, $\{X_{14}\}$, $\{X_{15}\}$, $\{X_{16}\}$, $\{X_{17}\}$, $\{X_{18}\}$, $\{X_{19}\}$, $\{X_{20}\}$, $\{X_{21}\}$, $\{X_{22}\}$, $\{X_{23}\}$, $\{X_{24}\}$, $\{X_{25}\}$, $\{X_{26}\}$, and $\{X_{27}\}$.

Table 4. Main sub-event failures of a hydraulic system.

Code	Failure Mode	Code	Failure Mode
H_1	Oil passage blocked	H_5	Oil temperature too high
H_2	Leakage	H_6	Too much noise
H_3	Insufficient or fluctuating flow	H_7	Heavy vibration
H_4	Insufficient or fluctuating pressure	H_8	Hydraulic elements fault

Table 5. Symbols used in the fault trees.

Symbol	Meaning	Symbol	Meaning
	Top event		AND gate
	Intermediate event		OR gate
	Basic event		Transfer-in
	Undeveloped event		Transfer-out

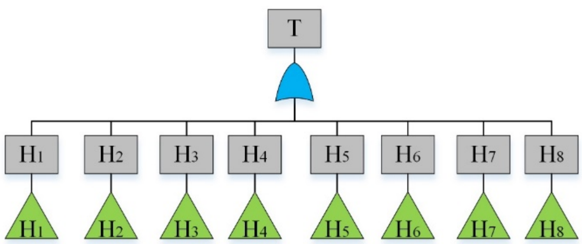


Figure 2. Fault tree of a hydraulic system: main tree.

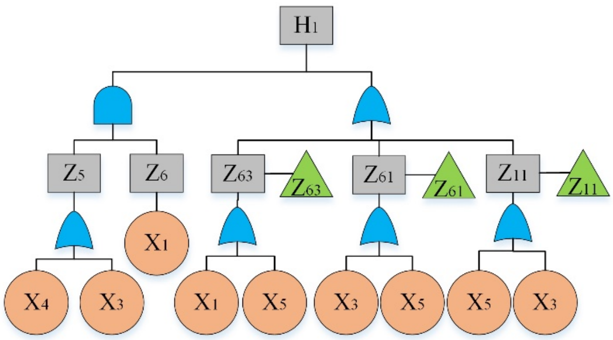


Figure 3. Fault tree of a hydraulic system: sub-tree I.

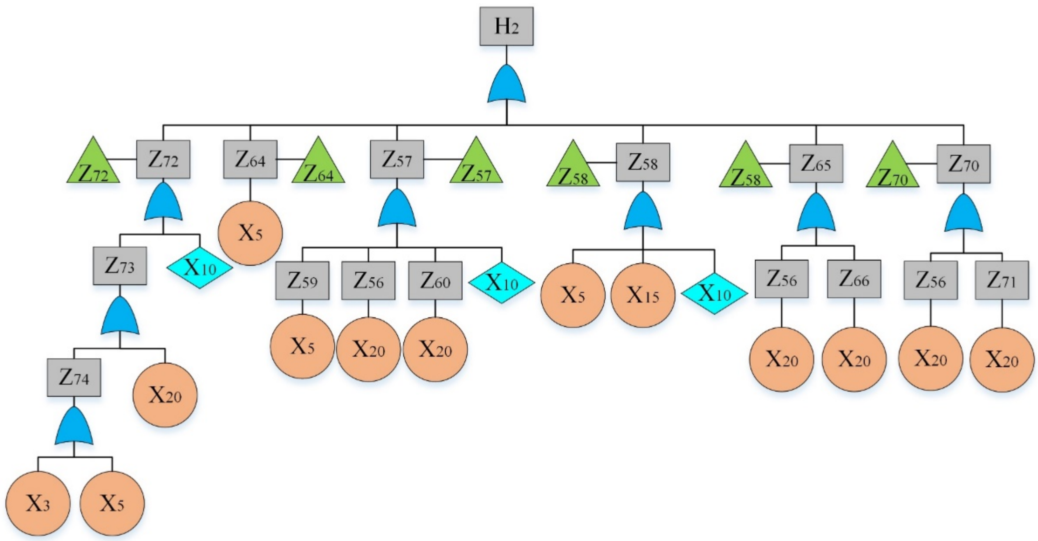


Figure 4. Fault tree of a hydraulic system: sub-tree II.

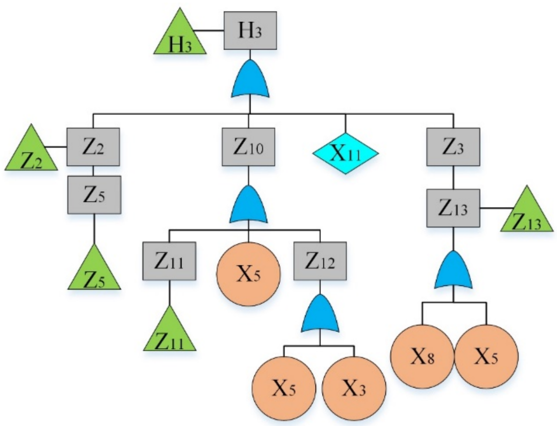


Figure 5. Fault tree of a hydraulic system: sub-tree III.

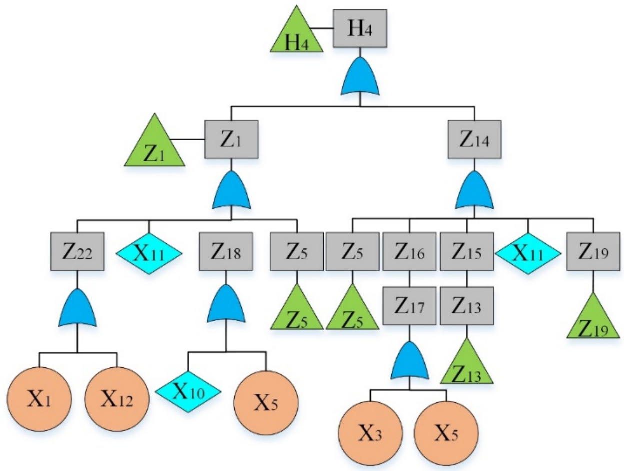


Figure 6. Fault tree of a hydraulic system: sub-tree IV.

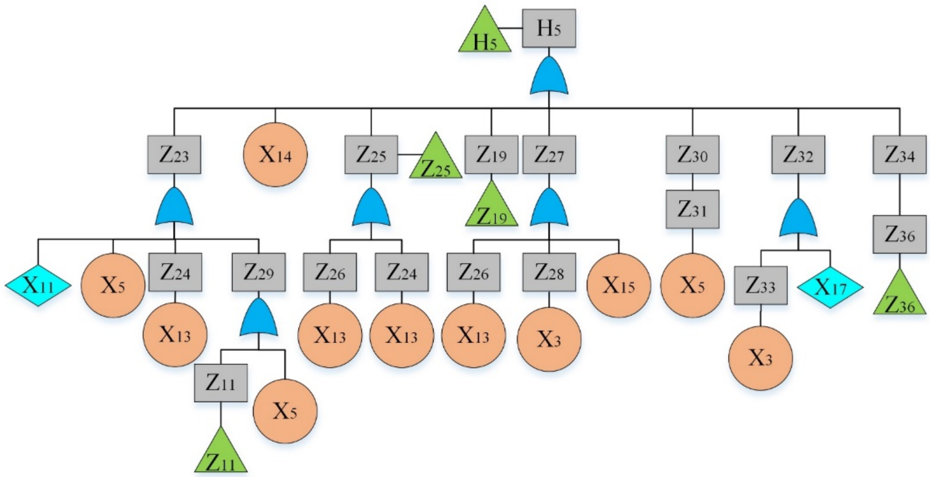


Figure 7. Fault tree of a hydraulic system: sub-tree V.

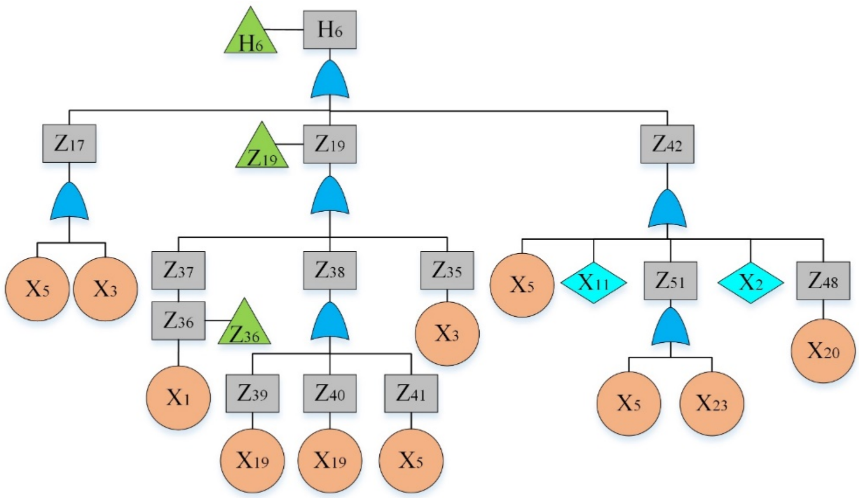


Figure 8. Fault tree of a hydraulic system: sub-tree VI.

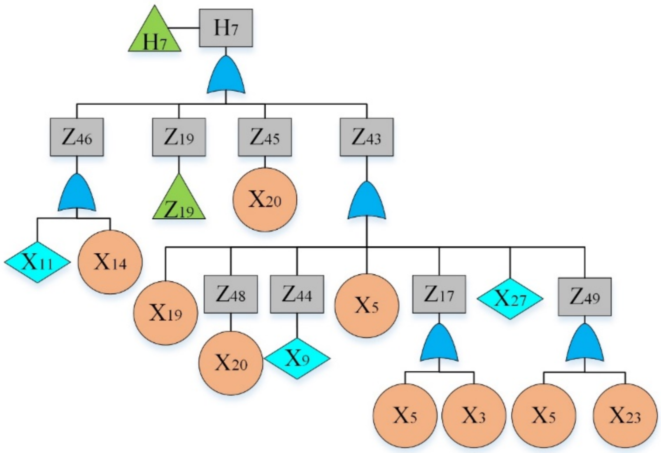


Figure 9. Fault tree of a hydraulic system: sub-tree VII.

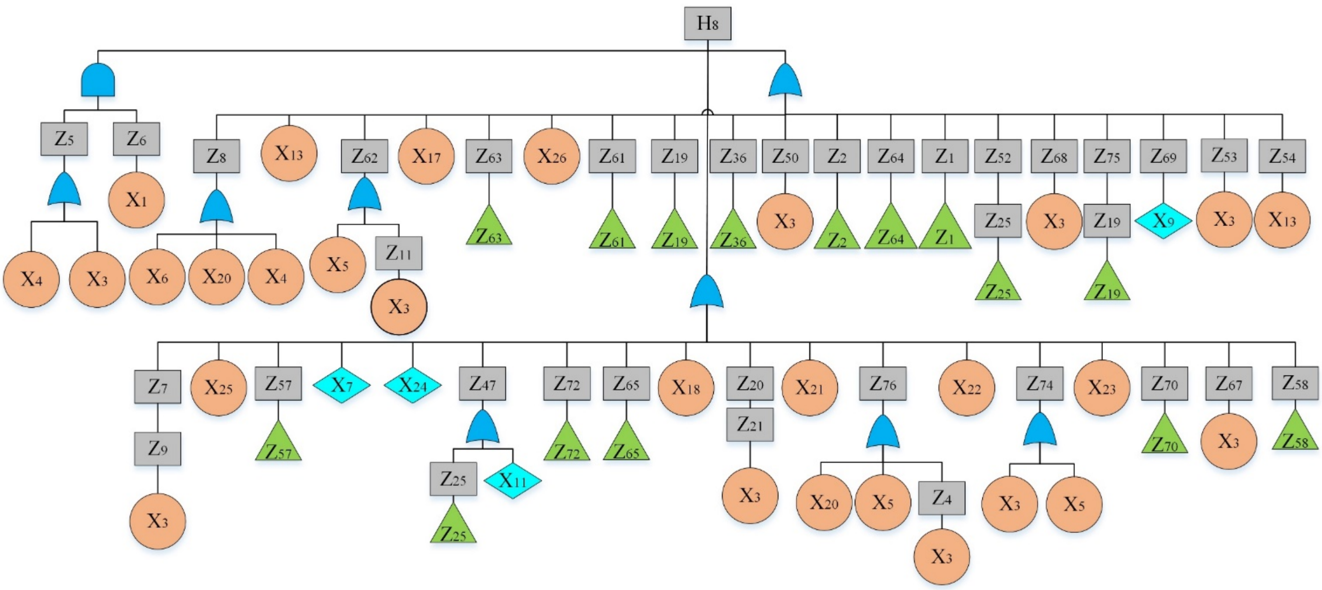


Figure 10. Fault tree of a hydraulic system: sub-tree VIII.

Table 6. Events in the fault tree.

Event	Content	Event	Content
Z_1	Lack of pressure	Z_{53}	Impurity interference
Z_2	Lack or fluctuation of oil flow in filter	Z_{54}	Improper set value of sensor
Z_3	Pump Flow unstable	Z_{55}	Seal wear
Z_4	Impurity entry the execute component	Z_{56}	Poor sealing
Z_5	Deposition of contaminants in filter	Z_{57}	Pipe joint leakage
Z_6	Filter not replaced or cleaned	Z_{58}	Pipe leakage
Z_7	Filter element damage	Z_{59}	Poor pipe joint quality
Z_8	Bypass leakage of filter too much	Z_{60}	Pipe joints loose
Z_9	Impact of oil contamination	Z_{61}	Pipe wear
Z_{10}	Lack or fluctuation of oil flow in the valve	Z_{62}	Oversize gap between the throttle valve body and spool
Z_{11}	Valve wear	Z_{63}	Pipes bending deformation
Z_{12}	Valve rust	Z_{64}	Valve Leakage
Z_{13}	Pump unstable	Z_{65}	Junction between the valve and pipe leakage
Z_{14}	Fluctuation of oil flow	Z_{66}	Junction between the valve and pipe loose
Z_{15}	Oil pressure of the pump unstable	Z_{67}	Impurity entry to the throttle valve
Z_{16}	The pump–outlet pressure unstable	Z_{68}	Flow area of the throttle too small
Z_{17}	Internal pump wear	Z_{69}	Throttle position change
Z_{18}	Insufficient pump oil pressure	Z_{70}	Hydraulic actuator junction leakage

Table 6. *Cont.*

Event	Content	Event	Content
Z_{19}	Air gets into the pump	Z_{71}	Junction of actuator loose
Z_{20}	The movement of the valve core of the overflow valve not sensitive	Z_{72}	Actuator leakage
Z_{21}	Impurity entry to the overflow valve	Z_{73}	Internal clearance in actuator too large
Z_{22}	Oil starvation in tank	Z_{74}	Internal wear in actuator
Z_{23}	Inside leakage	Z_{75}	Air into the actuator
Z_{24}	Pressure set of the relief valve too large	Z_{76}	Actuator gets stuck
Z_{25}	Improper pressure setting	X_1	Improper maintenance
Z_{26}	Pressure setting of the back pressure valve too large	X_2	Rotors of motor loose
Z_{27}	Oil return resistance too large	X_3	Oil pollution
Z_{28}	Oil discharge filter plug	X_4	Wrong choice of filter
Z_{29}	Valve gap too large	X_5	Outsourced parts fault
Z_{30}	Excessive friction between hydraulic elements	X_6	Poor processing quality of parts
Z_{31}	Valve gap too narrow	X_7	Other mechanical faults
Z_{32}	Poor heat dissipation	X_8	Motor supply voltage not stable
Z_{33}	Deposition of contaminants in heatsink	X_9	Vibration of mechanical system too heavy
Z_{34}	Insufficient circulating oil	X_{10}	Product damage
Z_{35}	Plugged oil inlet	X_{11}	Excessive oil viscosity
Z_{36}	Low oil level	X_{12}	Tank leakage
Z_{37}	Filter above oil level	X_{13}	Parameter setting error
Z_{38}	Suction line leakage	X_{14}	Wrong choice of oil
Z_{39}	Suction line loose	X_{15}	Piping delaminating
Z_{40}	Suction line damaged	X_{16}	Oil viscosity too low
Z_{41}	Suction line seal damaged	X_{17}	Radiator failure
Z_{42}	Hydraulic station too loud	X_{18}	Material aging
Z_{43}	Vibration of hydraulic station too heavy	X_{19}	Pipeline is not fixed
Z_{44}	Fixing bolt of motor is loose	X_{20}	Improper assembly
Z_{45}	Coupling loose between the motor and pump	X_{21}	Motor power fault
Z_{46}	Bubbles generate in the oil	X_{22}	Motor supply voltage too low
Z_{47}	Pump load too heavy	X_{23}	Motor bearings not sufficiently lubricated
Z_{48}	Misalignment of coupling	X_{24}	Motor rotor stuck
Z_{49}	Excessive motor bearing clearance	X_{25}	Motor overheating
Z_{50}	The suction line plugs	X_{26}	Motor supply voltage too high
Z_{51}	Motor bearing wear	X_{27}	Motor rotor unbalanced
Z_{52}	The pressure gauge over range		

3.2. Quantitative Analysis

The results of frequency assessment based on failure data are shown in Table 7. As one can see, there are 21 failures evaluated as "uncertain," i.e., Type I data.

Table 7. The result of the frequency assessment.

BE	Frequency	BE	Frequency	BE	Frequency
X_1	29	X_{10}	15	X_{19}	4
X_2	2	X_{11}	12	X_{20}	2
X_3	95	X_{12}	1	X_{23}	1
X_4	4	X_{13}	1	X_{25}	1
X_5	23	X_{15}	3	X_{26}	1
X_6	3	X_{16}	1	Uncertain	21
X_7	4	X_{17}	3		
X_9	4	X_{18}	1		

For the purpose of illustration, one of the Type I data, which is the "check valve leakage," was taken as an example for analysis. Two maintenance personnel gave three possible reasons for the failure: "Internal leakage caused by wear," "Quality problems of check valve," and "Connection looseness caused by mechanical vibration," which constituted the frame of discernment $\mathbf{D} = \{D_1 = X_3, D_2 = X_5, D_3 = X_9\}$. Four possible combinations are determined as focal elements, the BPA of each focal element was assigned, and the aggregated BPA was obtained by combining evidence, as shown in Table 8. Then, the frequency interval of D_1, D_2, and D_3 was calculated, as shown in Table 9. The results were consequently merged into corresponding BEs in Table 6. After the remaining Type I data were processed, the objective occurrence was obtained.

Table 8. The BPA of each combination.

Combination	M_1	M_2	M
$\{D_1\}$	0.6	0.7	0.859
$\{D_2\}$	0.15	0.15	0.043
$\{D_3\}$	0.15	0.15	0.082
$\{D_1, D_2, D_3\}$	0.1	0.1	0.016

Table 9. The confidence interval of D_1, D_2, and D_3.

BE	D_1	D_2	D_3
Confidence interval	[0.859,0.875]	[0.043,0.059]	[0.082,0.098]

There are six BEs with a Type II problem, which are expressed as a set $\mathbf{T} = \{T_1 = X_8, T_2 = X_{14}, T_3 = X_{21}, T_4 = X_{22}, T_5 = X_{24}, T_6 = X_{27}\}$. The occurrence estimation was given by the designers, maintainers, and users, respectively, in the form of an interval rough number, as shown in Table 10.

Table 10. The occurrence estimation given by experts.

BE	Designers F_1	Maintainers F_2	Users F_3
X_8	([0.003, 0.005], [0.002, 0.008])	([0.002, 0.004], [0.002, 0.005])	([0.003, 0.004], [0.003, 0.007])
X_{14}	([0.008, 0.012], [0.005, 0.015])	([0.007, 0.011], [0.004, 0.012])	([0.007, 0.012], [0.005, 0.014])
X_{21}	([0.002, 0.004], [0.001, 0.005])	([0.002, 0.004], [0.002, 0.005])	([0.003, 0.004], [0.002, 0.006])
X_{22}	([0.003, 0.005], [0.002, 0.008])	([0.001, 0.004], [0.001, 0.005])	([0.002, 0.003], [0.001, 0.004])
X_{24}	([0.004, 0.006], [0.003, 0.008])	([0.005, 0.006], [0.004, 0.007])	([0.003, 0.005], [0.003, 0.008])
X_{27}	([0.007, 0.009], [0.005, 0.013])	([0.006, 0.008], [0.005, 0.011])	([0.008, 0.009], [0.006, 0.011])

The positive and negative ideal point of F_j is given as: ξ_1^+ = ([0.008, 0.012], [0.005, 0.015]), ξ_1^- = ([0.002, 0.004], [0.001, 0.005]), ξ_2^+ = ([0.007, 0.011], [0.005, 0.012]), ξ_2^- = ([0.001, 0.004], [0.001, 0.005]), ξ_3^+ = ([0.008, 0.012], [0.006, 0.014]), and ξ_3^- = ([0.002, 0.003], [0.001, 0.004]).

All the three experts prefer to avoid risks; thus, risk preference coefficient τ was determined as $\tau = 0.3$ to calculate the preference distance, of which the result is shown in Table 11. Then, the weight of expert was calculated, as shown in Table 12. By substituting w_j, we calculated the utility value and its expectation. Thus, the subjective occurrence was obtained, as shown in Table 13.

Table 11. The preference distance.

BE	Designers F_1			Maintainers F_2			Users F_3		
	d_{ij}^+	d_{ij}^-	Preference Distance	d_{ij}^+	d_{ij}^-	Preference Distance	d_{ij}^+	d_{ij}^-	Preference Distance
X_8	0.006	0.002	0.003	0.006	0.001	0.002	0.006	0.002	0.003
X_{14}	0	0.007	0.005	0.001	0.006	0.004	0.001	0.007	0.005
X_{21}	0.007	0	0.002	0.006	0.001	0.002	0.007	0.001	0.003
X_{22}	0.006	0.002	0.003	0.006	0	0.002	0.008	0	0.002
X_{24}	0.005	0.002	0.003	0.004	0.003	0.003	0.005	0.003	0.003
X_{27}	0.002	0.006	0.005	0.002	0.005	0.004	0.002	0.006	0.005

Table 12. The expert weight.

Index	F_1	F_2	F_3
e_j	0.977	0.973	0.975
w_j	0.311	0.364	0.325

Table 13. The subjective occurrence.

BE	Utility Value	Expectation
X_8	([0.003, 0.004], [0.002, 0.007])	0.004
X_{14}	([0.007, 0.012], [0.005, 0.014])	0.009
X_{21}	([0.002, 0.004], [0.002, 0.005])	0.003
X_{22}	([0.002, 0.004], [0.001, 0.006])	0.003
X_{24}	([0.004, 0.006], [0.003, 0.008])	0.005
X_{27}	([0.007, 0.009], [0.005, 0.012])	0.008

3.3. Importance Analysis and Decision Making

Next, the objective and subjective occurrence were combined to derive the comprehensive occurrence. Table 14 summarizes the results of quantitative analysis.

Table 14. Results of quantitative analysis.

Basic Event	Frequency	Objective Occurrence	Subjective Occurrence	Comprehensive Occurrence	Expectation
X_1	[32.752, 33.128]	[0.142, 0.143]	0	[0.137, 0.139]	0.138
X_2	[2, 2]	[0.009, 0.009]	0	[0.008, 0.008]	0.008
X_3	[103.951, 104.541]	[0.450, 0.453]	0	[0.434, 0.440]	0.437
X_4	[5.127, 5.225]	[0.022, 0.023]	0	[0.021, 0.022]	0.022
X_5	[24.896, 25.058]	[0.108, 0.108]	0	[0.104, 0.105]	0.105
X_6	[3, 3]	[0.013, 0.013]	0	[0.013, 0.013]	0.013
X_7	[4.657, 4.802]	[0.020, 0.021]	0	[0.019, 0.020]	0.020
X_8	0	0	0.004	[0.004, 0.004]	0.004
X_9	[4, 4]	[0.017, 0.017]	0	[0.017, 0.017]	0.017
X_{10}	[17.112, 17.308]	[0.074, 0.075]	0	[0.071, 0.073]	0.072
X_{11}	[12.989, 13]	[0.056, 0.056]	0	[0.054, 0.055]	0.054
X_{12}	[1, 1]	[0.004, 0.004]	0	[0.004, 0.004]	0.004
X_{13}	[1, 1]	[0.004, 0.004]	0	[0.004, 0.004]	0.004
X_{14}	0	0	0.009	[0.009, 0.009]	0.009
X_{15}	[3, 3]	[0.013, 0.013]	0	[0.013, 0.013]	0.013
X_{16}	[1, 1]	[0.004, 0.004]	0	[0.004, 0.004]	0.004
X_{17}	[3, 3]	[0.013, 0.013]	0	[0.013, 0.013]	0.013
X_{18}	[1, 1]	[0.004, 0.004]		[0.004, 0.004]	0.004
X_{19}	[4.866, 4.991]	[0.021, 0.022]	0	[0.020, 0.021]	0.021
X_{20}	[2, 2]	[0.009, 0.009]	0	[0.008, 0.008]	0.008
X_{21}	0	0	0.003	[0.003, 0.003]	0.003
X_{22}	0	0	0.003	[0.003, 0.003]	0.003
X_{23}	[1, 1]	[0.004, 0.004]	0	[0.004, 0.004]	0.004
X_{24}	0	0	0.005	[0.005, 0.005]	0.005
X_{25}	[1, 1]	[0.004, 0.004]	0	[0.004, 0.004]	0.004
X_{26}	[1, 1]	[0.004, 0.004]	0	[0.004, 0.004]	0.004
X_{27}	0	0	0.008	[0.008, 0.008]	0.008

Finally, the probability importance of each BE was calculated and shown in Table 15.

Table 15. Probability importance of each BE.

BE	Index	BE	Index	BE	Index
X_1	[0.3609, 0.3669]	X_{10}	[0.3350, 0.3411]	X_{19}	[0.3173, 0.3233]
X_2	[0.3133, 0.3194]	X_{11}	[0.3286, 0.3349]	X_{20}	[0.3133, 0.3194]
X_3	[0.5545, 0.5597]	X_{12}	[0.3120, 0.3181]	X_{21}	[0.3116, 0.3176]
X_4	[0.3176, 0.3237]	X_{13}	[0.3120, 0.3181]	X_{22}	[0.3116, 0.3176]
X_5	[0.3473, 0.3535]	X_{14}	[0.3134, 0.3195]	X_{23}	[0.3120, 0.3181]
X_6	[0.3146, 0.3207]	X_{15}	[0.3146, 0.3207]	X_{24}	[0.3122, 0.3183]
X_7	[0.3171, 0.3230]	X_{16}	[0.3120, 0.3181]	X_{25}	[0.3120, 0.3181]
X_8	[0.3119, 0.3180]	X_{17}	[0.3146, 0.3207]	X_{26}	[0.3120, 0.3181]
X_9	[0.3160, 0.3221]	X_{18}	[0.3120, 0.3181]	X_{27}	[0.3131, 0.3192]

According to the ranking rule of interval number, the probability importance of all BEs is listed in Table 16 and ranked as follows (largest to smallest):

$X_3 > X_1 > X_5 > X_{10} > X_{11} > X_4 \succ X_{19} \succ X_7 \succ X_9 \succ X_6 \succ X_{15} \succ X_{17} \succ X_{14} \succ X_2 = X_{20} \succ X_{27} \succ X_{24} \succ X_{12} = X_{13} = X_{16} = X_{18} = X_{23} = X_{25} = X_{26} \succ X_8 \succ X_{21} = X_{22}$

Table 16. Importance ranking of each BE.

BE	Index	BE	Index	BE	Index
X_1	0.363929987	X_{10}	0.338072619	X_{19}	0.320304036
X_2	0.316339954	X_{11}	0.331756299	X_{20}	0.316339954
X_3	0.557089359	X_{12}	0.315008549	X_{21}	0.314602054
X_4	0.320643759	X_{13}	0.315008549	X_{22}	0.314602054
X_5	0.350364665	X_{14}	0.316445615	X_{23}	0.315008549
X_6	0.317682661	X_{15}	0.317682661	X_{24}	0.315214182
X_7	0.320031414	X_{16}	0.315008549	X_{25}	0.315008549
X_8	0.314907821	X_{17}	0.317682661	X_{26}	0.315008549
X_9	0.319036815	X_{18}	0.315008549	X_{27}	0.316136855

For comparison purposes, the importance was measured and ranked in another three cases: In case 1 (C_1), Type I problem was ignored, that is, the failure data of which the reason was identified as "Uncertain" were not used for analysis; in case 2 (C_2), the Type II problem was ignored; in case 3 (C_3), both Type I and Type II problems were ignored, which amounts to a conventional FTA approach. The importance ranking in three cases was compared to the result by the proposed approach, which is marked as C_0, as shown in Figure 11. The results show that:

Compared to C_0, the ranking of X_{19} becomes lower in C_1, which means that ignoring type I problems will change the ranking of BEs to some extent.

The rankings of X_{14}, X_{24}, and X_{27} become lower in C_2 compared to C_0. It should be noted that the three BEs are all Type II problem-related. This indicates that the importance of some BEs will be underestimated due to the lack of data support if a Type II problem is ignored.

The ranking of X_{19}, X_{14}, X_{24}, and X_{27} changes in C_3, which is the aggregate result of C_1 and C_2. The main reason for the differences is that the failure data incompleteness and uncertainty are not considered in C_3 as compared to C_0.

Finally, as one can see from the result, the top three critical BEs are "X_3: Oil pollution," "X_1: Improper maintenance," and "X_5: Poor outsourced parts quality" in this case study, which make up more than 50% of the failure. Oil pollution is the most critical BE of a hydraulic system, which is the same as the result in [37]. This shows that the proposed approach ensures the veracity of analysis. Meanwhile, the result also gives advice about the reliability growth of the hydraulic system of HCMT: control the source of oil pollution and improve the filtering capacity. The service time threshold of key components should be clear, along with a proper maintenance plan, so that necessary repairs or replacements can be made in an appropriate time. In addition, the quality of outsourced parts should be strictly checked and the screen process should be carried out if necessary.

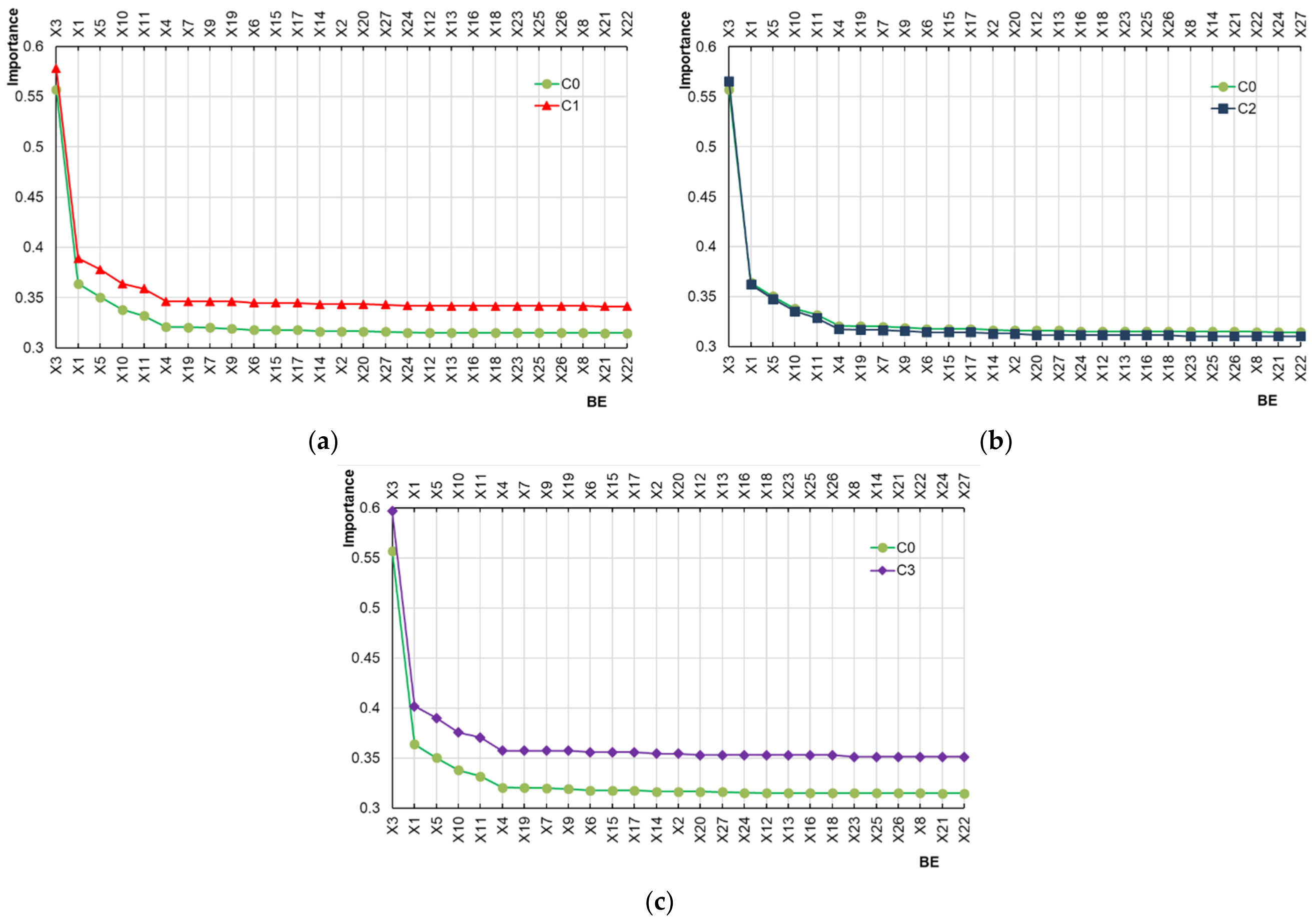


Figure 11. Comparison results of importance analysis in different cases: (**a**) Comparison between C_0 and C_1; (**b**) Comparison between C_0 and C_2; (**c**) Comparison between C_0 and C_3.

4. Conclusions

The hydraulic system of HCMT is a complex system with a high failure rate. For its fault tree quantitative analysis, failure data contains a lot of information about reliability and is useful for measuring the probability of BEs. However, conventional FTA approaches just using failure data have some limitations in quantitative analysis.

In this study, the proposed approach, which incorporates the experts' opinions and the conventional FTA technique, is demonstrated as a viable method for the estimation of the occurrence probability when encountered with data uncertainty and incompleteness. Through a case study, the fault tree of a hydraulic system of HCMT is constructed, and the result shows that there are 27 basic events that cause hydraulic failure in an HCMT, where oil pollution is the most critical basic event.

The function of experts' opinions is embodied from two aspects: (1) Experts' opinions are utilized for correcting failure data with uncertainty, so that the data can be used for quantitative analysis; (2) Experts' opinions are used as supplementary information for BEs with no observed data. The purpose is to integrate the subjective information with the objective information to improve the accuracy of quantitative analysis results. Therefore, based on the above idea, the proposed approach is also applicable to the fault tree quantitative analysis of other products with incomplete failure data.

Finally, although expert opinion was introduced for uncertainty and incompleteness of failure data, it more or less brought subjectivity. One solution is to detect the fault accurately through analyzing condition signals of hydraulic such as vibration, flow, leakage, oil pollution, and so on, without relying on the experience of experts. Due to the complexity and ambiguity of hydraulic failure mechanism, an intelligent diagnosis approach may be needed to learn fault features from fault data. In addition, considering there is no single intelligent diagnosis approach that can be suitable for all fault diagnosis tasks, ensemble methods, such as bagging, boosting, and other rules, are also needed to combine multiple base intelligent fault diagnosis approaches to become a strong learning mode. This put forward demands on the condition monitoring technique of a hydraulic system and related algorithms, which cannot be implemented in this article, because only fault event data were obtained. Nonetheless, it provides a direction for future FTA works.

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