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# A New Fault Diagnosis Method Based on Fault Tree and Bayesian Networks

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**Abstract**

This paper presents a novel method for diagnosing faults using fault tree analysis and Bayesian networks (BN) to optimize system diagnosis. All minimal cut sets were generated via qualitative analysis of fault tree using an efficient zero-suppressed binary decision diagram (ZBDD), while the diagnostic importance factor (DIF) of components and minimal cut sets were calculated by mapping fault tree into equivalent BN. Also, these analysis results such as minimal cut sets and DIF were updated after receiving the evidence data from sensors and used to develop an efficient diagnostic decision algorithm. Furthermore, a diagnostic decision tree (DDT) was generated to guide the maintenance personnel to repair the system. Finally, a real example is given to demonstrate the efficiency of this method.



Keywords: Fault Tree, Bayesian Networks, Diagnostic Importance Factor, Diagnostic Decision Tree.

## 1.Introduction

Recent developments in technology have led to an increase in the complexity of systems. The failures within these systems can cause disruption to the operational functionality. Fault location has therefore become a first objective in engineering applications. Several techniques have focused on identifying faults. Obviously, effective diagnostic approaches can decrease downtime and consequently enhance operational functionality. A new classification framework for fault diagnosis was proposed in [1], which divided fault diagnosis approaches into qualitative analysis approaches and quantitative analysis approaches. The former which is very suitable for diagnosing complex system is automatic, independent on mass failure data and can make full use of some quantitative data and structural information performed within the system design phase. Some recent approaches have used reliability assessment tools such as failure modes and effects analysis, fault tree analysis and Bayesian network. In [2, 3] components' DIF or minimal cut sets' DIF was calculated based on the static fault tree analysis, which

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determines the order of the system diagnosis. In [4] the ratio of efficiency to time for fault diagnosis was introduced to take into consideration the mean time to detection of each unit and find the best program to remove the faults. However, these methods determine the diagnostic sequence only by components' DIF or minimal cut sets' DIF alone, and usually causes minimal cut sets with a smaller DIF to be checked first [5]. To improve diagnostic efficiency, Assaf T. put forward an approach to incorporate evidence data from sensors into diagnostic process [6]. However the solution for dynamic fault tree was based on Markov model which has the infamous state space explosion problem. And, it hadn't inference capability and couldn't update the components' posterior failure probability based on the evidence data from sensors, which affected the diagnostic accuracy and efficiency. In [7, 8] BN was used to diagnose faults and the posterior failure probability could be updated after receiving the evidence data. But it was difficult to model BN, which always needed domain experts or mass historical data, and also these methods neglected system qualitative structure to locate faults.

To address these issues, we present a novel approach based on fault tree analysis and BN for fault diagnosis. It makes use of the advantages of the fault tree for modeling and BN for inference. The proposed method use fault tree model and need little expert knowledge. Also we present an efficient diagnostic decision algorithm based on the overall consideration of the fault tree analysis and BN inference and generate a DDT to guide the maintenance crew to make efficient decisions when trying to recover a system.

## 2.The Framework for Fault Diagnosis

The method for fault diagnosis uses system fault tree model. All minimal cut sets are generated using qualitative analysis of fault tree, while DIF is calculated via quantitative analysis. DIF is the corner stone of our methodology and provides an accurate measure of components' relevance from a diagnosis perspective [9]. The DIF is defined conceptually as the probability that an event has occurred given the top event has also occurred.

$$DIF_{MCS_n} = P(MCS_n \mid S), DIF_C = P(C \mid S) \tag{1}$$

$MCS_n$: $n^{th}$ minimal cut sets, $C$: a component in system $S$.

Due to the different complexity of components their test costs are different. A balance is needed between the DIF and test costs. Therefore, Ref. [2] proposed a new measure of importance called the cost and diagnostics importance measure (CDIF). This measure is simply the DIF per unit cost. The CDIF measure appears in (2).

$$CDIF_C = DIF_C / C_C \tag{2}$$

$C_c$: the test cost of the component $c$

Based on above analysis, a framework for fault diagnosis method is presented in Fig. 1. It uses fault tree model which can come from the system design phase for reliability analysis. We generate all minimal cut sets using qualitative analysis of fault tree and calculate DIF of components via mapping fault tree into BN. Meanwhile we update the sum of all minimal cut sets and the components' posterior failure probability based on the evidence data from sensors. Also, based on these results we design an efficient diagnostic decision algorithm and generate an efficient DDT, which reduces dependence on engineering expertise.

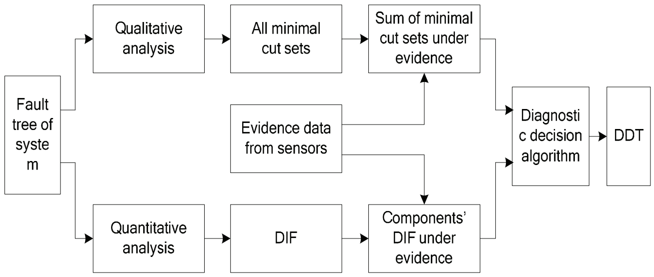


Fig. 1 The framework for proposed fault diagnosis method.

## 3.Fault Tree Analysis

### 3.1.Qualitative Analysis of Fault Tree

The algebraic minimization and Fussell-Vasely algorithm are the most effective method for generating minimal cut sets. But they are inappropriate to the complex system. For the complex system we can use BDD to solve all minimal cut sets. However, it's very difficulty to decide the order of the basic event for BDD solution. ZBDD can overcome the shortcoming. The *MCS* generation algorithm is executed recursively during the depth-first left-most traversal of a fault tree. Let $S_1$, $S_2$ be the input of *MCS*-*AND* and *MCS*-*OR* respectively, the basic set operations are as follow [10]:

$$\begin{gathered} S_c = S_1 \cap S_2,\, D_1 = S_1 - S_c,\, D_2 = S_2 - S_c \\ U = D_1 \cup D_2,\, P = D_1 * D_2,\, D_3 = U - P \end{gathered} \tag{3}$$

So the output of *MCS*-*AND* and *MCS*-*OR* are $MCS_{OR} = S_c \cup D_3$ and $MCS_{AND} = S_c \cup P$ respectively. The *MCS* generation algorithm is executed recursively during the depth-first left-most traversal of a fault tree. It first generates the *MCS* of the inputs of a connection gate, and then performs a serial of set operations to combine the *MCS* of the inputs into the *MCS* of the output of the connection gate [10]. At last we can get all the minimal cut sets.

### 3.2.Quantitative Analysis of Fault Tree

Quantitative analysis for fault tree is used to calculate the minimal cut sets' DIF and components' CDIF. In [5] DIF values are calculated from marginal importance factors produced by the sensitivity analysis of fault trees solved via BDD. The complexity of calculation depends critically on the basic event ordering of the fault tree, and it doesn't deal with the evidence data from sensors. So we map the fault tree into an equivalent BN and resort to its inference engine to calculate the posterior probability of components. Conceptually it is straightforward to convert a fault tree into a Bayesian network. Ref. [11, 12] shows the conversion of an OR and an AND gate into equivalent nodes in a BN. Parent nodes are assigned prior probabilities, which coincident with the probability values assigned to the corresponding basic nodes in the fault tree, and child node is assigned its conditional probability table.

Once the structure of a BN is known and all the probability tables are filled, we used an open source MATLAB toolbox: The Bayes Net Toolbox (BNT) to calculate DIF. We enter the evidence that the system has failed, $P_S(state = fault) = 1$ , and solving the BN using a clustering algorithm gives the following posterior failure $P_C(state = fault)$, which is the component's DIF. If there are some evidence data from sensors, similarly, we set their probability as 1 and feed them into BN to update the component's DIF.

The DIF of minimal cut sets is calculated using (4).

$$DIF_{MCS_n} = P(MCS_n) / P(S) \tag{4}$$

$P(S)$: the unreliability of the system.

### 3.3.Processing Evidence data

When a system failure is observed, sometimes additional evidence can be observed too. We can make use of these evidence data. Since, examining a cut set that engendered the system to fail then repairing the bad components in the same cut set should recover the system, we can enhance diagnosis by reducing the number of cut sets examined. An efficient method for using evidence is developed to reduce the number of suspected minimal cut sets [6]. The cut sets under evidence (CUE) is introduced and it is the set of all essential minimal cut sets obtained after evidence eliminates some cut sets. In this paper, we not only update the CUE, but also update the DIF of components and CUE. The updating of components' DIF is very simply, while the updating CUE's DIF is calculated using (5).

$$DIF_{CUE} = \frac{P(CUE, E, S)}{P(S)DIF_E} \tag{5}$$

$E$: the variables with given evidence.

### 3.4.Diagnostic Decision Algorithm

As cut sets represent minimal sets of component failures that can cause a system failure, we should diagnose them one by one to find the reason of system failure. Only when we finish diagnosing a minimal cut set can we do next. The order by which cut sets are checked depends on the DIF ordering, while the order of components in the same minimal cut set is determined by their CDIF. The minimal cut sets with larger DIF are checked first. Accordingly, components with larger CDIF in a cut set are checked first. This assures a reduced number of system checks while fixing the system. Based on quantitative and qualitative data obtained from reliability analysis of fault tree as well as the algorithm in [5, 13], diagnostic decision algorithm is as follows:

**Step1.** Rank all cut sets and select the cut sets with highest DIF value.

**Step2.** Check the component *C* with highest CDIF in the cut sets.

**Step3.** Split the cut sets into those with *C* and those without.

- If *C* failed test we take the set of cut sets that include *C*
    - Select the cut sets untested with highest DIF value.
    - And recursively repeat Step2 - Step3.
- b) If *C* has not failed test we take the other set of cut sets
    - Select the cut sets untested with highest DIF value.
    - And recursively repeat Step2 - Step3.

The diagnosis strategy can easily be captured in the graphical DDT. The DDT provides us with a map that allows us to recognize the failing components [2, 9]. Once the order of components is determined, we can generate the DDT.

## 4.A Case Study

The system of aircraft engine oil pressure warning instructions is an important subsystem of the aircraft control system. It is composed of the oil pressure instructions part and oil pressure warning part. The fault tree for the engine damage is shown in Fig. 2 [5]. We generate 21 minimal cut sets via ZBDD. Assume a sensor monitors the failure of $X_1$ and $X_3$, and detects a failure; the following CUE function is generated:

$$F_{CUE} = X_2 + X_4 + X_5 + X_6 + X_{10}X_{11} + X_{10}X_{12} \tag{6}$$

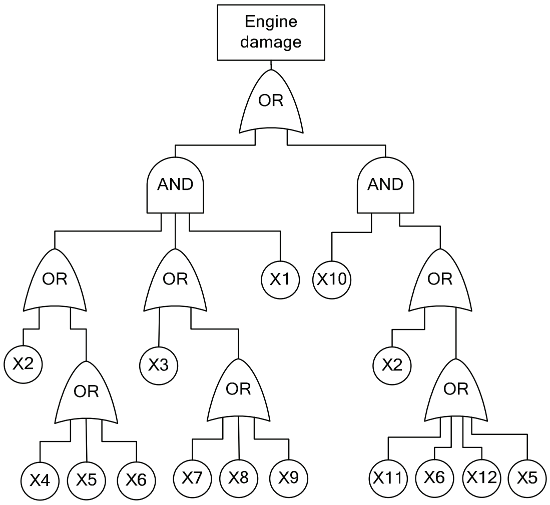


Fig. 2 Fault tree for the failure of oil pressure warning instructions system

Now because engine damage, $X_1$ and $X_3$ have been set as evidence, their failure probability should be set as 1. Solving the BN using BNT tool gives the results of some importance factors in Table 1. For simplicity, we assume all components have a unit test cost. Based on the diagnostic decision algorithm above mentioned, we can generate its DDT which is shown in Fig. 3. Since sensor monitors the failure of $X_1$ and $X_3$, $X_1$ and $X_3$ should be checked prior to generating the DDT. The produced DDT demonstrates the advantage of evidence incorporation into the fault diagnosis. The reduction of the characteristic function into the $F_{\text{CUE}}$ as a result of evidence has produced a smaller DDT comparing with the result in [5].

TABLE I Diagnostic data for oil pressure warning instructions system failure.

| Order | Cut sets | Cut sets' DIF | Components' DIF |
|---|---|---|---|
| 1 | X2 | 0.653 | 0.653 |
| 2 | X5 | 0.348 | 0.348 |
| 3 | X10. X11 | 4.84e-5 | 1.95e-5, 1.2e-3 |
| 4 | X10. X12 | 4.03e-5 | 1.95e-5, 1e-3 |
| 5 | X4 | 4.35e-6 | 4.35e-6 |
| 6 | X6 | 2.17e-6 | 2.17e-6 |

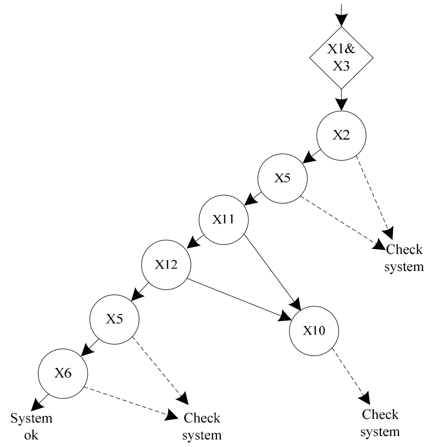


Fig. 3 DDT for the failure of oil pressure warning instructions system

## 5.Conclusions and Future Work

A novel approach of fault tree and Bayesian networks for fault diagnosis has been proposed which there may be little expert knowledge. It makes full use of the advantages of both fault tree for modeling and BN for the inference ability. Using the proposed approach, we can acquire all minimal cut sets by zero-suppressed binary decision diagram, calculate the components' DIF and update them after receiving the evidence data from the sensors by mapping the fault tree into equivalent BN. Furthermore, based on the reliability analysis data, we present an efficient diagnostic decision algorithm and generate a DDT to guide the maintenance crew to make more efficient decisions when trying to recover a system. Finally, we have tested our methodology on a real system to demonstrate its diagnostic efficiency.

In the future work, we will focus on the sensors' reliability as well as placement and improving the effectiveness of our algorithms.

## 6.Acknowledgment

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