

# Exploiting Bayesian Networks for Fault Isolation: A Diagnostic Case Study of Diesel Fuel Injection System

Jinxin Wang <sup>a</sup>, Zhongwei Wang <sup>a, \*</sup>, Viacheslav Stetsyuk <sup>b</sup>, Xiuzhen Ma <sup>a</sup>, Fengshou Gu <sup>b</sup>, Wenhui Li <sup>a</sup>

<sup>a</sup> College of Power and Energy Engineering, Harbin Engineering University, Harbin 150001, China.

<sup>b</sup> Centre for Efficiency and Performance Engineering, University of Huddersfield, Huddersfield HD1 3DK, UK.

**Abstract:** Fault isolation is known to be a challenging problem in machinery troubleshooting. It is not only because the isolation of multiple faults contains considerable number of uncertainties due to the strong correlation and coupling between different faults, but often massive prior knowledge is needed as well. This paper presents a Bayesian network-based approach for fault isolation in the presence of the uncertainties. Various faults and symptoms are parameterized using state variables, or the so-called nodes in Bayesian networks (BNs). Probabilistically causality between a fault and a symptom and its quantization are described respectively by a directed edge and conditional probability. To reduce the qualitative and quantitative knowledge needed, particular considerations are given to the simplification of Bayesian networks structures and conditional probability expressions using rough sets and noisy-OR/MAX model, respectively. By adopting the simplified approach, symptoms under multiple-fault are decoupled into the ones under every single fault, while the quantity of the conditional probabilities is simplified into the linear form of the faults quantity. Prior knowledge needed in Bayesian network-based diagnostic model is reduced significantly, which decreases the complexity in establishing and applying this diagnosis model. The computational efficiency is improved accordingly in the simplified BN model, after eliminating the redundant symptoms. The fault isolation methodology is illustrated through an example of diesel engine fuel injection system to verify the developed model.

**Keywords:** fault isolation; Bayesian network; diagnosis under uncertainty; knowledge reduction; diesel engine fuel injection system

## 1. Introduction

In modern society, mechanical systems have deepened their influence on various

---

\* Corresponding author. E-mail address: [wangzw@hrbeu.edu.cn](mailto:wangzw@hrbeu.edu.cn)

fields of worldwide economy. Especially, the ever-increasing requirement of machinery reliability and security has become one of the most important issues to be solved for reduced cost of machine operations and maintenances. Fault diagnosis provides an effective means to monitoring online the continuous deterioration of mechanical properties due to the alternating stress as well as due to other factors, and thereby to ensure the availability and high-performance of machines.

Currently, single faults diagnosis has already received a considerable amount of attention from various researchers and engineers. A number of useful diagnostic approaches have been developed and applied to improve fault detection mechanisms [1-3]. However, studies on isolating multiple-fault have been found very limited [4]. In practice, a set of faults may be considered as various options when a component or mechanical system breakdowns, e.g. failures of gearbox tooth may take the form of cracks, spalling and wear, e.g. loose joints and imbalance are among the common faults of a rotating machinery. The real root cause among the various faults of an abnormality is completely unknown before carrying out the diagnostics. Accordingly, it would be more reasonable to take all the potential faults into consideration, or the so-called fault isolation, in the process of troubleshooting, rather than a certain fault of interested. Nevertheless, one major issue that lies in front of this diagnostic strategy is the inherently strong correlation and coupling between different faults. A symptom is not only affected by individual faults, but also by multiple faults in a coupled way, which makes mapping a single/multiple symptom(s) exactly into the real root cause a great challenge.

Some works have attempted to investigate and separate multiple faults, e.g. multisource signals separation [4,5], ensemble deep learning [6] and nonlinear dynamic models [7]. Although these approaches focus on the decouple of multiple faults, they consider deterministic models in which all the parameters and features are assumed to be identifiable, and uncertainties are not directly accounted for. In fact, fault isolation is plagued severely by considerable number of uncertainties which are contained in the complicated correspondence between multiple faults and symptoms. One primary reason of this problem is the limited knowledge of mechanical systems behavior under

60 varying operational scenarios. Physics-based modeling and simulation is accepted as  
61 an effectively way to understand the systems behavior and outcomes. However, higher-  
62 fidelity models are not always available, especially for the complex systems, while  
63 simplified models are unsatisfactory for characteristic analysis. In addition, the ever-  
64 increasing complexity and automaticity of mechanical systems are supposed to have  
65 shifted physical models towards a limited capability of characteristic analysis [8].  
66 Besides the epistemic scarcity or lack-of-knowledge, these uncertainties also arise from  
67 different random factors [8,9]. Useful information is difficult to be gathered due to the  
68 environmental conditions variability and the imperfect communication channels, which  
69 makes a completely accurate description of faults difficult to achieve in real-world. Due  
70 these issues, the correspondence between symptoms and multiple faults has some  
71 unfavorable but inherent characteristics: the existence of symptoms when a certain fault  
72 presents are not guaranteed, and the origin of an abnormality may be unstable, which  
73 should be given full consideration in the isolation of multiple faults.

74 Fuzzy sets theory [10] and Dempster-Shafer (D-S) evidence theory [11] are known  
75 as two primary uncertainty analysis methods for mechanical fault diagnosis. The vague  
76 and imprecise information can be well described using fuzzy sets theory because of its  
77 permission for gradual degrees of membership. However, the fuzzy sets theory has  
78 limitations when handling rejection classes in pattern recognition [8]. A rejection class,  
79 which does not belong to any classes of interested, often cannot be well isolated using  
80 fuzzy sets theory. This deficiency could be likely to cause a false alarm in fault  
81 diagnosis. Instead of using membership functions to capture system uncertainties, D-S  
82 evidence theory takes advantage of a belief function to describe the belief degree of a  
83 proposition. The D-S theory has unique advantage in handling the uncertain and  
84 imprecise information. However, the unreliable of evidence combination and  
85 probabilities updating is generated if the data is found highly conflictive. Furthermore,  
86 these two methods cannot make effective use of prior knowledge about historical  
87 running condition of mechanical systems, which is an important guidance to analyze  
88 the mechanical systems characters and find out the root causes resulting in the current  
89 breakdown.

An alternative view on the fault isolation with consideration of uncertainties is by means of probabilistic representation of the indeterminate causal relationships, and decision-making under uncertainties. Bayesian networks (BNs) [12] is a graphical probabilistic model, in which a node represents a random variable or event and the directed edge connect a parent to a child if there is a probabilistic dependency. The abilities of knowledge-representing and decision-making under uncertainties of BNs have led to their application in a variety of real-world problems [13-15]. Many researchers also explored the BN-based approach for fault isolation and multiple-fault diagnosis of different machinery systems [16-18], e.g. centrifugal compressors [19], chillers [20,21], chemical processes [22] and gear pumps [23]. Cai and his research team carried out a series of works on machinery fault diagnosis using BNs and the extension over the years [9,24-26]. Recently, he presented a comprehensive review of the BN-based approach for fault diagnosis [27]. Although considerable works have been carried in this area, there still remains some problems to be solved, the complexity of modelling being one of them. The BN-based diagnostic model always calls for an incredible amount of prior knowledge, which has turned establishing BN-based diagnostic model into an unrealistic work. Take the BN-based model of ground-source heat pump as an example [24], in total 15 symptoms and up to 214 conditional probabilities (to quantize the causalities) are required to identify 8 faults. Despite novel learning algorithms for establishing BNs from data keep coming up [28,29], they all depend on the extensive training data, which are not always available in reality. Consequently, simplifying the establishment of BN-based model becomes an urgent problem in order to apply this diagnostic technology to real-world successfully. Some researchers have given their attention to the simplification of BNs [24,25,30]. However, the existing approaches focus only on one aspect, either directed acyclic graph [30] or parameters [24], then, or can be only applicable to the machineries with specific structures [25]. To our best knowledge, little research provides a comprehensive as well as general view on this problem.

In this paper, we propose a BN-based approach for fault isolation in the presence of uncertainties. Compared with the existing research, the contributions of this paper is

summarized in: (i) a procedure for simplifying BN-based diagnostic models structures and conditional probability expressions are proposed using rough sets and noisy-OR/MAX model, respectively; (ii) a novel BN structure is presented in this paper to specify prior probability based on multiple experts' knowledge by appending an auxiliary node; and (iii) a new judgment basis is utilized to improve the rationality and accuracy of the diagnosis.

The rest of this paper is organized as follows. Section 2 describes the proposed methodology for fault isolation. Section 3 illustrates the proposed approach by taking IC engine fuel injection system as an example. The isolation of multiple faults is performed based on the developed model. Finally, section 4 summarizes the paper.

## 2. Proposed Methodology

### 2.1. BNs for fault isolation

A BN is defined as a pair  $B = \langle G, P \rangle$ , where  $G = \langle V, D \rangle$  denotes a directed acyclic graph (DAG);  $V$  represents a set of nodes or random variables of interest;  $D$  corresponds to the directed edges where each of them indicates a probabilistic dependency from one node, namely parent, to the other, namely child. The dependency is quantified via a conditional probability distribution (CPD)  $P$ . As for node with no parents, a prior distribution is defined to assign the probability to each state. Figure 1 shows a simple BN over 3 binary variables. The probability of  $V_3 = T$  given  $V_1 = T$  and  $V_2 = F$  is  $P(V_3 = T | V_1 = T, V_2 = F) = 0.7$ . The prior probability of each state of  $V_1$  is specified as  $P(V_1) = P(V_1 = T, V_1 = F) = (0.12, 0.88)$ .

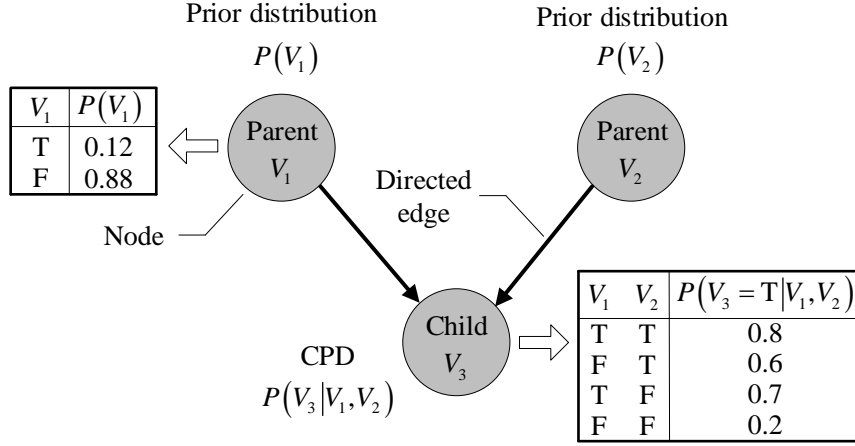


Figure 1: A simple Bayesian network

In fault diagnostics, the DAG of a BN is viewed as a causal structure in which the parents and children are instantiated as faults and symptoms, respectively (we do not differentiate nodes or parents/children from faults/symptoms hereafter). An edge  $V^f \rightarrow V^s$  is added if a fault  $V^f$  is perceived to be a direct cause of an abnormality  $V^s$ . The associated CPD indicates the likelihood to having an abnormality  $V^s$  with faults  $V^f$  presented, which can be used to quantify the strength of the influence of the fault  $V^s$  on the symptom  $V^f$ . The quantification is probabilistically sound so that it corresponds to being able to directly model the uncertainties of the causality.

Beyond the depiction of causal relationship qualitatively and quantitatively, BNs characterize the statistical information of machine fault logging by prior probabilities of root nodes. Fault logging contains the occurrence probability of each fault during the historical operation, which is an important guidance to analyze the mechanical systems characters and find out the root causes resulting in the current breakdown. Nodes with high prior probability are expected to be fault-prone. Given observed abnormalities or called evidence  $E$ , the prior probabilities are updated to indicate the probabilities of the presence of various faults. The evidence can be an instantiation of symptoms or faults, or both, which consists of two following parts.

- (1) the symptoms as well as faults known to be present  $E^+ = \{V_i\}$  or

161  $E^+ = \{V_i = T\};$

162 (2) the symptoms as well as faults known to be absent  $E^- = \{\bar{V}_j\}$  or

163  $E^- = \{V_i = F\};$

164 It is worth noting that whether some faults present or not is also an important  
 165 evidence for troubleshooting because the absence of some faults will increase the  
 166 occurrence probabilities of others since they share the same joint probability  
 167 distribution. The probability a fault making for an abnormality is inferred based on Bayes'  
 168 theorem. For the diagnostic BN shown in Figure 2, the probability  
 169  $P(V_1^f = T | V_1^s = T, V_2^s = F)$  if given evidence  $E = E^+ \cap E^- = \{V_1^s, \bar{V}_2^s\}$  is inferred as

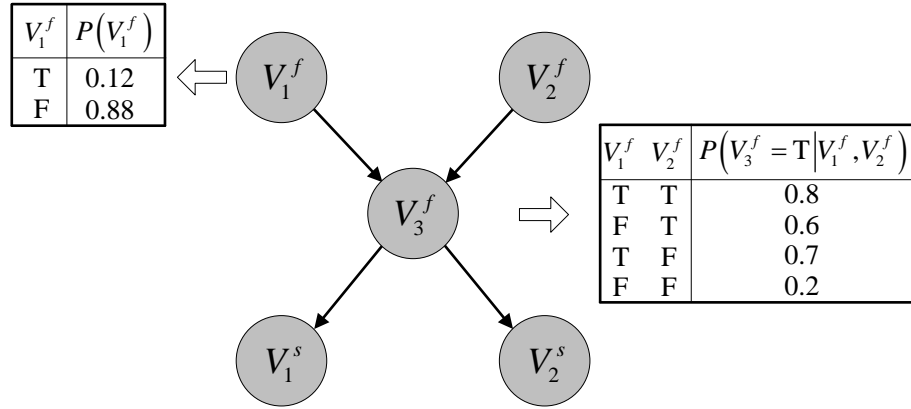


Figure 2: A BN-based diagnostic model

172 
$$P(V_1^f = T | V_1^s = T, V_2^s = F) = \frac{P(V_1^f = T, V_1^s = T, V_2^s = F)}{P(V_1^s = T, V_2^s = F)} \quad (1)$$

173 where

174 
$$P(V_1^f = T, V_1^s = T, V_2^s = F) = \sum_{V_2^f, V_3^f} P(V_1^f = T, V_2^f, V_3^f, V_1^s = T, V_2^s = F) \quad (2)$$

175 
$$P(V_1^s = T, V_2^s = F) = \sum_{V_1^f, V_2^f, V_3^f} P(V_1^f, V_2^f, V_3^f, V_1^s = T, V_2^s = F) \quad (3)$$

176 In BN-based diagnostic model, the causality has been described via the directed  
 177 edge, a symptom is therefore thought to only be induced by the faults it connects with.  
 178 According to these modeling rules together with the chain rule, the joint probability  
 179 distribution can be written as

$$P(V_1^f V_2^f V_3^f V_1^s V_2^s) = \prod P(V | pa(V)) \quad (4)$$

where  $pa(V)$  is the parents of  $V$ . Hence, Eqs. (2) and (3) can be simplified respectively as follows.

$$P(V_1^f = T, V_1^s = T, V_2^s = F) = \sum_{V_2^f, V_3^f} P(V_1^f = T) P(V_2^f) P(V_3^f | V_1^f = T, V_2^f) \cdot \sum_{V_2^f, V_3^f} P(V_1^s = T | V_3^f) P(V_2^s = F | V_3^f) \quad (5)$$

$$P(V_1^s = T, V_2^s = F) = \sum_{V_1^f, V_2^f, V_3^f} P(V_1^f) P(V_2^f) P(V_3^f | V_1^f, V_2^f) P(V_1^s = T | V_3^f) \cdot \sum_{V_1^f, V_2^f, V_3^f} P(V_2^s = F | V_3^f) \quad (6)$$

Eqs. (1), (5) and (6) reveal the essence of BN-based fault diagnosis under uncertainties. The result indicates the likelihood that a particular fault makes for the abnormality. Fault maximizing the posterior probability  $P(V^f | E)$  is considered to be the most likely origin of the abnormality.

## 2.2. Procedure for simplifying BN-based diagnostic model

### 2.2.1. Motivation

In the conventional BN-based diagnostic model shown in Fig. 2, the conditional probabilities associated with symptoms are required to be specified for a quantitative relationship between faults and symptoms. The conditional probability distribution is encoded over all possible configurations of the related faults, which calls for an incredible amount of prior knowledge during the modeling process. Such enormous demand for quantitative knowledge makes the BN-based diagnostic models over-complex, which prohibits these models being widely applied to the real-world machine systems.

One major reason for this problem is the existence of multidimensional causal relationships between faults and symptoms. It is a time-consuming or even impossible task to set a complete CPD when multiple faults share a common signature, since the



CPD expresses the quantitative relationship conditional on every possible instantiation of all associated faults. Consider a general case: supposing a sub-model consisting of a symptom  $s$  ( $V^f$  and  $V^s$  are denoted as  $f$  and  $s$  for short) that has a domain size  $d_s$  for various potential outputs, e.g. higher, lower and normal, and  $n$  associated faults where each of them has  $d_f$  states representing different severity or failure modes, e.g. short, open and working, a complete CPD for this sub-model requires  $(d_s - 1) \cdot d_f^n$  non-redundant probabilities. This presents a practical difficulty that the CPD of a symptom grows exponentially with the number of the associated faults, and therefore lead to the research of decoupling the multidimensional causality between symptom and multiple faults to decrease the parameters needed.

Besides the multidimensional causality, the complexity of model structure is also perceived to be an origin of the over-need for prior knowledge. Problem that involves in this aspect mainly refers to the existence of redundant symptoms. In a diagnostic model, a variety of symptoms are often used to describe a fault from different perspectives, which unavoidably leads to the existing of equivalency or called redundancy. CPDs are directly associated with symptom nodes in a BN so that this redundancy of symptoms brings about considerable amount of quantitative knowledge in a diagnostic model. Revisit the example above, suppose the entire BN model has  $m$  symptoms with same local structure, viz., they have an equal number of parents, the parameters needed of the model increases to  $m \cdot (d_s - 1) d_f^n$ , a factor of  $m$  than the single one. Consequently, in addition to decoupling causality, the simplification of BN-based diagnostic model can be pursued via a second way: eliminating the redundant symptoms. The following parts study the simplifying of BN model from these two directions, respectively. Structural consideration is presented firstly as the order of modeling procedure.

### 2.2.2. Eliminating redundant symptoms

The elimination of redundant symptoms is carried out by taking the advantage of

the attributes reduction in rough sets, which is known as a purely structural method for eliminating redundancies in knowledge base and finding a subset of attributes that contains the same information as the original one.

A knowledge base with conditional attributes as well as decision attributes is known as a decision system in rough sets theory. It can be defined as follows.

**Definition 2.1** [31,32] An decision system is a 4-tuple  $S = \langle U, A, V, f \rangle$ , where  $U = \{u_i\} (i=1, \dots, n)$  is a non-empty finite set of objects called universe;  $A = C \cup D$  is a set of attributes, in which  $C$  represents the set of conditional attributes,  $D$  represents the decision attributes;  $V$  is the codomain of  $A$ ,  $V = \bigcup_{a \in A} V_a$ , where  $V_a$  is the set of values of attribute  $a$ ;  $f$  is the mapping from  $U \times A$  into  $V$ .

The decision system  $S$  describes knowledge base by means of mathematical method. The attributes in the decision system can be a representation of any kind of symptoms, which makes rough sets a general approach for redundant elimination. In this paper, we consider the symptoms and the faults as the condition attributes and the decision attributes respectively. The mapping  $f$  describes the causal relationship between the faults and the symptoms with symbolic attribute values. As a result, the knowledge base for fault diagnostics is represented as a decision system  $S$  and can be dealt with accordingly.

To give a matrix representation for storing the sets of attributes that discern pairs of objects, Skowron A. [33] provides the concept of discernibility matrix thereafter, which turns out to be an effective way for attributes reduction of decision system.

**Definition 2.2** [33] Let  $S = \langle U, C \cup D, V, f \rangle$  be a decision system as definition 2.1. Its discernibility matrix  $M(S) = (\alpha(u_i, u_j))_{n \times n}$  is defined in the following way

$$\alpha(u_i, u_j) = \begin{cases} \{c \mid c \in C \wedge c(u_i) \neq c(u_j)\}, & d(u_i) \neq d(u_j) \\ \emptyset, & \text{otherwise} \end{cases} \quad (7)$$

where  $c \in C$ ,  $d \in D$ ;  $c(u)$ ,  $d(u)$  denote the values of object  $u$  on  $c$  and  $d$ , respectively.

Intuitively,  $M(S)$  is a symmetric matrix and its non-empty elements  $\alpha(u_i, u_j)$  represents the necessary condition attribute(s) to distinguish object  $u_i$  from  $u_j$ ;  $\alpha(u_i, u_j) = \emptyset$  means the objects  $u_i$  and  $u_j$  are indiscernible. A discernibility function  $f(S)$  of decision system  $S$  is defined accordingly.

$$f(S) = \bigwedge \{ \bigvee c \mid c \in \alpha(u_i, u_j), \alpha(u_i, u_j) \neq \emptyset \} \quad (8)$$

where  $\bigvee c$  is the disjunction of attributes  $c$  such that  $c \in \alpha(u_i, u_j)$ ;  $\bigwedge c$  is the conjunctive of  $c$ .

The discernibility function  $f(S)$  contains all the necessary condition attribute(s) to discern pairs of objects in decision system  $S$ . Each conjunctive form in the minimal disjunctive normal form of  $f(S)$  is a subset of condition attributes that has the same capability to classify pairs of objects as the original one. Consequently, we can eliminate the redundant symptoms from prior knowledge based on the attributes reduction method in rough sets after describing the knowledge base as a decision system.

### 2.2.3. Decoupling causality

In this section, we exploit the semantics of noisy-OR model or its generalization, the noisy-MAX model [12, 34] to decouple the multidimensional causal relationships between faults and symptoms.

First, we make a following assumption on the relationships between faults and symptoms of mechanical systems.

**Assumption:** The causal mechanism that a fault influences a symptom is independent from others if multidimensional causality exists.

This assumption means that the occurrence of one fault does not affect the causal relationship between the symptom and other faults. It is well-founded with two factual bases: (i) different faults vary in propagation mechanisms; and (ii) there is no necessary connection between two faults. It should be noted that sequentially dependent faults are not included since this paper focuses on the relationship between faults and symptoms.

Based on this assumption, the multidimensional causality can be described by the decomposed probabilistic models of noisy-OR/MAX relation shown in Fig. 3.

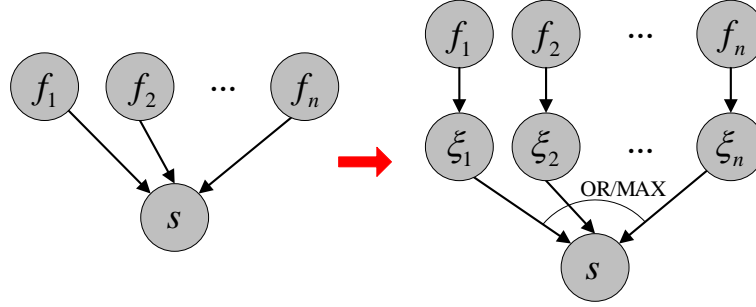


Figure 3: Noisy-OR/MAX model

Suppose there are several different faults  $f_1, \dots, f_n$  with Boolean-valued domains leading to an abnormality  $s$ , see Fig. 3 (OR). Let  $P_i$  be the probability that the fault  $f_i$  ( $1 \leq i \leq n$ ) is sufficient to cause the abnormality  $s$  while other faults are absent. It can be written as follows then.

$$P_i = P(\xi_i = T | f_i = T) = P(s = T | f_i = T, f_j = F_{[\forall j, j \neq i]}) \quad (9)$$

The combining effect of multiple faults, that is the CPT, can be easily generated from  $P_i$  according to the OR logical relation.

$$P(s | \xi_1, \dots, \xi_n) = \begin{cases} 1, & \text{if } s = \xi_1 \vee \dots \vee \xi_n \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

It can be also converted into a more computable form as

$$\begin{cases} P(s=F | pa(s)) = \prod_{i: f_i \in pa(s)^+} (1 - P_i) \\ P(s=T | pa(s)) = 1 - \prod_{i: f_i \in pa(s)^+} (1 - P_i) \end{cases} \quad (11)$$

where  $pa(s)^+$  denotes the set of faults with presence. We assume that  $P(s = T | f_1 = F, \dots, f_n = F) = 0$  since the abnormality cannot be present if all components are functional.

A symptom may have a multi-valued domain to represent various potential outputs in some cases; it is also the faults. The domains of these nodes are assumed to be ordered and the values are referred to as the degree or the severity of the symptoms/faults.

Suppose  $d_s$  and  $d_{f_i}$  is the domain sizes of the symptom  $s$  and a fault  $f_i$  in Fig. 3, and the domains are given by a finite set of integers  $\{0, 1, \dots, d_s - 1\}$  and  $\{0, 1, \dots, d_{f_i} - 1\}$ , respectively, in which 0 represents the fact that a symptom or a fault is absent. Let  $P_{i,a}^{b_i}$  be the probability that the symptom presents a certain state given a certain configuration of the faults,

$$P_{i,a}^{b_i} = P\left(s = a \mid f_i = b_i, f_j = 0_{[\forall j, j \neq i]}\right) \quad \begin{array}{l} i = 1, \dots, n \\ a = 0, \dots, d_s - 1 \\ b_i = 1, \dots, d_{f_i} - 1 \end{array} \quad (12)$$

The complete causal relationships can be deduced using the MAX arithmetic relation, as

$$P(s = a \mid pa(s)) = \begin{cases} P(s \leq 0 \mid pa(s)) & \text{if } a = 0 \\ P(s \leq a \mid pa(s)) - P(s \leq a - 1 \mid pa(s)) & \text{if } a > 0 \end{cases} \quad (13)$$

and

$$P(s \leq a \mid pa(s)) = \prod_{\substack{i=1 \\ b_i \neq 0}}^n \sum_{a'=0}^a P_{i,a'}^{b_i} \quad (14)$$

Suppose all of the domain sizes of faults are equal to  $d_f$ , the number of non-redundant probabilities one need to specify is dramatically reduced to  $(d_s - 1)(d_f - 1) \cdot n$ , the linear form of fault quantity, compared with  $(d_s - 1)d_f \cdot d_f^{n-1}$  in conventional BN models, the exponential form. This demonstrates that decoupling the symptom under multiple-fault into the one under every single fault and then combining the effect using logical relationship (OR) or arithmetic relationship (MAX) can be an effective way to significantly decrease the complexity to establish a BN-based diagnostic model.

### 2.3. Prior probability from expert

As previously mentioned, prior probabilities used to characterize the historical running condition of mechanical systems are of significant importance in machinery

fault diagnosis. Parameters learning is usually exploited for extracting this information. However, this approach is often inapplicable due to the limited quantity of training data, especially when it comes to the catastrophic faults that cannot be repeated in large quantity. Alternatively, one can assign the prior probability of multiple faults in light of experts' knowledge. While subjective determination provides a way to specify these parameters, however, uncertainties due to the bias of expert opinion are brought at the same time. An effective approach for solving this problem is to gather different judgments from various domain experts and assign the parameters through fusing these different opinions. To this end, this paper presents a novel BN structure to specify prior probability based on multiple experts' knowledge by appending an auxiliary node.

The modified BN is shown as Fig. 4. It is assumed that  $k$  domain experts have been involved in the establishment of BN-based model. The newly added node *Expert* is used to be an auxiliary node to capture expert opinions on the prior occurrence probability of modeled faults. The relationships that the directed edges from the auxiliary node to various faults represent are not cause-and-effect links but the ones in BN syntax. The node *Expert* assigns a different state to each expert, e.g. states  $\text{exp}1, \dots, \text{exp}k$  denotes the  $k$  experts. Each state is associated with a different belief to represent the reliability degree of the corresponding expert, viz.,  $P_i$  ( $i = 1, \dots, k$ ) denotes the reliability of the  $i$ th expert ( $\text{exp}i$ ). The sum of these beliefs ought to be 1.0. Experts are asked to assess the prior occurrence probabilities of the modeled faults according to their own knowledge. The prior probability  $Pr_i = P(f = T | \text{exp}i)$  represents the occurrence probability of fault  $f$  before taking some evidence into account based on the  $i$ th expert's opinion, and the parameters from different domain experts are independent from each other. Therefore, the modified BN structure makes it possible to reduce the uncertainties resulting from the subjective determination of single expert by incorporating the judgments of various domain experts.

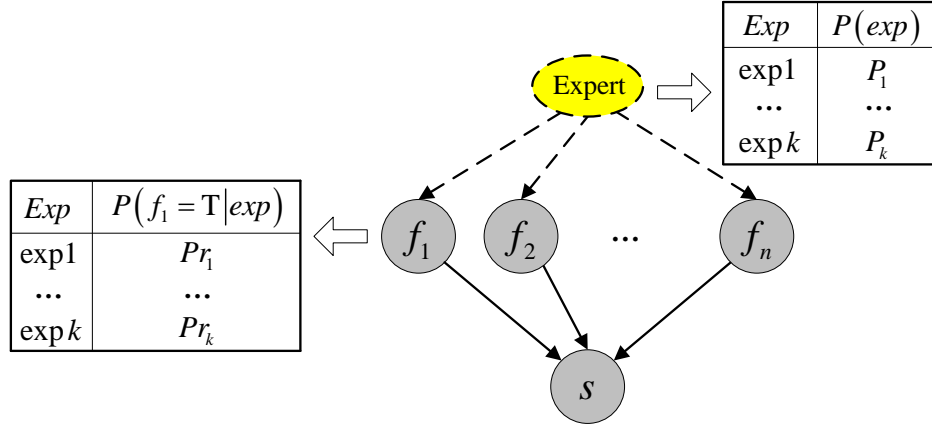


Figure 4: Modified BN to capture expert opinions

#### 2.4. Decision rules

BN updates the prior probability given some new observations to show the occurrence probability of a particular fault under the occurrence of a certain abnormality (so called posterior probability). Most existing researches take posterior probability as a judgment basis for the diagnosis. The larger the posterior probability is, the higher the possibility that the corresponding fault occurs. Nevertheless, the pure value of posterior probability does not draw a diagnostic result clearly because this parameter is affected not only by the evidences inputted but also the prior probability of a fault. This impact can be observed from the mathematics of Bayesian inference in section 2.1, where the prior probability is a multiplier in Bayes formula. As a result, a fault may have a high posterior probability due to the predetermined prior probability even though no corresponding abnormality has presented. To improve the rationality and accuracy of the diagnosis, inspired by the similar research in [25], two following decision rules are used in this paper to determine the diagnosis result.

*Rule A:* a failure is reported if the difference between posterior and prior probability of a certain fault is equal to or larger than  $l_1$ , or if this value is  $l_2$  percent higher than the second largest one; and

*Rule B:* a warning is reported if the difference between posterior and prior

probability of a fault is equal to or larger than  $l_3$  but less than  $l_1$ .

The thresholds  $l_1$ ,  $l_2$  and  $l_3$  can be specified according to engineering experience.

### 3. Case study

In this section, we illustrate the proposed approach by using the fuel injection system of a diesel engine. Eight faults of a number of components ranging from a high pressure fuel pump to an injector nozzle are taken into account by the developed BN model.

#### 3.1. Description of fuel injection system

Fuel injection system is the most vital subsystem of a diesel engine. The function of this system is to spray a predefined amount of fuel in an atomized form into the engine cylinders. Fuel injection system has a dominating influence on the performance of the engine, e.g. power output, emissions etc., and hence, detecting potential faults of this system in the early stage is an effective way to ensure the safe and efficient operation of the engine.

A mechanical fuel injection system consists of several components, including a high pressure fuel injection pump, a delivery valve, high pressure pipes assembly and a fuel injector. Figure 5 shows a typical mechanical fuel injection system. Injection pump is used to provide a high pressure to the fuel to meet the need for well atomization. The internal structure of injection pump is depicted in Fig. 6. A plunger is the critical component to control the timing and volume of the injection for desired power. It is actuated directly by the camshaft which is connect with the crankshaft through a transmission mechanism. The rotating movement of the camshaft is converted to a reciprocating motion via a roller located at the bottom this device. Fuel in the cylindrical tube called plunger sleeve is expelled out through a longitudinal groove when the plunger rises enough to produces the fuel pressure necessary to open the delivery valve. The delivery valve is back on its seat when the fuel pressure gets released to prevent



the backflow of the fuel. From the injection pump the fuel enters the high pressure pipe where the fuel pressure is kept at a certain range. Fuel then enters into the injector which is responsible for the atomization of the fuel. The high-pressure fuel supplied by the injection pump exerts sufficient force against the compression spring to lift the needle valve. Fuel is injected into the engine cylinder through the nozzle as finely atomized particles. Since only a small amount of fuel is allowed to spray into the combustion chamber, the spill over in the injector is flow back into the fuel tank for the next cycle.

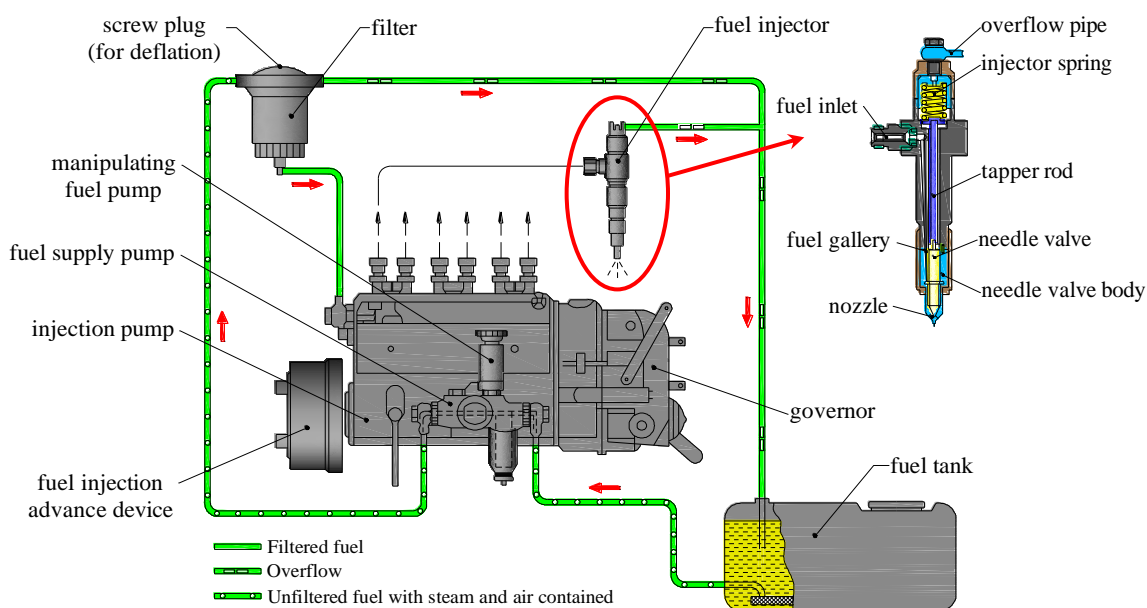


Figure 5: Fuel injection system for a diesel engine

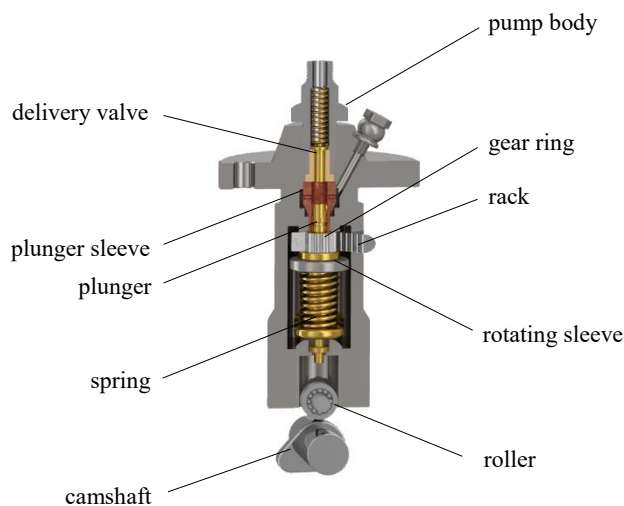


Figure 6: Section view of a plunger assembly of HP fuel pump

### 3.2. The development of BN-based diagnostic model

Some of the common faults of diesel fuel injection system can be listed as columns 1 and 2 of Table 1. In order to effectively distinguish and identify these faults, the abnormal changes of various time domain parameters are chosen as fault symptoms, see columns 3 and 4 of Table 1, where all of the parameters are the common technical indicators of fuel injection systems and can be extracted easily from the hydraulic waveform of high pressure pipe.

Table 1

Common faults and symptoms of engine fuel injection systems

Nodes	Faults	Nodes	Symptoms
$f_1$	Injector spring broken	$s_1$	Pressure rise rate decreases
$f_2$	Delivery valve invalidation	$s_2$	Injection duration extended
$f_3$	Cavitation erosion of plunger	$s_3$	The aftermath width decreases
$f_4$	Carbon deposition on nozzle	$s_4$	Peak factor increases
$f_5$	Needle valve stuck (upside)	$s_5$	Injection starting pressure decreases
$f_6$	Injector leak	$s_6$	The amplitude of the aftermath oscillation decreases
$f_7$	High pressure pipe leak	$s_7$	Peak injection pressure decreases
$f_8$	Improper injection timing	$s_8$	residual pressure in high pressure pipe decreases
		$s_9$	Injection duration shortened
		$s_{10}$	Impulse factor decreases

According to the literatures and the practical experience of domain experts, the causal relationships between these faults and symptoms are shown in Table 2, in which T (T stands for True) represents the fault/symptom is present, and F (F stands for False) denotes the fault/symptom is absent [35]. Take row 5 as an example. It means the

deposition of carbon on injector nozzles ( $f_4 = T$ ) will result in the extended of injection duration ( $s_2 = T$ ) and the increases of peak factor of hydraulic waveform in high pressure pipe ( $s_4 = T$ ). Besides that, it can also lead to the decreases of aftermath width ( $s_3 = T$ ) as well as the amplitude of the aftermath oscillation ( $s_6 = T$ ). Meanwhile, other parameters are not affected by this fault significantly.

Table 2

The causal relationships between faults and symptoms of engine fuel injection system

Set of faults $F$	Set of symptoms $E$									
	$s_1$	$s_2$	$s_3$	$s_4$	$s_5$	$s_6$	$s_7$	$s_8$	$s_9$	$s_{10}$
$f_1 = T$	T	F	F	F	T	F	T	F	T	T
$f_2 = T$	F	F	F	F	T	T	T	T	F	F
$f_3 = T$	T	T	T	F	F	F	T	F	F	F
$f_4 = T$	F	T	T	T	F	T	F	F	F	F
$f_5 = T$	T	T	T	F	T	T	T	T	F	T
$f_6 = T$	T	F	T	F	F	F	F	T	T	F
$f_7 = T$	F	F	F	T	T	T	T	T	T	F
$f_8 = T$	T	F	F	F	F	F	T	F	T	F

The qualitative knowledge contained within Table 2 can be viewed as a decision system  $S$  through the method described in Section 2.2.2, where the set of symptoms  $E = \{s_1, \dots, s_{10}\}$  is abstracted as the conditional attributes, and the set of faults  $F = \{f_1, \dots, f_8\}$  for the decision attributes; the causal relationships between faults and symptoms is described by the mapping  $f$ . Based on this analogy, the redundant

symptoms in Table 2 can be eliminated by means of the attributes reduction method in rough sets. The discernibility matrix  $M(S)$  of this decision system can be calculated from Eq. (7) as follows:

$$M(S) = \begin{bmatrix} \emptyset & & & & & & & & & & \\ \{s_1, s_6, s_8, s_9, s_{10}\} & \emptyset & & & & & & & & & \\ \{s_2, s_3, s_5, s_9, s_{10}\} & E \setminus \{s_4, s_7, s_9, s_{10}\} & \emptyset & & & & & & & & \\ E \setminus \{s_8\} & E \setminus \{s_1, s_6, s_9, s_{10}\} & \{s_1, s_4, s_6, s_7\} & \emptyset & & & & & & & \\ \{s_2, s_3, s_6, s_8, s_9\} & \{s_1, s_2, s_3, s_{10}\} & \{s_5, s_6, s_8, s_{10}\} & E \setminus \{s_2, s_3, s_6, s_9\} & \emptyset & & & & & & \\ \{s_3, s_5, s_7, s_8, s_{10}\} & E \setminus \{s_2, s_4, s_8, s_{10}\} & \{s_2, s_7, s_8, s_9\} & E \setminus \{s_3, s_5, s_7, s_{10}\} & E \setminus \{s_1, s_3, s_4, s_8\} & \emptyset & & & & & \\ \{s_1, s_4, s_6, s_8, s_{10}\} & \{s_4, s_9\} & E \setminus \{s_7, s_{10}\} & E \setminus \{s_1, s_4, s_6, s_{10}\} & E \setminus \{s_5, s_6, s_7, s_8\} & E \setminus \{s_2, s_8, s_9, s_{10}\} & \emptyset & & & & \\ \{s_5, s_{10}\} & \{s_1, s_5, s_6, s_8, s_9\} & \{s_2, s_3, s_9\} & E \setminus \{s_5, s_8, s_{10}\} & E \setminus \{s_1, s_4, s_7\} & \{s_3, s_7, s_8\} & \{s_1, s_4, s_5, s_6, s_8\} & \emptyset & & & \end{bmatrix}$$

where  $E \setminus \{s_i\}$  denotes the subset of  $E$  after removing  $\{s_i\}$ .

The discernibility function  $f(S)$  and the minimal disjunctive normal form can be easily deduced from the matrix  $M(S)$  using Eq. (8) as.

$$\begin{aligned} f(S) &= (s_1 \vee s_6 \vee s_8 \vee s_9 \vee s_{10}) \wedge \cdots \wedge (s_1 \vee s_4 \vee s_5 \vee s_6 \vee s_8) \\ &= s_1 s_2 s_3 s_4 s_5 + s_1 s_2 s_3 s_4 s_{10} + s_1 s_2 s_4 s_5 s_7 + \cdots + s_3 s_5 s_7 s_8 s_9 \end{aligned}$$

The conjunctive forms in  $f(S)$  show different reductions of this decision system, more specifically, the symptoms for distinguishing multiple faults of engine fuel injection system. One of the reductions  $E^* = \{s_3, s_5, s_7, s_8, s_9\}$  is used in this paper to identify these 8 faults in Table 1 considering the difficulty of detecting and extracting these parameters. The reduced causal knowledge and the corresponding diagnostic rules are shown in Table 3. The BN-based diagnostic model of fuel injection system according to the qualitative knowledge is shown in Fig. 7.

Table 3

The reduced causal knowledge as well as the corresponding production rules

Set of faults	Subset of symptoms $E^*$					Production rules
	$s_3$	$s_5$	$s_7$	$s_8$	$s_9$	
$f_1$	F	T	T	F	T	If $s_5=T, s_7=T, s_9=T$ , then $f_1 = T$

$f_2$	F	T	T	T	F	If $s_5=T, s_7=T, s_8=T$ , then $f_2=T$
$f_3$	T	F	T	F	F	If $s_3=T, s_7=T$ , then $f_3=T$
$f_4$	T	F	F	F	F	If $s_3=T$ , then $f_4=T$
$f_5$	T	T	T	T	F	If $s_3=T, s_5=T, s_7=T, s_8=T$ , then $f_5=T$
$f_6$	T	F	F	T	T	If $s_3=T, s_8=T, s_9=T$ , then $f_6=T$
$f_7$	F	T	T	T	T	If $s_5=T, s_7=T, s_8=T, s_9=T$ , then $f_7=T$
$f_8$	F	F	T	F	T	If $s_7=T, s_9=T$ , then $f_8=T$

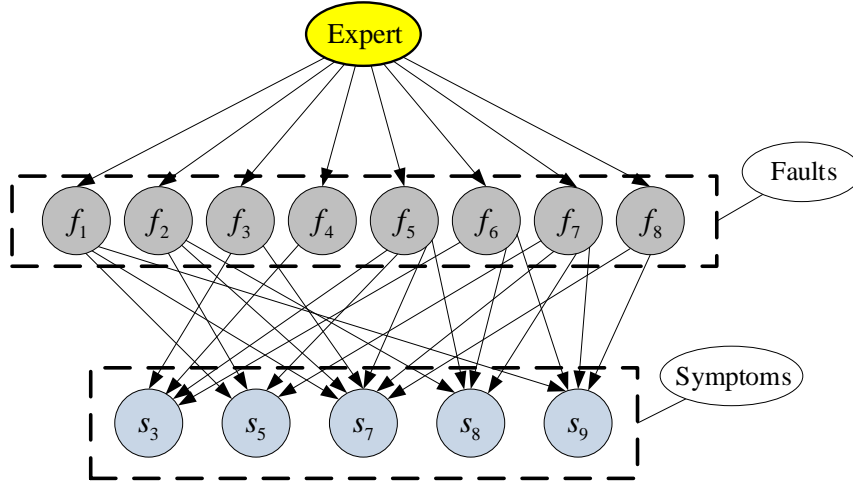


Figure 7: The simplified BN-based diagnostic model of fuel injection system

The quantitative knowledge of this model is derived from domain experts. In this paper, two experts are invited to give their judgement on the prior probabilities of faults and the conditional probabilities of symptoms as well. The conditional probabilities of symptoms are specified using the noisy-OR model, since all the faults and symptoms are assumed to be binary. A probability scale presented in Fig. 8 is designed to facilitate the expression of experts' knowledge. The causal effect is firstly described via a phrase, and then is transformed into the corresponding numerical value. Table 4 shows the quantized causal effect of faults on symptoms with noisy-OR semantic, e.g. the bold number 0.85 means  $P(s_5 = T | f_1 = T) = 0.85$ . Apart from the known faults, a *base rate probability* [36, 37]  $P(s = T | Leak) = 0.05$  is assigned to each symptom in this

example to represent the influence from all missed cause. As for the prior probability of each fault, the newly proposed BN structure is applied for this end, see Fig. 7. Experts vary in reliabilities when incorporating these different opinions, where the reliability degree of expert 1 is 0.6, while that of expert 2 is 0.4. Table 4 lists the prior probabilities of multiple faults from the experts. Node *Leak* has no prior probability, for more details see [36, 37].

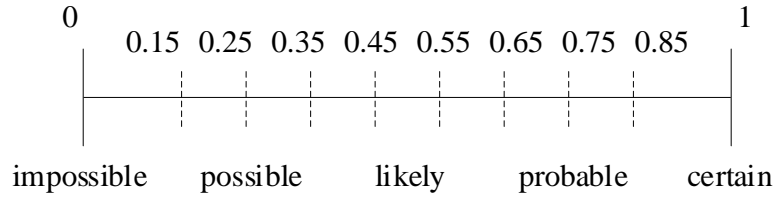


Figure 8: Probability scale for capturing experts' knowledge

Table 4

Prior probabilities and conditional probabilities from an expert

Faults	Prior probabilities		Conditional probabilities of Symptoms $E^* = T$				
	Expert 1	Expert 2	$s_3$	$s_5$	$s_7$	$s_8$	$s_9$
$f_1$	0.15	0.10	-	<b>0.85</b>	0.45	-	0.45
$f_2$	0.15	0.10	-	0.25	0.25	0.85	-
$f_3$	0.10	0.15	0.25	-	0.65	-	-
$f_4$	0.20	0.20	0.85	-	-	-	-
$f_5$	0.10	0.15	0.85	0.45	0.25	0.65	-
$f_6$	0.20	0.15	0.45	-	-	0.25	0.25
$f_7$	0.10	0.10	-	0.85	0.85	0.65	0.65
$f_8$	0.15	0.10	-	-	0.25	-	0.25
Leak	-	-	0.05	0.05	0.05	0.05	0.05

Figure 9 presents the BN model of the engine fuel injection system, which is

constructed by means of the conventional method. As for symptom  $s_2$ ,  $2^3$  parameters are needed for a complete conditional probability distribution if all events are assumed to be binary, either present or absent. The model includes 10 symptoms in total and, therefore,  $2^5 + 2^3 + 2^4 + 2^2 + 2^4 + 2^4 + 2^6 + 2^4 + 2^4 + 2^2 = 192$  conditional probabilities are required for the model. Unacceptable amount of prior knowledge is needed to develop such a complex model. Table 5 compares the number of involved items in conventional BN model with the ones in Fig. 7. It is clear to see that there is a remarkable decrease in the demand for the qualitative and quantitative knowledge after using the approach proposed in this paper.

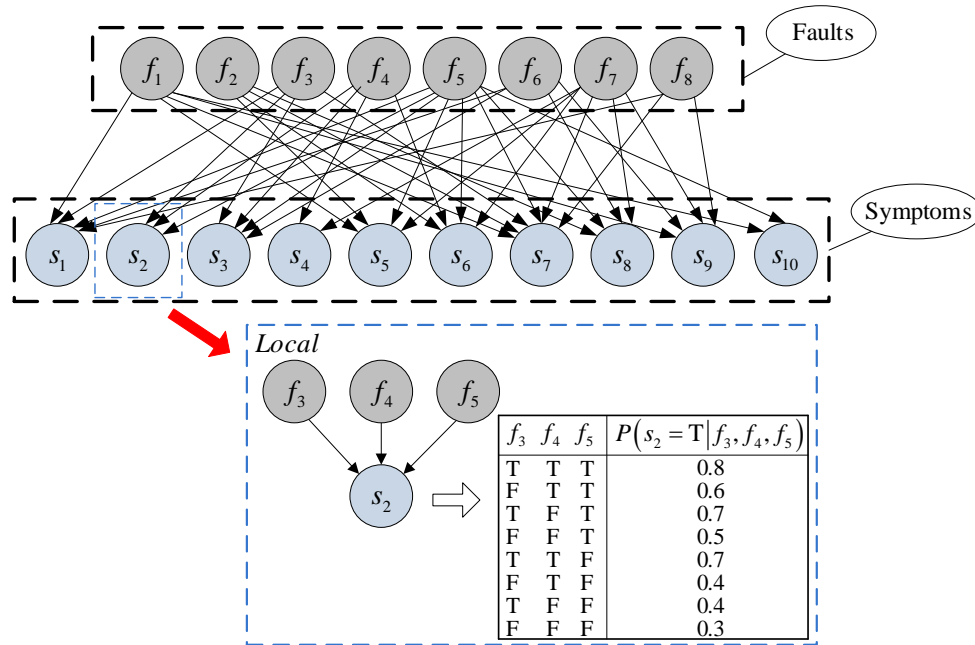


Figure 9: The conventional BN diagnostic model of diesel engine fuel injection system

Table 5

Comparison between conventional BN model and the simplified one

	Conventional model	The simplified BN model	
		Structural simplification	Decoupling the causality
symptoms	10	<b>5</b>	-
Causal relationships	38	<b>22</b>	-
Conditional	192	128	<b>22</b>

### 3.3. Diagnosis and discussions

Experimental data from [38] is used to validate the diagnostic model of fuel injection system. In their study, the damage of high pressure pipe is introduced to a 12150L diesel engine. The hydraulic waveform of the high pressure pipe is detected through a clamp-on pressure transducer. Parameters presented in Table 1, are thus extracted from the waveform and the abnormal parameters are shown in Table 6. As may be noticed, injection starting pressure and peak injection pressure are far less than normal values when the fault is present. The injection duration also shows a downward trend. In contrast, the peak factor is larger the normal one if fuel is let out of high pressure pipe.

Table 6

Some parameters under normal and fault condition of diesel engine

	Injection starting pressure/V	Peak injection pressure/V	Injection duration/ms	Peak factor
Normal	2.25	3.04	1.90	7.29
High pressure pipe leak	1.65	2.12	1.80	7.41

The abnormalities above are input to the BN diagnostic model as evidence, and the faults finding is carried out through Junction Tree algorithm [39]. Diagnostic results based on the simplified BN model are shown in “Simplified BN model” of Table 7. The prior probabilities of faults in the table are obtained from the weighted average of the experts’ estimations. The thresholds  $l_1$ ,  $l_2$  and  $l_3$  for reporting diagnostic results are specified respectively as 30%, 40%, 15% based on experts’ suggestion.

Table 7

Probabilities of various faults based on the abnormality in Table 6



Faults	Nodes	Simplified BN model			Conventional BN model		
		Prior	Posterior	differences	Prior	Posterior	differences
Injector spring broken	$f_1$	0.13	0.4403	<b>0.3103</b>	0.13	0.3281	<b>0.1981</b>
Delivery valve invalidation	$f_2$	0.13	0.1588	0.0288	0.13	0.1498	0.0198
Cavitation erosion of plunger	$f_3$	0.12	0.1486	0.0286	0.12	0.1402	0.0202
Carbon deposition on nozzle	$f_4$	0.20	0.2000	0	0.20	0.4765	<b>0.2765</b>
Needle valve stuck (upside)	$f_5$	0.12	0.1541	0.0341	0.12	0.1436	0.0236
Injector leak	$f_6$	0.18	0.2149	0.0349	0.18	0.2068	0.0268
High pressure pipe leak	$f_7$	0.10	0.6212	<b>0.5212</b>	0.10	0.7823	<b>0.6823</b>
Improper injection timing	$f_8$	0.13	0.1750	0.0450	0.13	0.1626	0.0326
Diagnostic reports		<b>Faults:</b> Injector spring broken or High pressure pipe leak <b>Warnings:</b> None			<b>Faults:</b> High pressure pipe leak <b>Warnings:</b> Injector spring broken and Carbon deposition on nozzle		

The fault *high pressure pipe leak* has the maximum posterior probability after updating, which is 62.12%, far more than that of other faults. The difference between posterior and prior probabilities is 52.12% so that this fault is identified as the real root causes of the abnormalities based on *Rule A*. Comparing the diagnosis with the experiment in [38], we can find that the diagnostic conclusion is consistent well with the experiment, which indicates that the BN can distinguish the multiple faults effectively and pinpoint the real origin of the abnormalities. In addition, the diagnostic report also issues a fault about *injector spring broken* for its high occurrence probability. The posterior probability of this fault is calculated as 44.03% with, for certain, 31.03% as its difference. This fault also has a high chance to present because it shares the same symptoms with *high pressure pipe leak*, that is *injection starting pressure decreases*  $s_5$ , *peak injection pressure decreases*  $s_7$  and *injection duration shortened*  $s_9$ .

534 Additionally, the occurrence probabilities of *carbon deposition on nozzle* remain  
535 unchanged after updating because the symptoms presented have no direct relevance  
536 with this fault. The diagnostic results indicate that BN can evaluate the causalities and  
537 association strength of various faults with the certain symptoms synthetically and find  
538 out the most likely option at last. The diagnostics are carried out through fuzzy C-means  
539 clustering in [38], and the same conclusion is got. Compared with their study, the BN  
540 model has distinct advantage on computational conciseness and efficiency since the  
541 inference has no need for multiple loop iteration.

542 Fault diagnosis is also implemented through conventional BN model to research  
543 the changes of diagnostic reports after simplification. The quantitative information of  
544 the diagnostic model is also obtained through the approaches above. Since the  
545 conventional model contains all 10 symptoms, *peak factor increases*  $s_4$  is also set as  
546 evidence. Table 7 presents the diagnostic result as column 4. *High pressure pipe leak*  
547 and *injector spring broken* have 78.23% and 32.81% chance respectively to occur, with  
548 68.23% and 19.81% as their own differences. Therefore, these two faults are reported  
549 as the real root cause and a warning respectively according to the decision-making rule.  
550 The conventional BN model outputs the similar assessment report with simplified one,  
551 which means that the BN constructed with simplifying procedure has the same  
552 resolving ability of multiple faults. Beyond that, to the contrary of simplified model,  
553 the report shows the posterior probability is 47.65% when it comes to *carbon deposition*  
554 *on nozzle*, which turns out to be a false alarm according to the experiment in [38].  
555 Besides, there is a notable improvement in the computational efficiency after  
556 eliminating the redundant symptoms. According to the probabilistic reasoning of BN  
557 shown in Section 2.1, up to  $2^{13}$  possible configurations of state variables are required  
558 to infer the posterior probability of the faults. By contrast, since the redundant  
559 symptoms have been eliminated using rough sets in simplified BN, only  $2^9$  possible  
560 configurations are needed. It shows that the computational efficiency is improved  
561 remarkably in the simplified BN model.

562 In order to further illustrate the proposed approach and the unconverted ability for

diagnosing of simplified model, two cases possible to present during the varying operation of diesel are discussed. Due to space limitation, the faults with probabilities exceeding the thresholds are shown only in Table 8. Abnormities vary under different fault scenarios of the fuel injection system. The abnormities are input to the diagnostic models with probabilistic forms. The diagnostic reports of the simplified BN model and the conventional one are presented in Table 8 respectively. *Injector spring broken*  $f_1$  and *high pressure pipe leak*  $f_7$  are recognized as the root causes of the abnormality in case No.1 based on *Rule A*, with 36.41% and 39.16% as their respective differences. More symptoms are needed to distinguish these two faults. Similar diagnostic result is reported in conventional BN model. Some false-alarm are also issued by the diagnostic model since the input redundant symptom *pressure rise rate decreases*  $s_1$  are in favor of the presence of the related faults. With the abnormities input identical, as case No.2, the same diagnostic reports are presented by simplified and the conventional BN model.

Table 8

Two diagnostic cases of engine fuel injection system

No.	Abnormities	Evidence input	Diagnosis reports of simplified model		Diagnosis reports of conventional model	
			Faults	Warnings	Faults	Warnings
1	Pressure rise rate decreases	$P(s_1 = T) = 100\%$	$f_1$ (difference 36.41%)	None	$f_1$ (difference 44.83%)	$f_6$ (difference 17.62%)
	Injection starting pressure decreases	$P(s_5 = T) = 100\%$	$f_7$ (difference 39.16%)			$f_7$ (difference 29.04%)
	Injection duration shortened	$P(s_9 = T) = 100\%$				$f_8$ (difference 18.46%)
2	The aftermath width decreases	$P(s_3 = T) = 100\%$	$f_5$ (difference 48.39%)	$f_4$ (difference 15.3%)	$f_5$ (difference 48.39%)	$f_4$ (difference 15.3%)
	Injection starting pressure decreases	$P(s_5 = T) = 100\%$		$f_7$ (difference 22.99%)		$f_7$ (difference 22.99%)
	Residual pressure decreases	$P(s_8 = T) = 100\%$				

#### 4. Conclusions

In this paper, a novel fault isolation approach using Bayesian networks is proposed with significant reduction of structure and parameters. The approach is applied to a

diesel engine fuel injection system as an illustration to verify its validity. The main conclusions are listed as follows:

(1) The strong correlation and coupling of different faults can be depicted intuitively through the topological structure of BN. The causal relationship between a fault and a symptom is quantized by conditional probabilities. The fault isolation with consideration of uncertainties is realized accordingly.

(2) The simplified model decreases the demand for prior knowledge and improves the computational efficiency of probabilistic reasoning, which lessen the difficulty to apply the BN-based diagnosis technique into practice.

(3) The diagnosis for engine fuel injection system shows that the proposed approach keeps the ability of fault isolation unchanged while simplifying the BN model.

This diagnostic technique and the simplifying procedure for BN are illustrated by taking advantage of diesel engine fuel injection system. The proposed method is also applicable to the diagnosis of other mechanical systems. Since computing posterior probabilities on a BN model is considered to be NP-hard [40], the method is not appropriate for safety critical systems where remedial actions have to be taken very fast so that performance/stability of the system is maintained.

## References

- [1] Muszynska A, Bently DE. Anti-swirl arrangements prevent rotor/seal instability. *J Vib Acoust* 1989; 111(2):156-62.
- [2] Bachschmid N, Pennacchi P, Tanzi E. Some remarks on breathing mechanism, on non-linear effects and on slant and helicoidal cracks. *Mech Syst Signal Pr* 2008; 22(4):879-904.
- [3] Liang X, Zuo M, Feng Z. Dynamic modeling of gearbox faults: a review. *Mech Syst Signal Pr* 2018; 98:852-76.
- [4] Li Z, Jiang Y, Hu C, Peng Z. Recent progress on decoupling diagnosis of hybrid failures in gear transmission systems using vibration sensor signal: a review. *Measurement* 2016; 90:4-19.
- [5] Zhang S, He Q, Ouyang K, Xiong W. Multi-bearing weak defect detection for wayside acoustic diagnosis based on a time-varying spatial filtering rearrangement. *Mech Syst Signal Pr* 2018; 100:224-41.

- [6] Shao H, Jiang H, Lin Y, Li X. A novel method for intelligent fault diagnosis of rolling bearings using ensemble deep auto-encoders. *Mech Syst Signal Pr* 2018; 102:278-97.
- [7] Diehl EJ. Predictive modeling of a two-stage gearbox towards fault detection. *Shock Vib* 2016; 2016(17):1-13.
- [8] Lopez I, Sarigul-Klijn N. A review of uncertainty in flight vehicle structural damage monitoring, diagnosis and control: challenges and opportunities. *Prog Aerosp Sci* 2010; 46(7):247-73.
- [9] Cai B, Zhao Y, Liu H, Xie M. A data-driven fault diagnosis methodology in three-phase inverters for PMSM drive systems. *IEEE Trans Power Electr* 2017; 32(7):5590-600.
- [10] Lau CK, Heng YS, Hussain MA, Nor MIM. Fault diagnosis of the polypropylene production process (UNIPOLPP) using ANFIS. *ISA Trans* 2010; 49(4):559-66.
- [11] Lin Y, Li YY, Yin XH, Dou Z. Multisensor fault diagnosis modeling based on the evidence theory. *IEEE Trans Reliab* 2018; 67(2):513-21.
- [12] Pearl J. Probabilistic reasoning in intelligent systems: networks of plausible inference. San Mateo, CA: Morgan Kaufmann; 1988. p. 29-39.
- [13] Weber P, Medina-Oliva G, Simon C, Iung B. Overview on Bayesian networks applications for dependability, risk analysis and maintenance areas. *Eng Appl Artif Intel* 2012; 25(4):671-82.
- [14] Yodo N, Wang P. Resilience modeling and quantification for engineered systems using Bayesian networks. *J Mech Design* 2016; 138(3):031404.
- [15] Zhu X, Yuan Y, Hu X, Chiu Y, Ma Y. A Bayesian network model for contextual versus non-contextual driving behavior assessment. *Transport Res C-Emer* 2017; 81:172-87.
- [16] Leng D, Thornhill NF. Process disturbance cause and effect analysis using Bayesian networks. in: 9th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes, Paris, France; September 2-4, 2015. p. 1457-64.
- [17] Mechraoui A, Medjaher K, Zerhouni N. Bayesian based fault diagnosis: application to an electrical motor. in: 17th IFAC world congress, Seoul, Korea; July 6-11, 2008. p. 7381-6.
- [18] Gonzalez R, Huang B, Lau E. Process monitoring using kernel density estimation and Bayesian networking with an industrial case study. *ISA Trans* 2015; 58:330-47.
- [19] Jun HB, Kim D. A Bayesian network-based approach for fault analysis. *Expert Syst Appl* 2017; 81:332-48.
- [20] He S, Wang Z, Wang Z, Gu X, Yan Z. Fault detection and diagnosis of chiller using Bayesian

network classifier with probabilistic boundary. *Appl Therm Eng* 2016; 107:37-47.

[21] Wang Z, Wang Z, He S, Gu X, Yan Z. Fault detection and diagnosis of chillers using Bayesian network merged distance rejection and multi-source non-sensor information. *Appl Energ* 2017; 188:200-14.

[22] Gharahbagheri H, Imtiaz SA, Khan F. Root cause diagnosis of process fault using KPCA and Bayesian network. *Ind Eng Chem Res* 2017; 56(8):2054-70.

[23] Liu Z, Liu Y, Shan H, Cai B, Huang Q. A fault diagnosis methodology for gear pump based on EEMD and Bayesian network. *Plos One* 2015; 10(5):e0125703.

[24] Cai B, Liu Y, Fan Q, Zhang Y, Liu Z, Yu S, Ji R. Multi-source information fusion based fault diagnosis of ground-source heat pump using Bayesian network. *Appl Energ* 2014; 114(2):1-9.

[25] Cai B, Liu H, Xie M. A real-time fault diagnosis methodology of complex systems using object-oriented Bayesian networks. *Mech Syst Signal Pr* 2016; 80:31-44.

[26] Cai B, Liu Y, Xie M. A dynamic-Bayesian-network-based fault diagnosis methodology considering transient and intermittent faults. *IEEE Trans Autom Sci Eng* 2017; 14(1):276-85.

[27] Cai B, Huang L, Xie M. Bayesian networks in fault diagnosis. *IEEE Trans Ind Inform* 2017; 13(5):2227-40.

[28] de Campos CP, Ji Q. Efficient structure learning of Bayesian networks using constraints. *J Mach Learn Res* 2011; 12:663-89.

[29] Amirkhani H, Rahmati M, Lucas P, Hommersom A. Exploiting experts' knowledge for structure learning of Bayesian networks. *IEEE Trans Pattern Anal* 2017; 39(11):2154-70.

[30] Yu J, Huang W, Zhao X. Combined flow graphs and normal native Bayesian classifier for fault diagnosis of gear box. *P I Mech Eng C-J Mec* 2016; 230(2):303-13.

[31] Pawlak Z. Information systems theoretical foundations. *Inform Syst* 1981; 6(3):205-18.

[32] Tsang ECC, Chen DG, Yeung DS, Wang XZ, Lee JWT. Attributes reduction using fuzzy rough sets. *IEEE Trans Fuzzy Syst* 2008; 16(5):1130-41.

[33] Skowron A, Rauszer C. The discernibility matrices and functions in information systems. Dordrecht: Kluwer Academic Publisher; 1991. p. 331-62.

[34] Good IJ. A causal calculus. *Brit J Philos Sci* 1961; 12(44):305-18.

[35] Huang Y, McMurran R, Dhadyalla G, Jones RP. Probability based vehicle fault diagnosis: Bayesian network method. *J Intell Manuf* 2008; 19(3):301-11.

- 670 [36] Henrion M. Practical issues in constructing a Bayes' belief network. *Comput Sci* 2013; 2:132-  
671 9.
- 672 [37] Bobbio A, Portinale L, Minichino M, Ciancamerla, E. Improving the analysis of dependable  
673 systems by mapping fault trees into Bayesian networks. *Reliab Eng Syst Safe* 2001; 71(3):249-  
674 60.
- 675 [38] Deng G, Cao L, Liu J, Li J, Pu H. A new method of diesel engine fuel system fault diagnosis.  
676 *J Chongqing Univ* 2004; 27(10):8-13. (In Chinese)
- 677 [39] Lauritzen SL, Spiegelhalter DJ. Local computations with probabilities on graphical structures  
678 and their application to expert systems. *J R Stat Soc B* 1988; 50(2):157-224.
- 679 [40] Cooper G. The computation complexity of probabilistic inference using Bayesian belief  
680 networks. *Artif Intell* 1990; 42 (2-3):393-405.