

## Research Article

# Reliability Analysis of a Complex Multistate System Based on a Cloud Bayesian Network

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This study focused on mixed uncertainty of the state information in each unit caused by a lack of data, complex structures, and insufficient understanding in a complex multistate system as well as common-cause failure between units. This study combined a cloud model, Bayesian network, and common-cause failure theory to expand a Bayesian network by incorporating cloud model theory. The cloud model and Bayesian network were combined to form a reliable cloud Bayesian network analysis method. First, the qualitative language for each unit state performance level in the multistate system was converted into quantitative values through the cloud, and cloud theory was then used to express the uncertainty of the probability of each state of the root node. Then, the  $\beta$ -factor method was used to analyze reliability digital characteristic values when there was common-cause failure between the system units and when each unit failed independently. The accuracy and feasibility of the method are demonstrated using an example of the steering hydraulic system of a pipelayer. This study solves the reliability analysis problem of mixed uncertainty in the state probability information of each unit in a multistate system under the condition of common-cause failure. The multistate system, mixed uncertainty of the state probability information of each unit, and common-cause failure between the units were integrated to provide new ideas and methods for reliability analysis to avoid large errors in engineering and provide guidance for actual engineering projects.

## 1. Introduction

A Bayesian network (BN) is an inheritance and development of the fault tree. It can be used for system modeling through a directed acyclic graph. It is based on a set of mathematical models that define complete probabilistic reasoning [1]. A Bayesian network has the advantages of describing node relationships and polymorphism, convenient modeling, efficient calculation, and accurate analysis results. It is a powerful tool for two-way reasoning and probability analysis, and it is used to express and process uncertain knowledge [2]. The Bayesian network was first proposed by Pearl [3] in the 1980s. Then, domestic and foreign scholars continued to improve it. Bayesian networks have been widely used in machinery [4–7], electric power [8–11], civil

engineering [12–14], nuclear technology [15, 16], communications [17, 18], and other fields for system reliability analysis [4, 19], safety analysis [20], and fault diagnosis of key units [21]. For the reliability analysis of multistate systems, Wilson [22] and Graves et al. [23] studied the method of applying BNs to establish a multistate system model. Zhou [24] and Zhai [25] used static Bayesian networks to evaluate and analyze the reliability of multistate systems. Tong and Tien [26] used the characteristics of civil infrastructure systems to establish a system of many interconnected units. Then they used Bayesian networks to infer the management decisions of these systems for understanding the probability dependence between the unit and system performance. In view of the limitations of the reliability analysis of static Bayesian networks, Boudali and

Dugan [27, 28] established reliability models of discrete-time Bayesian networks and continuous-time Bayesian networks to ensure the reliability of the system. Nima et al. [29] used a discrete-time Bayesian network method to solve the system design of a risk process using dynamic fault trees instead of Markov chains. Wu et al. [30] adopted a dynamic Bayesian network for a tunnel construction safety decision support method to address the problem of road damage over time and track the characteristics of geological, design, and mechanical variables as they are updated along with the progress of construction.

In the reliability analysis of complex multistate systems, ambiguity in the state probability information of each unit and the uncertainty of the fault logic relationship are unavoidable issues. The state probability information of each unit often has random uncertainties and cognitive uncertainties. If one uses accurate values to describe the fuzzy possibility of node failure, the calculated results often have unacceptable errors, and the traditional Bayesian network method is not appropriate. Methods such as fuzzy theory, interval theory, and Dempster-Shafer (DS) evidence theory can be integrated with a Bayesian network to analyze the reliability of the uncertainty problem of a multistate system with unit state probability information. Ma et al. [31] used triangular fuzzy numbers to describe the failure probabilities of nodes in different states and account for the existence of ambiguity in the failure probabilities of different states of the system, and, after averaging, defuzzification, normalization, and Bayesian network inference, the failure probability of different states was obtained. Chen and Yao [32] introduced fuzzy set theory to Bayesian network reliability analysis, established a fuzzy multistate system reliability analysis model, and analyzed the hydraulic system of a truck's hydraulic suspension. Chen et al. and Yao et al. [33, 34] used Takagi and Sugeno (TS) fault tree to accurately describe system failure mechanism, used the TS rule to solve the problem of assignment of the conditional probability table, used a Bayesian network for two-way reasoning, and organically combined the two methods. Their approach overcame the issue that the TS fuzzy fault tree analysis method is complicated and can only enable one-way inference in the process of hydraulic system reliability analysis. Zhang et al. [35] incorporated fuzzy theory into the Bayesian network model and established an analysis model based on the fuzzy Bayesian network for the reliability analysis of subway tunnel construction. Zhang et al. [36] studied the shortcomings of traditional system reliability analysis methods in dealing with fuzzy information and established a multistate system reliability analysis method based on interval triangular fuzzy Bayesian networks. Chen and Yao [37] introduced the hyperellipsoid model into Bayesian network reliability analysis and used the hyperellipsoid to describe the uncertainty interval variables. They obtained the reliability, importance, and sensitivity of the system. The results showed that the Bayesian network reliability analysis method based on the hyperellipsoid model provides a basis for the improvement of system reliability. Qiao et al. [38] used the dynamic fuzzy Bayesian network method to analyze the human factors of maritime accidents. Although fuzzy mathematics methods

can express the uncertainty of the information parameters, the fuzzy Bayesian method may result in partial loss of the information in a subsystem or unit. Moreover, the calculation requirement is large, and the calculation process is complicated. However, the interval method has issues of interval expansion and overvaluation, and its reliability has certain limitations in accuracy. Therefore, in recent years, many scholars have used the combination of evidence theory and Bayesian networks to obtain the upper and lower limits of probability by using multivalue mapping. These works have demonstrated a strong ability to express and deal with cognitive uncertainty. Zhao et al. [39] combined evidence theory and static Bayesian networks in the reliability analysis of distribution systems and described the upper and lower limits of interval model parameters through trust functions and likelihood functions. Suo Bin et al. [40] combined evidence theory with a Bayesian network for reliability analysis and reported a method to solve the failure probability of Bayesian network nodes with cognitive uncertainty. They proposed a method to reflect the poor information of the root node. The concept of the impact of changes on the output of leaf nodes, namely, cognitive importance, enhances the ability of Bayesian networks to describe uncertain information. The reliability of missile engines has been analyzed. The analysis results obtained for the hydraulic system are more in line with the actual situation. Chen et al. [41] proposed hydraulic system evidence to solve the uncertainty of the hydraulic system due to complex structure, lack of data, and insufficient human cognitive level. They also analyzed multistate problems of the hydraulic system, such as multiple performance and failure states. Liu et al. [42] proposed an improved Bayesian network hydraulic system model based on evidence theory for reliability analysis. This method has strong uncertainty information processing capabilities and polymorphism analysis capabilities. The analysis results verified the effectiveness of the method. Pan et al. [43] proposed an improvement to interval-valued fuzzy sets and DS evidence theory based on the fuzzy Bayesian network method for risk analysis. Their method serves as a systematic decision support method for security guarantees throughout the life cycle of complex systems under uncertainty. There are certain limitations when analyzing the reliability of mixed uncertain information in the information parameters, such as the state probability of each unit of the multistate system. In 1995, academician Li [44, 45] proposed the cloud theory with the cloud model as the core, which combines the characteristics of randomness and ambiguity to realize the conversion between qualitative language and quantitative values. Reliability analysis using the cloud model solves the mixed uncertainties of randomness and ambiguity in the unit information of the multistate system [46]. Reliability data in actual engineering often have randomness and ambiguity. Cloud models are used to represent the uncertainty of unit or subsystem state probability information and state performance information, and Bayesian networks are used for causal inference calculations for multistate systems. The establishment of the cloud Bayesian network and the reliability analysis of complex multistate systems are more in line with actual engineering conditions.

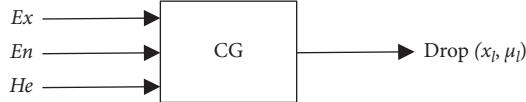


FIGURE 1: Forward generator.

When analyzing the reliability of complex multistate systems, it is usually assumed that failures between units are independent of each other. However, this assumption often fails to reflect the real situation in actual engineering. Failures between units are not independent of each other; there are related failures. In complex multistate systems, the related failures are ignored, and the calculated results often have errors. Researchers have proposed many methods to describe common-cause failures, such as  $\beta$ -factor model [47], basic parameter model [48], mixed parameter model [49],  $\alpha$ -factor model [50], and the square root model [51]. Yin et al. [52] used Bayesian networks to establish a common-cause failure system reliability model. Mi et al. [53] used the ability of Bayesian networks to represent complex dependencies between random variables and proposed a reliability modeling and evaluation method for multistate systems with common-cause failures. The model was applied to a two-axis positioning mechanism transmission system to demonstrate its effectiveness and ability to directly calculate the system reliability on the basis of multistate probabilities of elements. Connor et al. [54] proposed a generalized dependence model, used a Bayesian network model to express the dependence of system components, and analyzed the influence of common-cause failure on system reliability. The comparison between the proposed method and the method without considering common-cause failure verifies the efficiency and accuracy of the proposed method. Li et al. [55] proposed a common-cause failure modeling method based on dynamic Bayesian networks from two perspectives and constructed a dynamic Bayesian network model for multicomponent failure. To reduce or eliminate the occurrence of common-cause failure events, different accelerated life test schemes were designed. The test results showed that increasing the difference between redundant components is a feasible way. Gu et al. [56] introduced a Bayesian network and  $\beta$ -factor model to the reliability analysis of a system to improve the accuracy of the reliability analysis of the multistate common-cause failure system and reduce the complexity of the calculation. The results showed that the proposed method can clearly express the common-cause failure problem of the system without calculating the minimum cut set and is suitable for the study of common-cause failure of complex mechanical systems. Mi et al. [57] used a complex multistate common-cause failure system based on the evidence network for reliability analysis and used the computer numerical control (CNC) heavy-duty horizontal lathe servo feed control system as an engineering example to verify the applicability of the method.

This study combines the multistate nature of the system, the mixed uncertainty of the state and state probability information of each unit, and the failure correlation between units for reliability analysis. We verify the applicability of

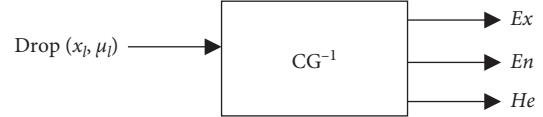


FIGURE 2: Reverse normal cloud generator.

our method using an engineering example of a pipelayer steering hydraulic system. The rest of this article is arranged as follows. Section 2 introduces the theory of cloud models. Section 3 introduces the modeling methods of Bayesian networks and cloud Bayesian networks. Section 4 adopts the  $\beta$ -factor model method assuming coexistence among system units and establishes the cloud Bayesian network model. Section 5 considers a pipelayer steering hydraulic system as an application example and compares and analyzes the reliability of each unit of the system in the cases of independent failure and common-cause failure. We suggest protective measures based on the analysis results. Section 6 concludes the article and provides directions for future research.

## 2. Cloud Model

### 2.1. Definition and Digital Characteristics of the Cloud

**2.1.1. Definition of Cloud.** The set quantity domain  $U$  is represented by an exact value. The qualitative concept of  $U$  is  $C$ . The quantitative value  $x \in U$  has a stable tendency random number  $y = \mu_C(x)$ , and  $C$  has a membership degree of  $x$ . The distribution of the membership degree  $y$  on the domain  $U$  is called the subordinate cloud, referred to as the “cloud.” The cloud is composed of a large number of cloud droplets, and each  $(x, y)$  is called a cloud drop. The generation process of cloud droplets represents a mutual mapping between qualitative and quantitative; it is a quantitative description of qualitative concepts. The cloud is the mapping of the domain  $X$  to the interval  $[0, 1]$  [45].

**2.1.2. Digital Characteristics of the Cloud.** The expected value  $Ex$ , entropy  $En$ , and superentropy  $He$  are numeric characteristic parameter values of the cloud.  $Ex$  is the central value of the domain and the most representative qualitative concept point.  $En$  is a qualitative measure of uncertainty, which reflects the randomness and fuzziness of a concept and its correlation [44]. The larger  $En$  is, the greater the degree of blur is.  $He$  is the entropy of entropy, which reflects the uncertainty of entropy  $En$  as determined by the randomness and fuzziness of entropy. The larger  $He$  is, the thicker the cloud is and the greater the degree of dispersion is.

**2.2. Cloud Generator.** The normal distribution in probability theory and the bell-shaped membership function in fuzzy set theory are the most common and expressive distribution

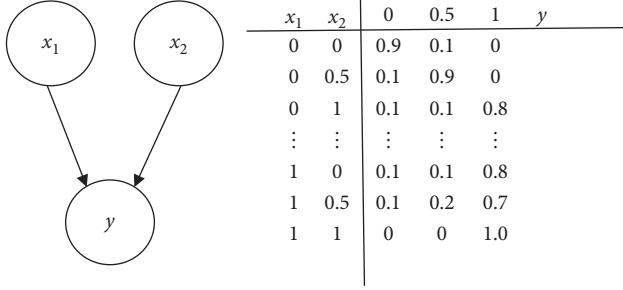


FIGURE 3: Multistate Bayesian network and conditional probability table.

functions. The cloud model developed on the basis of the two is called the normal cloud model. We use the normal cloud model, which is universal, to represent the uncertainty of unit state probability information [44].

**2.2.1. Positive Normal Cloud Generator.** The forward cloud generator is a process of generating cloud drops from digital feature parameter values to form a cloud, as shown in Figure 1. The digital characteristic parameters ( $Ex$ ,  $En$ , and  $He$ ) are inputs, and a normal cloud of  $m$  cloud droplets ( $x_l$ ,  $\mu_l$ ) ( $l=1, 2, \dots, m$ ) is the output, as follows:

- (1) Generate  $m$  normal random numbers  $En'_l = N(En, He)$ , where  $N(En, He)$  denotes a normal distribution
- (2) Generate  $m$  normal random numbers  $x_l = N(Ex, En'_l)$ , where  $N(Ex, En'_l)$  denotes a normal distribution
- (3) Generate the membership degree  $\mu_l = \exp[-(x_l - Ex)^2/2En'^2]$ , where  $x_l$  is the normal random number generated in step 2

**2.2.2. Reverse Normal Cloud Generator.** The reverse normal cloud generator obtains the numeric characteristic parameter values of the cloud according to a certain number of normally distributed cloud drops, as shown in Figure 2. We input  $m$  sample points  $x_l$  ( $l=1, 2, \dots, m$ ), and the digital characteristic parameters ( $Ex$ ,  $En$ ,  $He$ ) are the output. The inverse normal cloud generator algorithm is based on statistical principles and is divided into containing certainty

information and not containing certainty information. This study uses the algorithm proposed by Liu et al. [58], which contains no certainty information. The steps are as follows:

- (1) Calculate the mean of the sample  $\bar{X} = (1/m) \sum_{l=1}^m x_l$ , the absolute center distance of the first-order sample  $M = (1/m) \sum_{l=1}^m |x_l - \bar{x}|$ , and the variance of the sample  $S^2 = (1/m - 1) \sum_{l=1}^m (x_l - \bar{x})^2$
- (2)  $Ex = \bar{X}$
- (3)  $En = \sqrt{(\pi/2)} \times M$
- (4)  $He = \sqrt{S^2 - En^2}$

### 3. Cloud Bayesian Network

**3.1. Bayesian Network.** The Bayesian network is developed and formed on the basis of probability theory and graph theory. It mainly includes two parts: directed acyclic graph and conditional probability table, represented as  $N = ((X, E), P)$ .  $G = (X, E)$  represents the directed edges of  $n$  unit nodes to express causality and dependency between nodes;  $X$  represents each unit node; that is,  $X = \{x_1, x_2, \dots, x_n\}$ ; and  $E$  represents the set of directed edges of causality between each unit node.  $P$  represents the conditional probability distribution on each unit node, which constitutes the corresponding conditional probability table [24]. Suppose that  $A$  and  $B$  represent two random events. According to the Bayesian formula,

$$P(A|B) = \frac{P(A,B)}{P(B)} = \frac{P(B|A)P(A)}{P(B)}. \quad (1)$$

In formula (1),  $P(B|A)$  and  $P(A|B)$  represent the posterior probabilities of random events  $A$  and  $B$ , respectively, and  $P(A)$  and  $P(B)$  represent the prior probabilities of random events  $A$  and  $B$ , respectively.  $P(A, B)$  represents the joint probability of random events  $A$  and  $B$ . In a multistate system, assuming that  $A$  has  $n$  possible states  $a_1, a_2, \dots, a_n$ , according to the total probability formula, the expression of  $P(B)$  is as follows:

$$P(B) = \sum P(B|A=a_i)P(A=a_i). \quad (2)$$

Using the chain rule of the root joint probability distribution, the joint probability  $P(X)$  of the Bayesian network with  $n$  nodes can be expressed as follows:

$$\begin{aligned} P(X) &= P(x_1, x_2, \dots, x_n) = P(x_1)P(x_2|x_1)\dots P(x_n|x_1, x_2, \dots, x_{n-1}) \\ &= \prod_{i=1}^n P(x_i|x_1, x_2, \dots, x_{i-1}) = \prod_{i=1}^n P(x_i|pa(x_i)). \end{aligned} \quad (3)$$

In formula (3),  $pa(x_i)$  represents the variable set of all parent nodes of node  $x_i$ .

If there is an edge from node  $A$  to node  $B$  such that  $A$  points to  $B$ , then node  $A$  is the parent node of node  $B$ , and node  $B$  is the child node of node  $A$ . A node without an input

edge, that is, a node without a parent node, is called the root node. Figure 3 shows a simple multistate Bayesian network and conditional probability table, namely, a three-node, three-state Bayesian network, where  $x_1$  and  $x_2$  are parent nodes (root nodes) and  $y$  is the child node (leaf node).

### 3.2. Logic Gates of Bayesian Networks

**3.2.1. AND Gate.** The fault state of the intermediate node of the Bayesian network AND gate is the maximum value of the state value of all root nodes; that is,  $l = \max(x_1, x_2, \dots, x_k)$ . Therefore, under a certain combination of state  $i$  of the root node, the conditional probability distribution of the intermediate node  $y$  is

$$p(y = i | x) = \begin{cases} 1, & i = l, \\ 0, & i \neq l. \end{cases} \quad (4)$$

**3.2.2. OR Gate.** The fault state of the intermediate node of the Bayesian network OR gate is the minimum value of the state values of all root nodes; namely,  $m = \min(x_1, x_2, \dots, x_k)$ . Therefore, under a certain combination of state  $j$  of the root node, the conditional probability distribution of the intermediate node  $y$  is

$$p(y = j | x) = \begin{cases} 1, & j = l, \\ 0, & j \neq l. \end{cases} \quad (5)$$

**3.3. Cloud Bayesian Network.** The cloud model can realize the conversion between qualitative information and quantitative information and can better express information. The Bayesian network can accurately infer from the root node to the leaf node through the graph structure, and it has good inference computing capabilities. The cloud Bayesian network, which combines the advantages of the two, not only has good reasoning ability but also can express the randomness and ambiguity of information. Therefore, the cloud Bayesian network model can analyze the reliability of the unit information of the multistate system with mixed uncertainties.

The status and performance level information of each unit in a multistate system is sometimes described in subjective and qualitative language based on the experience of experts and on-site personnel. For example, the status and performance level information of the system or unit is often described as intact good, mild failure, and general failure. Vague qualitative language may be used to describe serious faults. Before analyzing the reliability of the multistate system, the cloud model conversion should be used to convert the qualitative language of the state performance level of each unit node into a quantitative value. According to the actual situation, assuming that the performance level interval of a certain state is  $[a_i, a_j]$ , the digital feature parameters of the cloud model can be obtained according to the index approximation method in the literature [59]:

$$\left\{ \begin{array}{l} Ex = \frac{(a_i + a_j)}{2}, \\ En = \frac{(a_j - a_i)}{6}, \\ He = \omega. \end{array} \right. \quad (6)$$

In formula (6),  $\omega$  is determined by the randomness and uncertainty of the language description. Generally,  $\omega = 0.05En - 0.15En$ .

The state probability information of each unit in a multistate system mainly comes from historical data, test data, physical characteristics, expert experience, and use experience. The more accurate the information is, the closer the estimate is to the actual value. However, in actual engineering, historical data, test data, and other quantitative data are due to test errors and inaccurate on-site monitoring, among other reasons, and qualitative information such as expert experience and use experience is due to the subjective difference of human judgments, resulting in random inconsistencies in these sources certainty (randomness) and cognitive uncertainty (ambiguity). Compared with the traditional Bayesian network, the cloud Bayesian network mainly replaces the state probability of each root node from a specific fixed probability to a state probability cloud representing mixed uncertainty according to Section 2.2.2. and 2.2.1.  $Ex$ ,  $En$ , and  $He$  are the digital characteristic parameter values of the state probability cloud. According to Bayesian inference and cloud operation rules, the probability cloud digital feature parameter value of each root node is used to obtain the system reliability cloud digital feature parameter value [60]. Table 1 shows the cloud operation rules.

## 4. Cloud Bayesian Network under Common-Cause Failure

Because it is difficult to accurately measure the occurrence probability of common-cause failure events, parametric modeling methods are usually used to quantify the occurrence probability of common-cause failures, such as the  $\alpha$ -factor method and the  $\beta$ -factor method. Owing to the limitation of parameter estimation in the  $\alpha$ -factor model when the data are insufficient, the  $\beta$ -factor model is used to calculate the probability of system common-cause failure events.

The key to establishing the Bayesian network model under the condition of common-cause failure is to decompose the failure rate  $\lambda$  of the common-cause unit into independent partial failure rate  $\lambda_i$  and common-cause failure partial failure rate  $\lambda_c$ . That is, the common-cause unit is transformed into two independent failure subunits and common-cause failure subunits connected in series, and then the relationship with other components is analyzed. According to the influence of common-cause failures on the system, it is also necessary to introduce corresponding intermediate nodes. Figure 4 is a Bayesian network diagram of a two-unit multistate system with common-cause failure.  $x_1$  and  $x_2$  are root nodes;  $c$  is a common-cause failure unit;  $d_1$  and  $d_2$  are intermediate nodes; and  $y$  is a leaf node. 0 represents a complete failure state; 0.5 represents a partial failure state; and 1 represents an intact state.

When  $x_1$  and  $x_2$  are connected in series,  $x_1$  and  $c$ ,  $x_2$  and  $c$ , and  $d_1$  and  $d_2$  are all connected in series. The mathematical expression of the reliability of the two-unit series system is

TABLE 1: Cloud operation rules.

Symbol	$Ex$	$En$	$He$
+	$Ex_1 + Ex_2$	$\sqrt{En_1^2 + En_2^2}$	$\sqrt{He_1^2 + He_2^2}$
-	$Ex_1 - Ex_2$	$\sqrt{En_1^2 + En_2^2}$	$\sqrt{He_1^2 + He_2^2}$
$\times$	$Ex_1 \times Ex_2$	$ Ex_1 Ex_2  \sqrt{(En_1/Ex_1)^2 + (En_2/Ex_2)^2}$	$ Ex_1 Ex_2  \sqrt{(He_1/Ex_1)^2 + (He_2/Ex_2)^2}$
$\div$	$Ex_1 \div Ex_2$	$ Ex_1/Ex_2  \sqrt{(En_1/Ex_1)^2 + (En_2/Ex_2)^2}$	$ Ex_1/Ex_2  \sqrt{(He_1/Ex_1)^2 + (He_2/Ex_2)^2}$

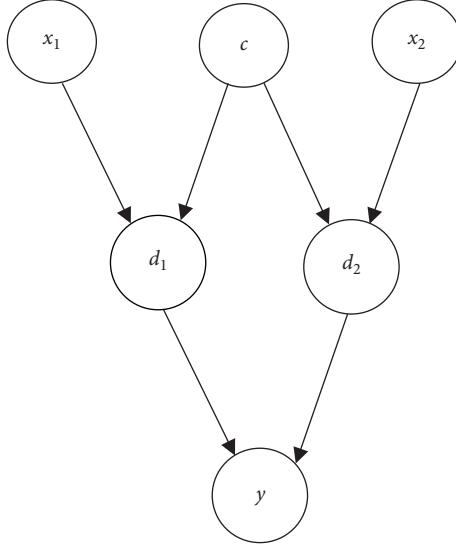


FIGURE 4: Multistate common-cause failure Bayesian network.

$$\begin{aligned}
P(y = 1) &= \sum_{x_1, x_2, c, d_1, d_2} P(x_1, x_2, c, d_1, d_2, y) = \sum_{d_1, d_2} \left\{ P(y = 1 | d_1, d_2) \sum_{x_1, c} [P(d_1 = 0 | x_1, c) P(x_1) P(c)] \right\} \\
&= \sum_{x_2, c} [P(d_2 = 0 | x_2, c) P(x_2) P(c)] \\
&= P(x_1 = 1) P(x_2 = 1) P(c = 1).
\end{aligned} \tag{7}$$

When  $x_1$  and  $x_2$  are connected in parallel,  $d_1$  and  $d_2$  are in parallel relationship, and the mathematical expression of the reliability of the two-unit series system is

$$\begin{aligned}
P(y = 1) &= \sum_{x_1, x_2, c, d_1, d_2} P(x_1, x_2, c, d_1, d_2, y) = \sum_{d_1, d_2} \left\{ P(y = 1 | d_1, d_2) \sum_{x_1, c} [P(d_1 = 0 | x_1, c) P(x_1) P(c)] \right\} \\
&= \sum_{x_2, c} [P(d_2 = 0 | x_2, c) P(x_2) P(c)] \\
&= P(x_1 = 1) P(c = 1) + P(x_2 = 1) P(c = 1) - P(x_1 = 1) P(x_2 = 1) P(c = 1).
\end{aligned} \tag{8}$$

Suppose that the total failure probability of a certain unit is  $P$ , the failure probability of the independent part is  $P_i$ , and the failure probability of the common-cause part is  $P_c$ .

$$P = P_i + P_c. \tag{9}$$

Assuming that the unit obeys an exponential distribution, parameter  $\beta$  is the proportion of the probability of related failure in the total failure probability.

TABLE 2: Main technical parameters of the DGY70H pipelayer.

Unit	Technical parameters	Parameter rating or range
Engine	Model	NTA855-C360
	Rated speed (r/min)	2,000
	Rated power (HP/kw)	320/235
	Fuel consumption (g/kWh)	242
Chassis hydraulic system	Model	DGY-70
	Variable speed rated pressure (MPa)	1.6–2.5
	Steering rated pressure (MPa)	0.9–1.7
	Brake rated pressure (MPa)	2.1–2.9
	Driving speed (km/h)	Going forward I gear 0–3.6 II gear 0–6.6 Back I gear 0–4.4 II gear 0–7.8
	Model	CBGJ3100/3100/1040
	Rated work stress (MPa)	20
Gear pump	Rated speed (r/min)	2,000
	Theoretical displacement (ml/r)	100/100/40

$$\beta = \frac{P_c}{P} = \frac{P_c}{P_i + P_c} = \frac{1 - e^{-\lambda_c t}}{1 - e^{-\lambda t}} \approx \frac{\lambda_c}{\lambda} = \frac{\lambda_c}{\lambda_i + \lambda_c}. \quad (10)$$

From this, we can deduce the following equations:

$$P_c = \beta P, \quad (11)$$

$$P_t = (1 - \beta)P. \quad (12)$$

The  $\beta$ -factor reflects the sensitivity of the relevant unit to environmental stress. The more sensitive the unit is to external environmental conditions, the greater  $\beta$  is, which can be obtained based on field data and expert experience. In general, the value range of  $\beta$ -factor is 0–0.25, and  $\beta=0$  means no common-cause failure occurs.

The specific steps of reliability analysis of a cloud Bayesian network multistate system based on common-cause failure are as follows:

- (1) Establish a Bayesian network based on actual engineering conditions. Based on the analysis of the functional structure and logical hierarchical relationship of each unit in the system, a Bayesian network graph model is constructed to determine the root node, intermediate node, leaf node, and the causal relationship of each node in the Bayesian network.
- (2) For fuzzy language description of the state performance level of the system and each unit, use equation (6) to perform cloud conversion to obtain the state value or interval of each node unit of the system, and form the unit state performance level cloud model conversion diagram.
- (3) Unit node types can be divided into discrete nodes and continuous nodes. When the node unit is a discrete node, the state probability sample information of the root node unit is passed through the algorithms in Section 2.2 (2) and (1), the state probability cloud digital feature parameter value of

the root node unit is formed, and the probability normal cloud graph is formed. When the element node type is a continuous node, the continuous observation node is discretized through cloud model conversion, so that the network is unified into a discrete Bayesian network. The state probability cloud number of the root node element is calculated according to the discrete node method using characteristic parameter values and the normal cloud graph. The specific conversion process of converting continuous nodes into discrete nodes is normalized according to Section 3.1 and literature [61].

- (4) According to the cloud Bayesian network model and the logical relationship between the nodes, the corresponding conditional probability table among the nodes of the cloud Bayesian network is obtained according to formulae (4) and (5).
- (5) Analyze the common-cause failure problem between the units in the system; introduce related common-cause nodes into the cloud Bayesian network model; and introduce intermediate nodes by connecting the root node and the common-cause node. According to the logical relationship formulae (4) and (5) generate the corresponding conditional probability table and thus finally obtain the cloud Bayesian network model with common-cause failures between units. Determine the beta factor sample according to the operating environment impact degree of the common factor group unit and engineering experience and obtain the digital feature parameter value of the  $\beta$ -factor. Determine the independent failure probability cloud digital feature of the unit node according to formulae (11) and (12) and parameter value and common-cause failure probability cloud digital characteristic parameter value.
- (6) Using the cloud Bayesian network inference algorithm, formula (3), and the cloud operation rules in Table 1, obtain the probability cloud digital feature parameter

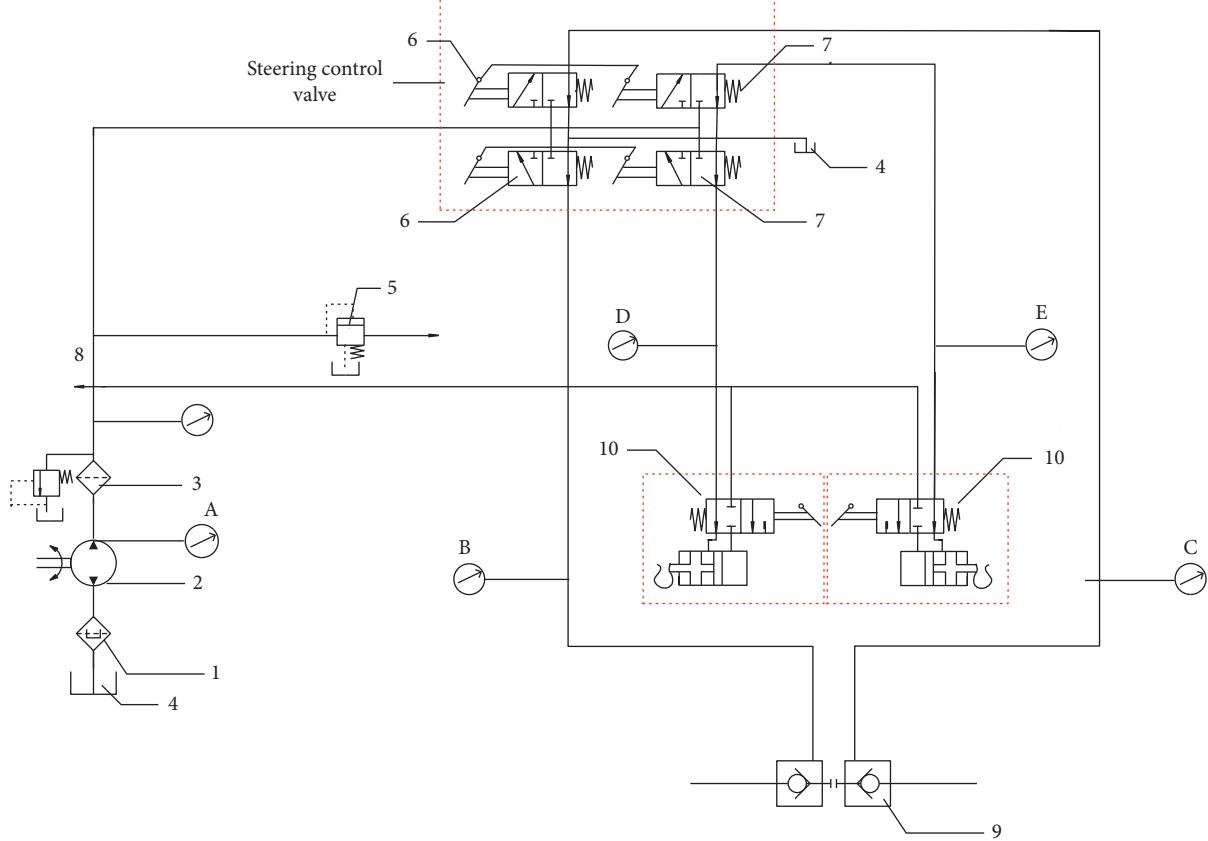


FIGURE 5: Working principle diagram of the steering hydraulic system of the pipelayer.

TABLE 3: The failure rate range of each root node of the steering hydraulic system of the pipelayer ( $10^{-6}/\text{h}$ ).

Root node unit	Range	Root node unit	Range
$x_1$	0.35–0.42	$x_6$	5.4–6.7
$x_2$	9.7–10.8	$x_7$	5.5–6.8
$x_3$	0.33–0.39	$x_8$	7.0–8.1
$x_4$	0.08–0.17	$x_9$	0.34–0.41
$x_5$	5.0–6.4	$x_{10}$	0.33–0.43

values and the probability normal cloud diagram of each state of the intermediate node unit and the leaf node (system), and finally get characteristic digital parameter values and reliability normal cloud diagrams when common-cause failure conditions occur in the system.

## 5. Case Analysis

This study took the hydraulic system of the crawler-type pipelayer with the hydraulic drive and rated lifting capacity of 70 t (DGY70H) pipelayer as the research object and used a cloud Bayesian network model for reliability analysis. A pipelayer is an important piece of equipment used in the construction of oil and natural gas pipelines. It is mainly used for pipe-laying, matching, and trenching operations of large-diameter pipes. Domestic oil and natural gas pipeline transportation projects have begun to align with international standards and are developing in the direction of large

pipelines and long distances. To improve the efficiency of laying pipelines, special equipment for the construction of various large- and medium-sized pipelines has also emerged in the field of pipeline construction. The most representative piece of construction equipment is the pipelayer. The pipelayer is composed of a luffing mechanism system, a lifting mechanism system, a counterweight mechanism system, a hydraulic system, a power system, a crawler walking device, and other auxiliary units. Owing to the complex structure of the equipment and the harsh field construction environment, the hydraulic system is prone to various failures, including the following: excessive oil temperature causes damage to the system leading to over heating of the solenoid valve; low oil temperature causes poor liquid fluidity and damage to oil pumps and pipelines and blockage and damage to the motor; system overpressure causes damage to parts such as hose blasting; and cavitation during the rotation of the motor can cause cavitation and noise in the hydraulic system. The main technical parameters of the DGY70H pipelayer are shown in Table 2.

The DGY70H pipelayer hydraulic system includes a bottom-car hydraulic system and an upper-car hydraulic system. The hydraulic system of the bottom car is divided into a variable speed hydraulic system, a steering hydraulic system, and a brake hydraulic system, which, respectively, control the speed, direction, and braking functions of the pipelayer during operation. The steering hydraulic system of the DGY70H pipelayer is an important part of the hydraulic

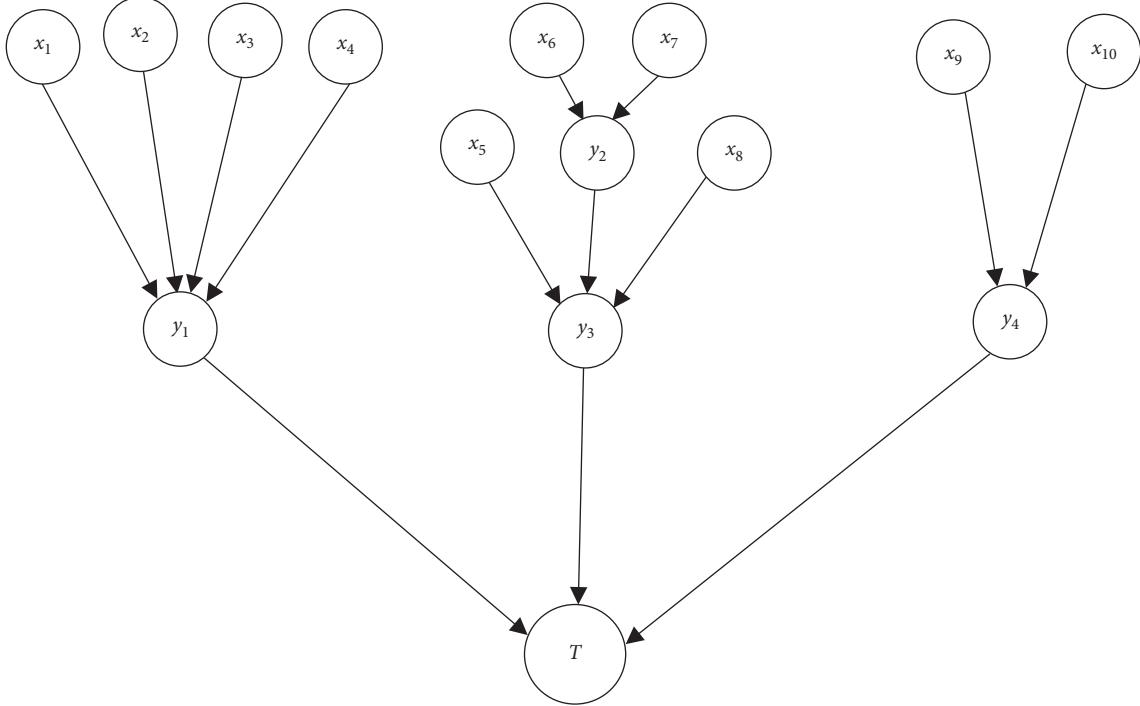


FIGURE 6: Bayesian network for the steering hydraulic system of the pipe crane.

TABLE 4: Judgment criteria for the state of each component.

Status	Degradation of function	Language description
Intact	0–10%	The unit is in a perfect functional state when it is working and can realize its function
Mild failure	10%–30%	The unit is in a state of slight failure when it is working and can realize most of its functions
Severe failure	30%–80%	The unit is in a severely failed functional state when working, and most of its functions are lost
Complete failure	80%–100%	The unit is in a completely disabled functional state and has completely lost its function

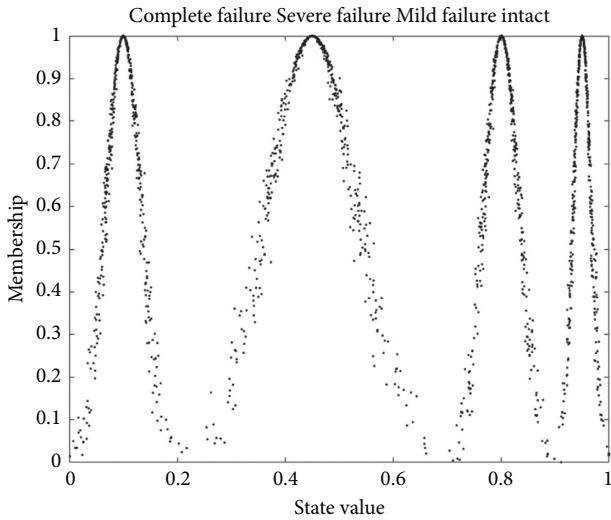


FIGURE 7: Partial cloud model conversion diagram.

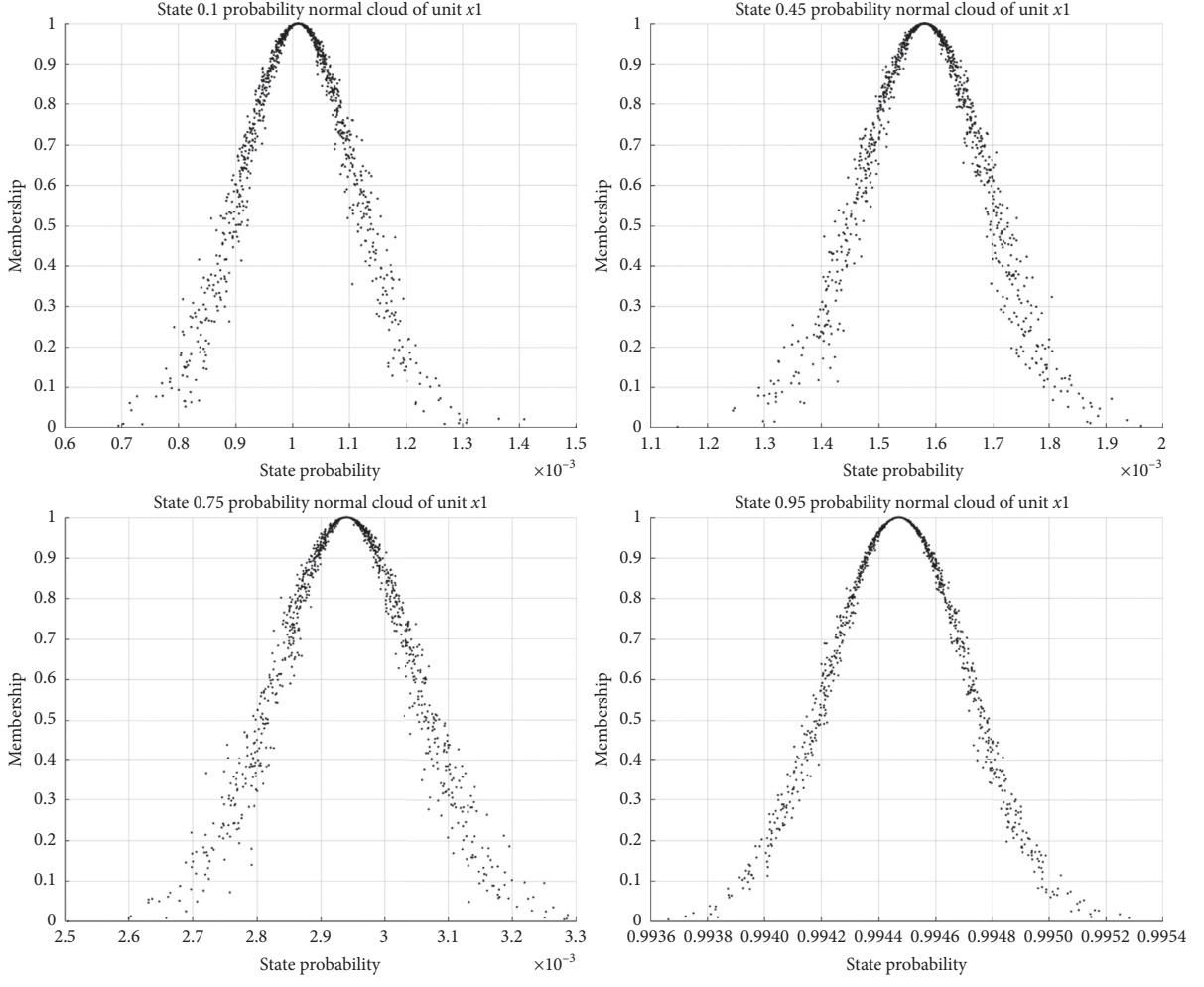
system of the bottom car; it controls the direction of pipelayer operation. If the steering hydraulic system of the pipelayer fails, the pipelayer will cause the direction of operation to fail during operation, which can easily cause

rolling and equipment tipping and harm to the surrounding people and the facilities. Therefore, analyzing the reliability of the steering hydraulic system of the pipelayer, reducing the failure of each unit (component), and improving reliability are of great significance for reducing and avoiding production safety accidents caused by pipelayer failure. The steering hydraulic system of the pipelayer is mainly composed of a magnetic coarse filter, steering pump, oil filter, rear axle box, steering valve, control valve, rotary servo valve, steering clutch, brake booster, and other unit components. Among them, the steering pump is a gear pump, which is connected to the transfer case, and its main purpose is to convert mechanical energy into hydraulic energy. The oil in the rear axle box passes through the magnetic coarse filter and is then sucked up by the steering pump and sent to the steering main pressure reducing valve steering, control valve, and brake booster through the oil filter. The overflowed oil from the main pressure reducing valve enters the torque converter circuit. The schematic diagram of the steering hydraulic system of the pipelayer is shown in Figure 5.

When performing reliability analysis of the steering hydraulic system of the pipelayer, the following basic assumptions are made:

TABLE 5: The numerical eigenvalues of the cloud probability of each root node.

Unit	$P_{0,1}^j$	$P_{0,45}^j$	$P_{0,75}^j$	$P_{0,95}^j$
$x_1$	(0.00101, $1.012 e^{-4}$ , $1.1908 e^{-5}$ )	(0.00158, $1.103e^{-4}$ , $1.3159 e^{-5}$ )	(0.00294, $1.093e^{-4}$ , $1.3048 e^{-5}$ )	(0.99447, $2.489e^{-4}$ , $1.3048 e^{-5}$ )
$x_2$	(0.02992, $3.745e^{-4}$ , $2.9871 e^{-5}$ )	(0.03110, $4.579e^{-4}$ , $3.1768e^{-5}$ )	(0.03192, $4.576e^{-4}$ , $3.1772e^{-5}$ )	(0.90706, 0.001124, $7.26948 e^{-5}$ )
$x_3$	( $9.3e^{-4}$ , $4.566e^{-5}$ , $3.2081 e^{-6}$ )	(0.00156, $7.743 e^{-5}$ , $5.3867 e^{-6}$ )	(0.00248, $1.273e^{-4}$ , $6.4945 e^{-6}$ )	(0.99503, $2.094e^{-4}$ , $1.1784 e^{-5}$ )
$x_4$	( $3.6e^{-4}$ , $4.496e^{-5}$ , $3.2074 e^{-6}$ )	( $8.5 e^{-4}$ , $4.489 e^{-5}$ , $3.2164 e^{-6}$ )	(0.00139, $5.877e^{-5}$ , $5.0139 e^{-6}$ )	(0.99740, $1.257e^{-4}$ , $7.2159 e^{-6}$ )
$x_5$	(0.0159, $2.345e^{-4}$ , $1.9931 e^{-5}$ )	(0.01667, $2.349 e^{-4}$ , $1.9932 e^{-5}$ )	(0.0175, $2.407e^{-4}$ , $1.9772 e^{-5}$ )	(0.94993, $5.953e^{-4}$ , $4.5783 e^{-5}$ )
$x_6$	(0.01605, $2.588e^{-4}$ , $1.9915 e^{-5}$ )	(0.01696, $2.344e^{-4}$ , $1.9929 e^{-5}$ )	(0.01764, $2.378e^{-4}$ , $1.9782e^{-5}$ )	(0.94935, $5.954e^{-4}$ , $4.5784e^{-5}$ )
$x_7$	(0.01608, $2.619e^{-4}$ , $2.1116 e^{-5}$ )	(0.01686, $2.498e^{-4}$ , $1.9986e^{-5}$ )	(0.01817, $5.794e^{-5}$ , $7.0937e^{-6}$ )	(0.94889, $5.539e^{-4}$ , $4.3617e^{-5}$ )
$x_8$	(0.02149, $2.829e^{-4}$ , $2.1399e^{-5}$ )	(0.02218, $2.937e^{-4}$ , $2.2356e^{-5}$ )	(0.02377, $2.944e^{-4}$ , $2.4282 e^{-5}$ )	(0.93347, $6.958e^{-4}$ , $6.0257e^{-5}$ )
$x_9$	( $9.5e^{-4}$ , $1.127e^{-4}$ , $9.3781 e^{-6}$ )	(0.00145, $7.811e^{-5}$ , $5.3227e^{-6}$ )	(0.00219, $1.273e^{-4}$ , $6.6874 e^{-6}$ )	(0.99541, $3.189e^{-4}$ , $1.9472e^{-5}$ )
$x_{10}$	(0.00106, $1.328e^{-4}$ , $9.3756 e^{-6}$ )	(0.00163, $1.282e^{-4}$ , $6.7322e^{-6}$ )	(0.00228, $1.212e^{-4}$ , $6.8834 e^{-6}$ )	(0.99503, $3.782e^{-4}$ , $2.3796e^{-5}$ )



(a)

FIGURE 8: Continued.

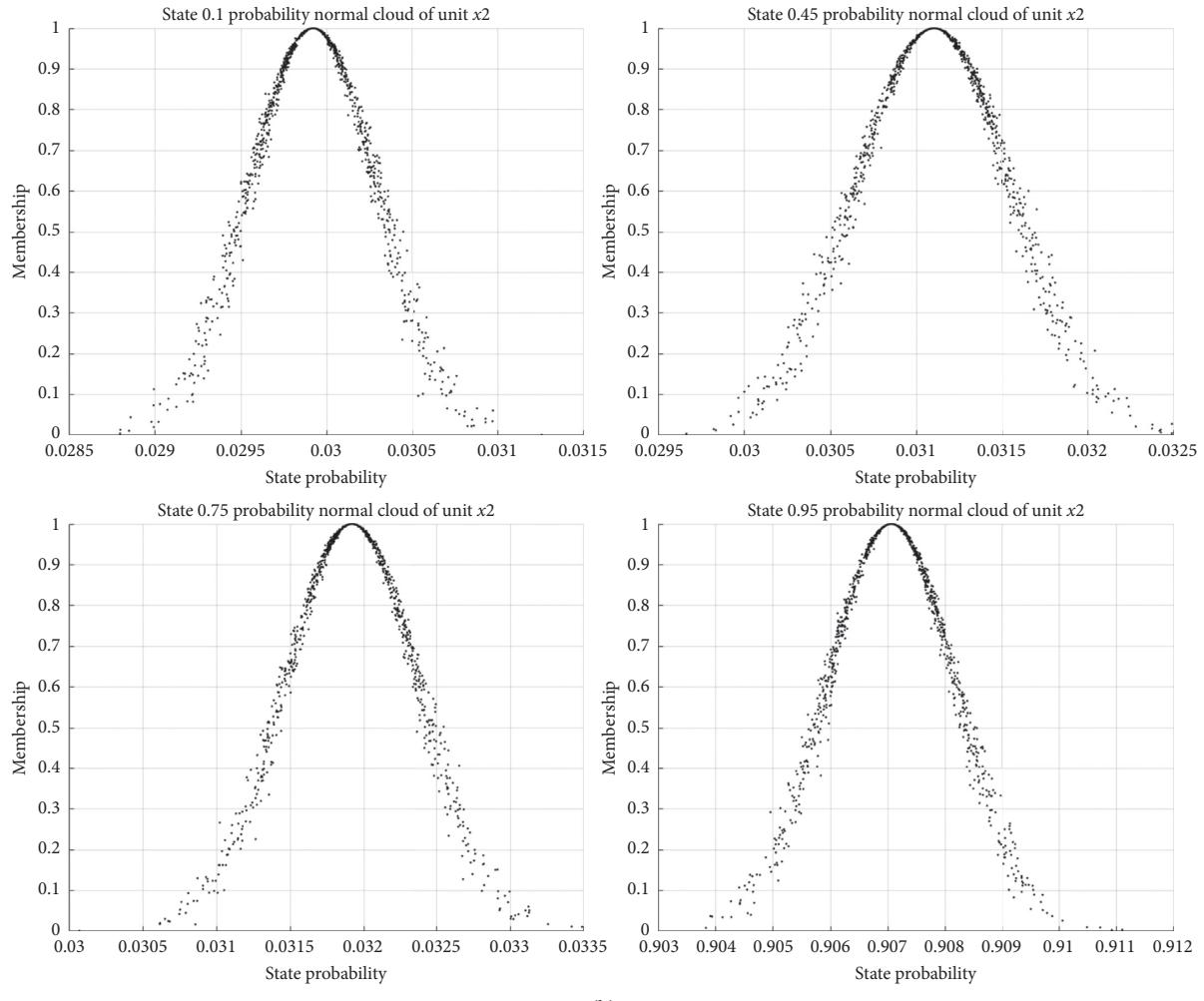
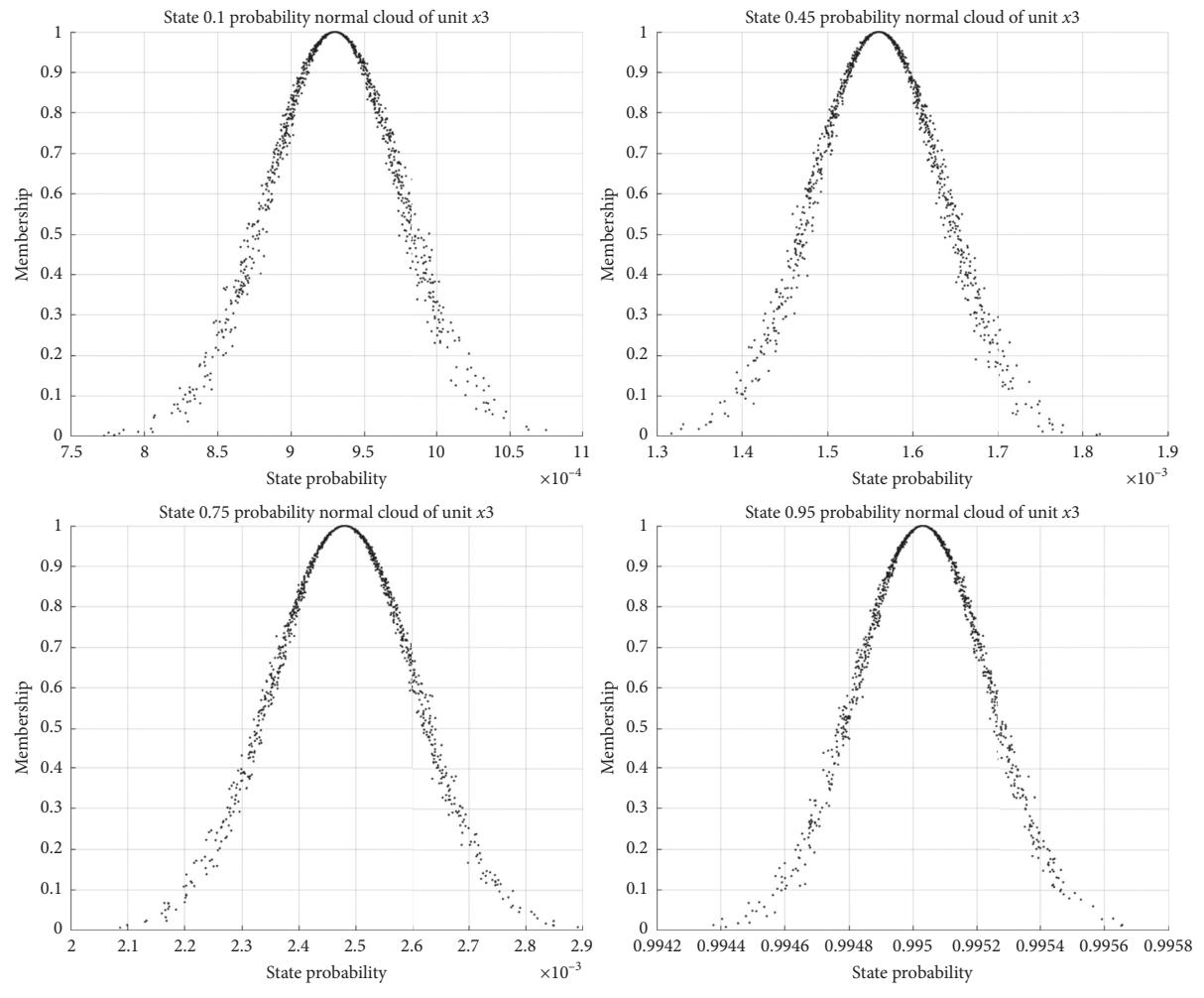
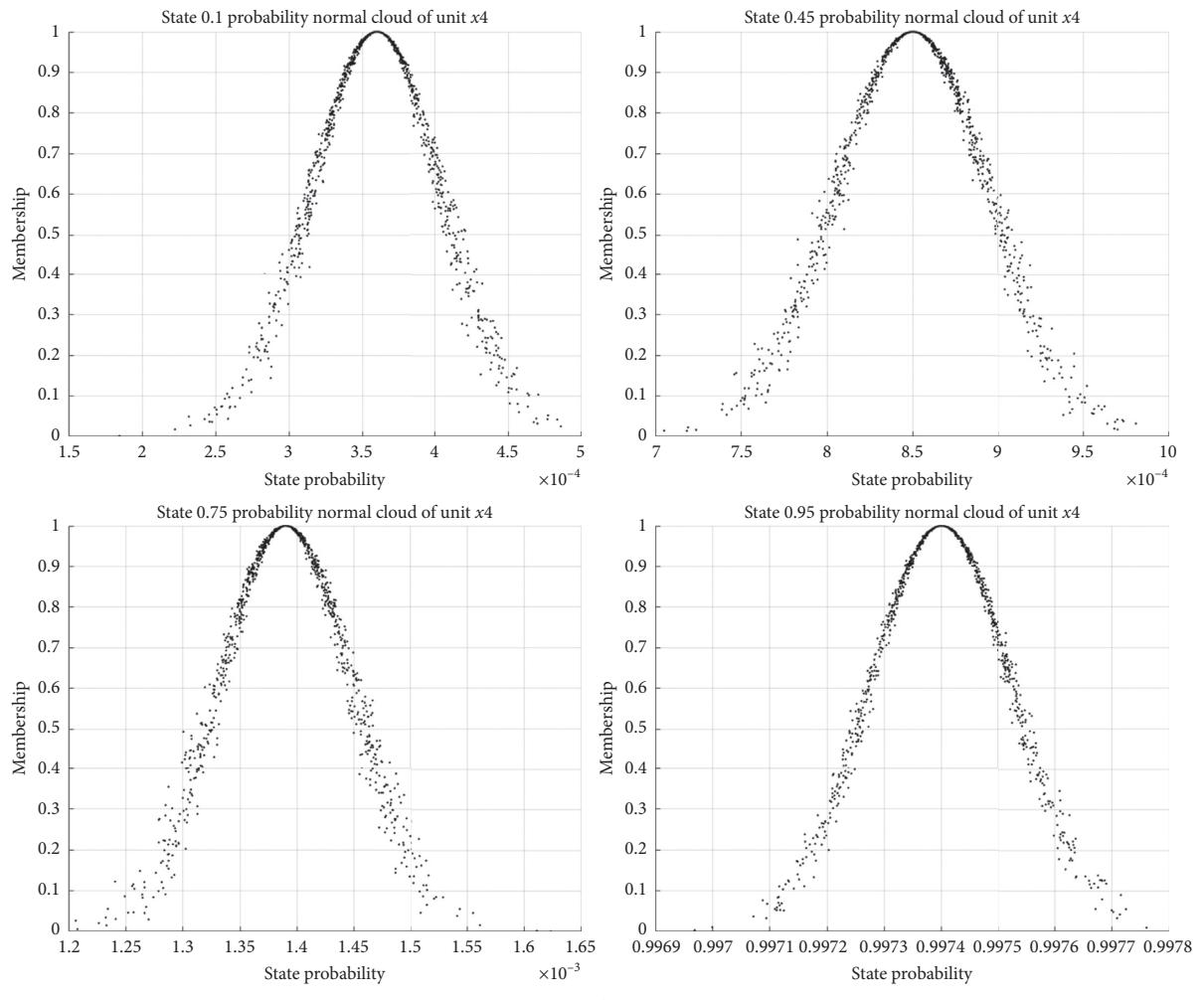


FIGURE 8: Continued.



(c)

FIGURE 8: Continued.



(d)

FIGURE 8: Continued.

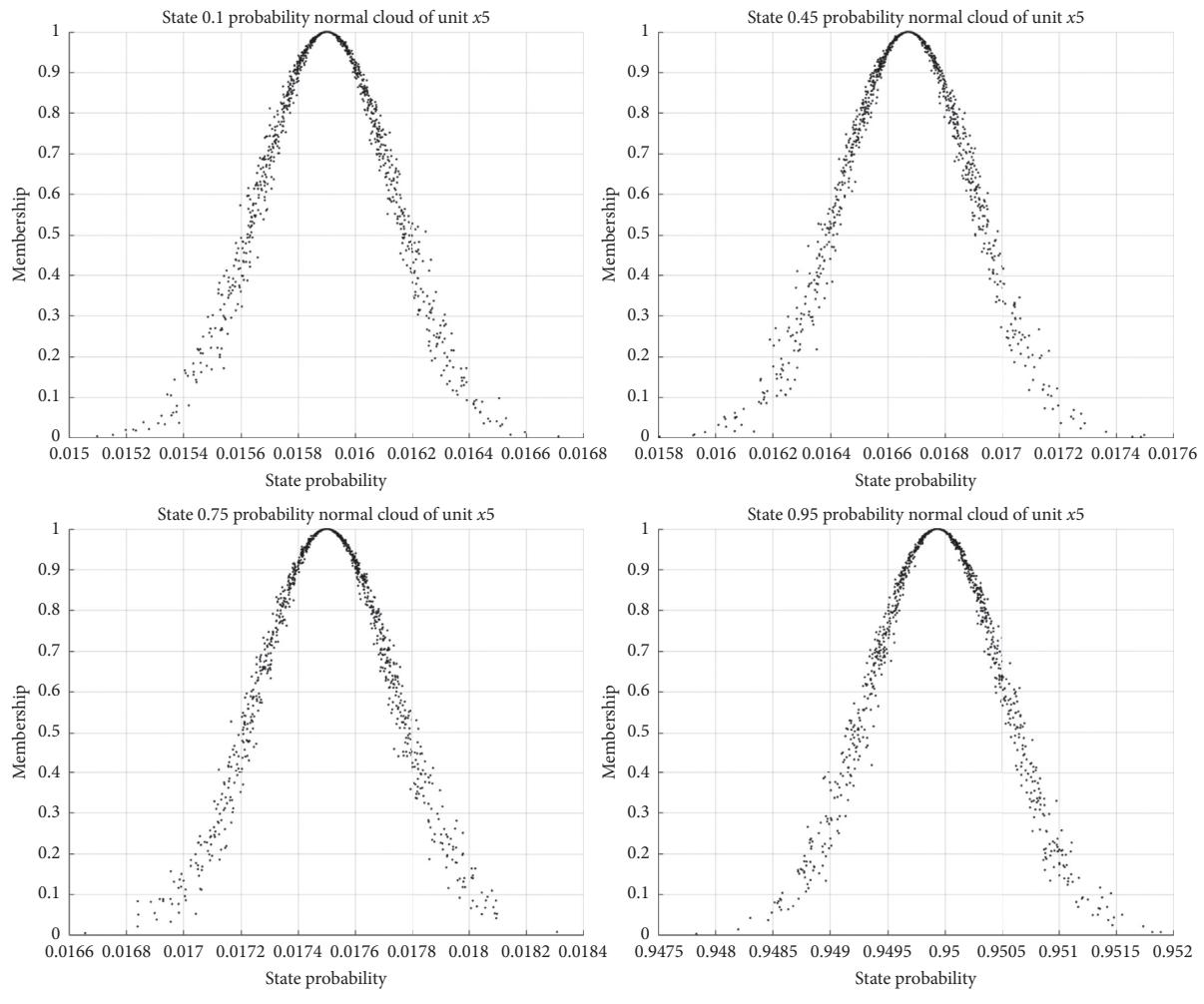
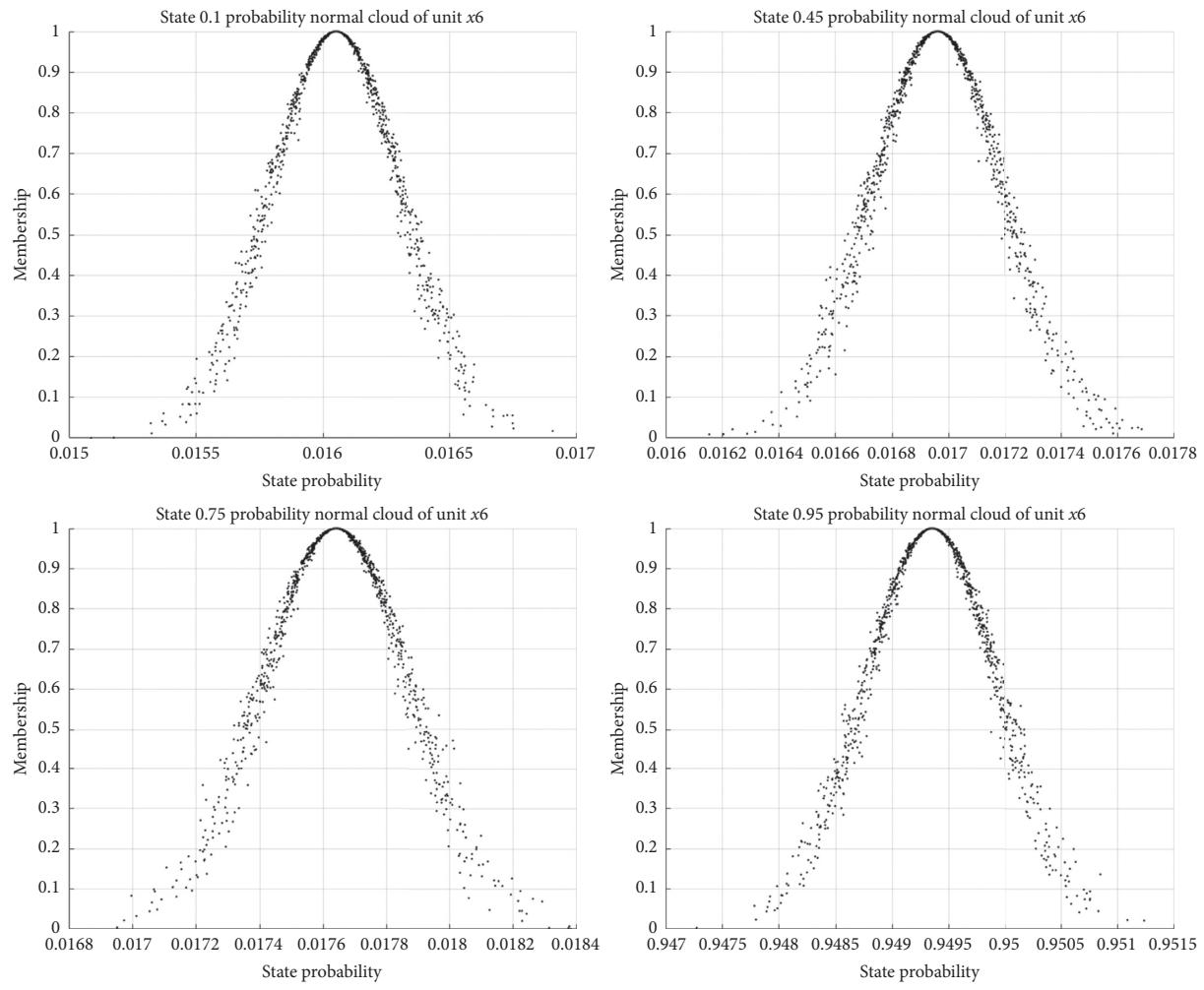
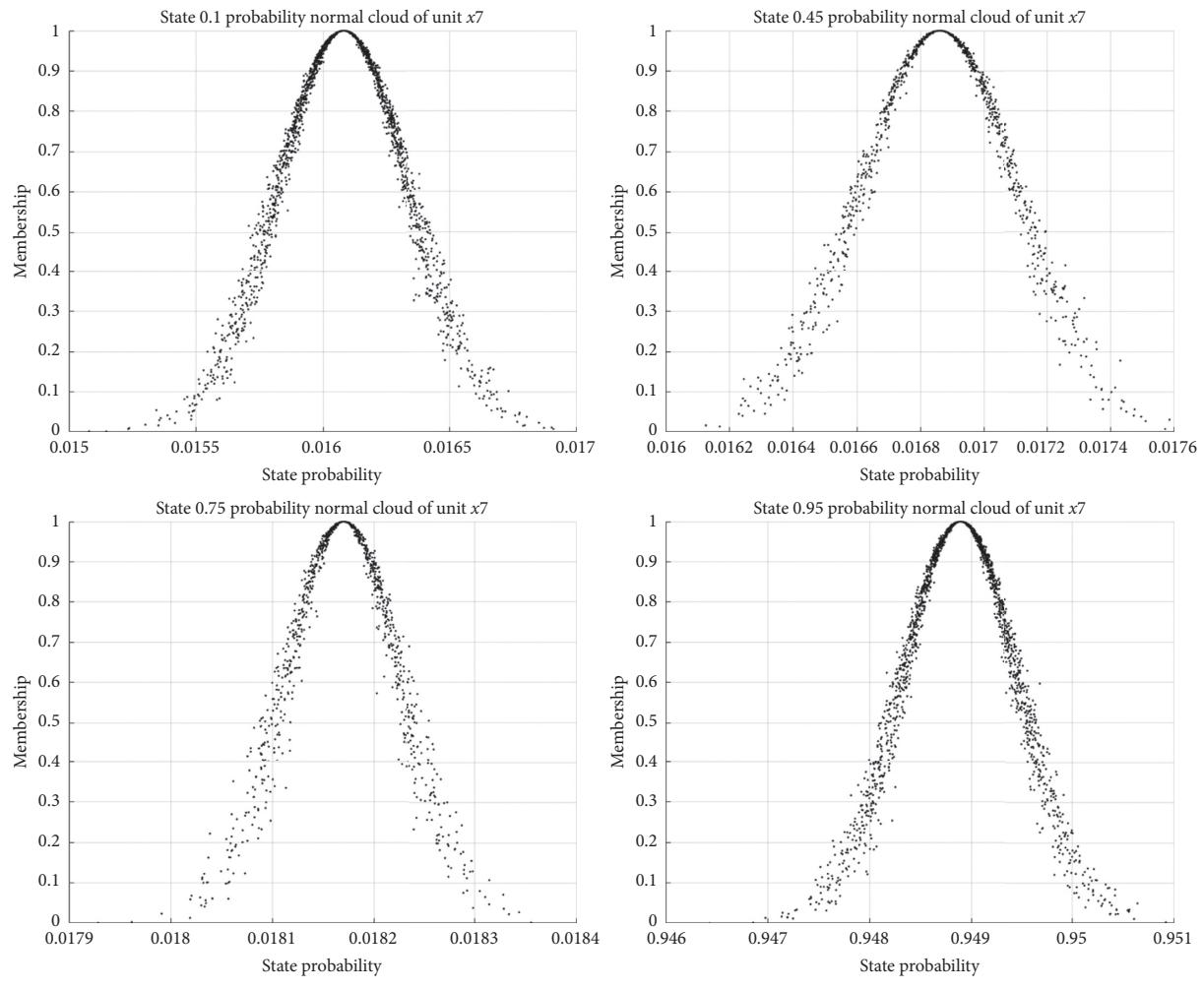


FIGURE 8: Continued.  
(e)



(f)

FIGURE 8: Continued.



(g)

FIGURE 8: Continued.

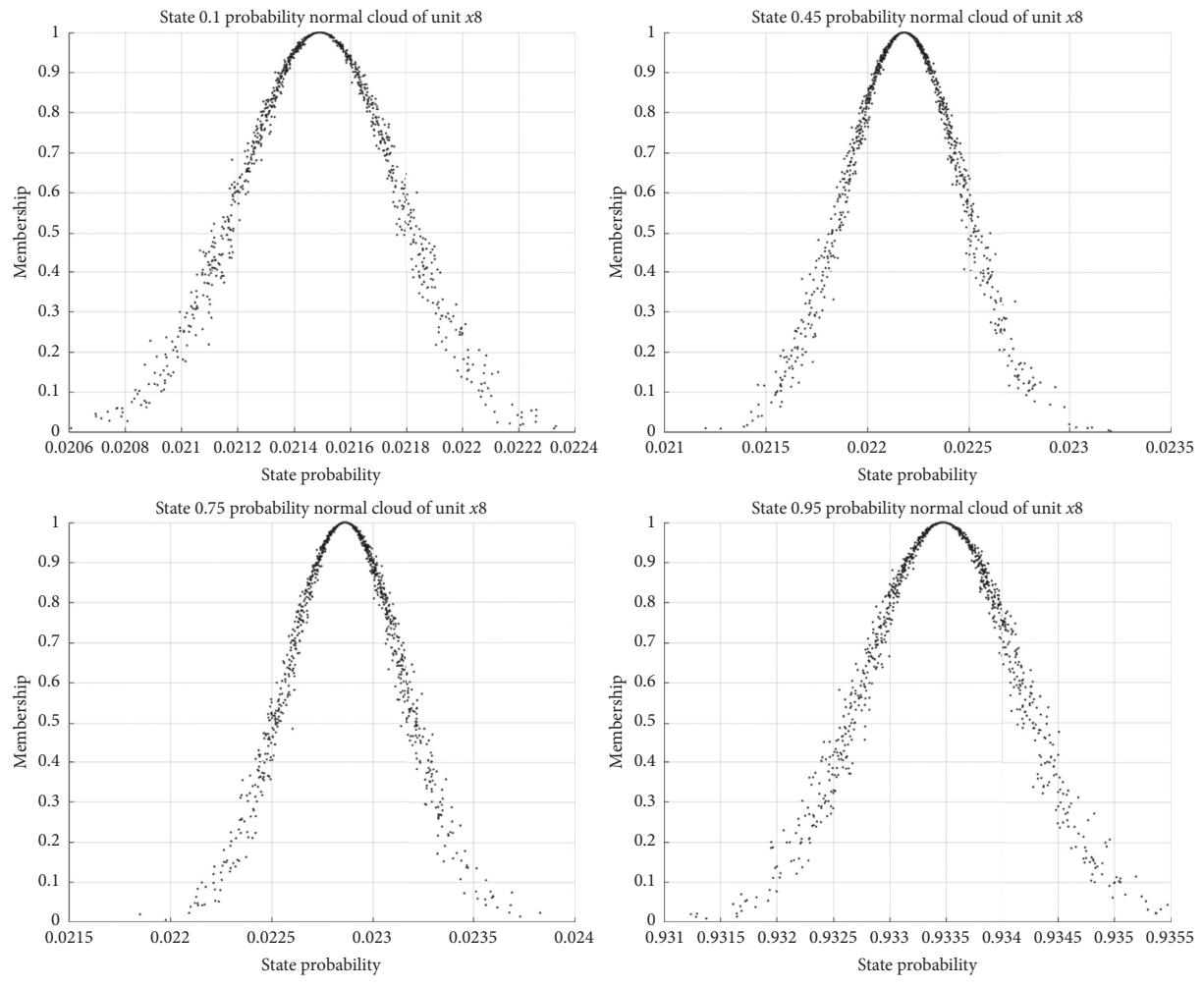
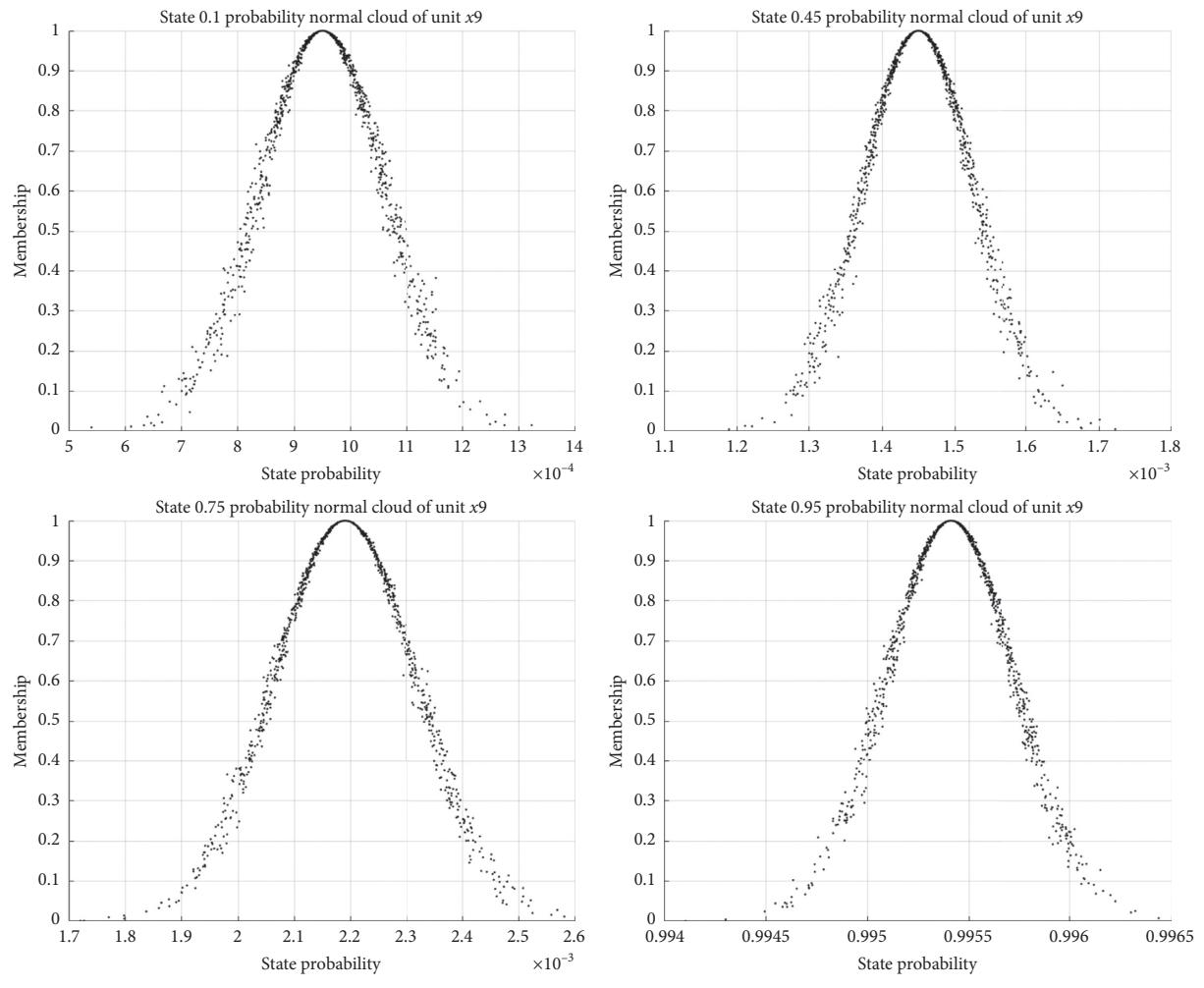


FIGURE 8: Continued.  
(h)



(i)

FIGURE 8: Continued.

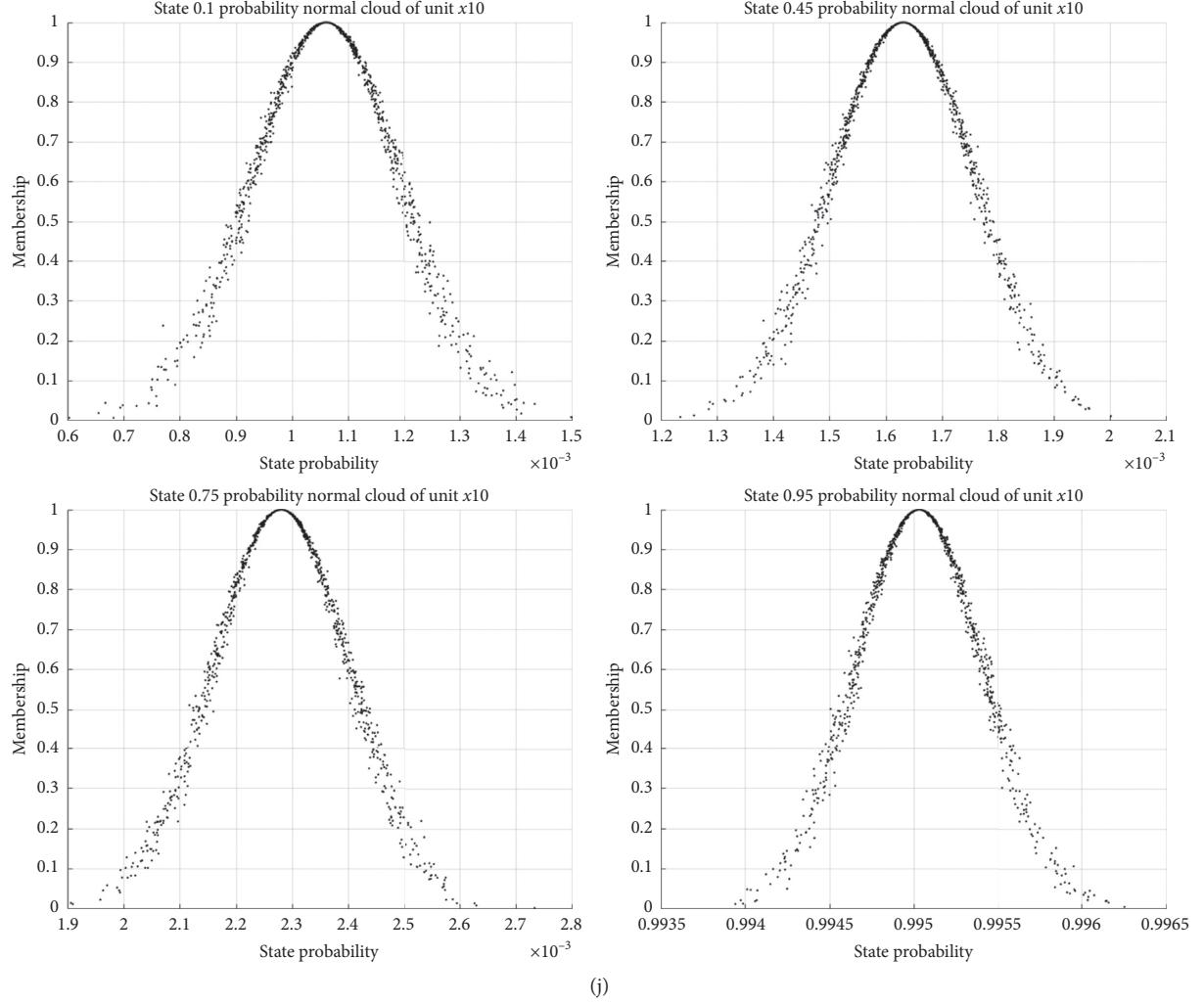


FIGURE 8: The state probability normal cloud of each root node. (a)  $x_1$  normal cloud with probability of each state. (b)  $x_2$  normal cloud with probability of each state. (c)  $x_3$  normal cloud with probability of each state. (d)  $x_4$  normal cloud with probability of each state. (e)  $x_5$  normal cloud with probability of each state. (f)  $x_6$  normal cloud with probability of each state. (g)  $x_7$  normal cloud with probability of each state. (h)  $x_8$  normal cloud with probability of each state. (i)  $x_9$  normal cloud with probability of each state. (j)  $x_{10}$  normal cloud with probability of each state.

TABLE 6: Conditional probability table for intermediate node  $y_1$ .

Root node				$P(y_1 x_1, x_2, x_3, x_4)$			
$x_1$	$x_2$	$x_3$	$x_4$	0.1	0.45	0.75	0.95
0.1	0.1	0.1	0.1	1	0	0	0
0.1	0.1	0.1	0.45	1	0	0	0
0.1	0.1	0.1	0.75	1	0	0	0
0.1	0.1	0.1	0.95	1	0	0	0
0.1	0.1	0.45	0.1	1	0	0	0
0.1	0.1	0.75	0.1	1	0	0	0
0.1	0.1	0.95	0.1	1	0	0	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
0.95	0.95	0.95	0.1	1	0	0	0
0.95	0.95	0.95	0.45	0	1	0	0
0.95	0.95	0.95	0.75	0	0	1	0
0.95	0.95	0.95	0.95	0	0	0	1

- (1) The unit or system has a finite number of discrete states; each state is determined; and the system is unrepairable.
- (2) The state probability of a unit or system has uncertainty. The unit node types in the Bayesian network are all discrete nodes.
- (3) There are  $n$  types of common-cause failure groups in the system, each composed of the same unit. The generalized intensity of the unit is statistically independent.
- (4) Owing to the common-cause failure caused by external environment or internal factors, the failure mechanism of the system is different, so the modeling method is also different. It is assumed that the

TABLE 7: Conditional probability table for intermediate node  $y_2$ .

Root node		$P(y_2 x_6, x_7)$				
$x_6$	$x_7$	0.1	0.45	0.75	0.95	
0.1	0.1	1	0	0	0	
0.1	0.45	1	0	0	0	
0.1	0.75	1	0	0	0	
0.1	0.95	1	0	0	0	
:	:	:	:	:	:	
0.95	0.1	1	0	0	0	
0.95	0.45	0	1	0	0	
0.95	0.75	0	0	1	0	
0.95	0.95	0	0	0	1	

TABLE 8: Conditional probability table for intermediate node  $y_3$ .

Root node		$P(y_3 x_5, y_2, x_8)$				
$x_5$	$y_2$	$x_8$	0.1	0.45	0.75	0.95
0.1	0.1	0.1	1	0	0	0
0.1	0.1	0.45	1	0	0	0
0.1	0.1	0.75	1	0	0	0
0.1	0.1	0.95	1	0	0	0
:	:	:	:	:	:	:
0.95	0.75	0.1	1	0	0	0
0.95	0.75	0.45	0	1	0	0
0.95	0.75	0.75	0	0	1	0
0.95	0.75	0.95	0	0	1	0
0.95	0.95	0.1	1	0	0	0
0.95	0.95	0.45	0	1	0	0
0.95	0.95	0.75	0	0	1	0
0.95	0.95	0.95	0	0	0	1

TABLE 9: Conditional probability table for intermediate node  $y_4$ .

Root node		$P(y_4 x_9, x_{10})$				
$x_9$	$x_{10}$	0.1	0.45	0.75	0.95	
0.1	0.1	1	0	0	0	
0.1	0.45	1	0	0	0	
0.1	0.75	1	0	0	0	
0.1	0.95	1	0	0	0	
:	:	:	:	:	:	
0.95	0.95	1	0	0	0	
0.95	0.95	0	1	0	0	
0.95	0.95	0	0	1	0	
0.95	0.95	0	0	0	1	

common-cause failure of the steering hydraulic system of the pipelayer is modeled due to the internal reasons of the unit. If the load is greater than the unit's endurance limit, the load on all units in the common-cause group will exceed strength limits, causing all components to fail simultaneously.

The reliability indicators of multistate systems mainly include system instantaneous reliability, instantaneous average performance, and instantaneous average performance shortage. Because the probability of each state of the unit is uncertain, this article mainly analyzes the instantaneous reliability of the system.

TABLE 10: Conditional probability table for leaf node  $T$ .

Intermediate node			$P(T y_1, y_3, y_4)$				
$y_1$	$y_3$	$y_4$	0.1	0.45	0.75	0.95	
0.1	0.1	0.1	1	0	0	0	
0.1	0.1	0.45	1	0	0	0	
0.1	0.1	0.75	1	0	0	0	
0.1	0.1	0.95	1	0	0	0	
:	:	:	:	:	:	:	
0.95	0.75	0.1	1	0	0	0	
0.95	0.75	0.45	0	1	0	0	
0.95	0.75	0.75	0	0	1	0	
0.95	0.75	0.95	0	0	1	0	
0.95	0.95	0.1	1	0	0	0	
0.95	0.95	0.45	0	1	0	0	
0.95	0.95	0.75	0	0	1	0	
0.95	0.95	0.95	0	0	0	1	

By analyzing the principle of the steering hydraulic system of the pipelayer, the logic relationship of each unit, and the mixed uncertainty of the unit probability, a Bayesian network model is established. In the steering hydraulic system of the pipelayer, the intermediate nodes of the Bayesian network are connected by the pump station  $y_1$ , the steering control valve  $y_2$ , the control element  $y_3$ , and the actuator  $y_4$ . The intermediate nodes  $y_1, y_2, y_3$ , and  $y_4$  are all OR gate connections. The leaf node  $T$  is the total failure of the steering hydraulic system of the pipelayer. The intermediate node  $y_1$  pump station is composed of root node magnetic coarse filter  $x_1$ , steering pump  $x_2$ , oil filter  $x_3$ , and rear axle box  $x_4$ . The intermediate node  $y_2$  steering control valve is composed of root node steering valve  $x_6$ , control valve  $x_7$ , and intermediate node  $y_3$ . The control element is composed of the root node steering main pressure reducing valve  $x_5$ , the steering control valve  $y_2$ , and the rotary servo valve  $x_8$ . The intermediate node  $y_4$  actuator is composed of the root node steering clutch  $x_9$  and the brake booster  $x_{10}$ . In Figure 5, A is the pressure measurement port of the transition main pressure reducing valve; B is the left clutch pressure measurement port; C is the right clutch pressure measurement port; D is the left brake booster pressure measurement port; and E is the right brake booster pressure measurement port. According to the experience of field engineers and experts, the failure rate range of each root node unit of the steering hydraulic system of the pipelayer is shown in Table 3. Figure 6 is the Bayesian network diagram of the steering hydraulic system of the pipelayer.

The state of the steering hydraulic system of each unit of the pipelayer is divided into intact, slight failure (fault), severe failure (fault), and complete failure (fault) (see Table 4 for the interval division criteria for describing the status of each unit based on language).

According to formula (6), the language description of each unit state in Table 4 is transformed into the cloud model according to the degree of function reduction, taking  $\omega = 0.10En$ . Figure 7 is the unit state cloud model transformation diagram.

Figure 7 converts the vague language description of each state of the pipelayer's steering hydraulic system into a cloud diagram, which solves the problem of the vagueness and

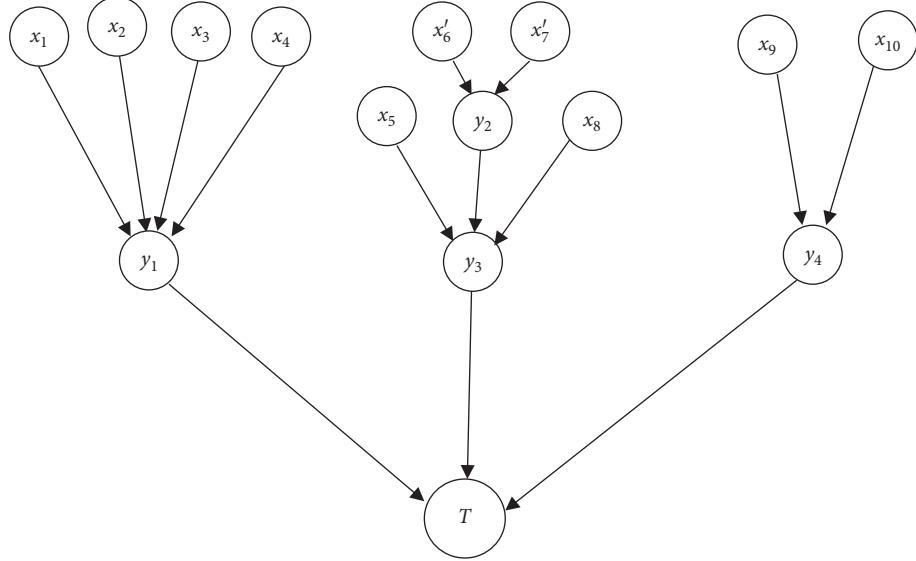


FIGURE 9: Bayesian network for common-cause failure of the steering hydraulic system of the pipelayer.

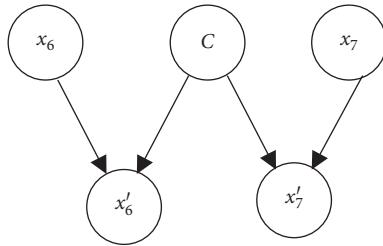


FIGURE 10: Common-cause failure group C Bayesian network.

TABLE 11: Conditional probability table for root nodes  $x_6'$  and  $x_7'$ .

Root node			$P(x_6' x_6, c)P(x_7' x_7, c)$			
$x_6$	$x_7$	C	0.1	0.45	0.75	0.95
0.1	0.1	0.1	1	0	0	0
0.1	0.1	0.45	0	1	0	0
0.1	0.1	0.75	0	0	1	0
0.1	0.1	0.95	0	0	0	1
:	:	:				
0.95	0.95	0.1	0	0	0	1
0.95	0.95	0.45	0	0	0	1
0.95	0.95	0.75	0	0	0	1
0.95	0.95	0.95	0	0	0	1

TABLE 12: Probability cloud digital feature value of each state of the leaf node.

State value	Digital feature value		
Independent failure	0.1	(0.09879, 0.006984, $6.97994 \times 10^{-4}$ )	
	0.45	(0.03509, 0.005884, $6.17531 \times 10^{-4}$ )	
	0.75	(0.03319, 0.005835, $6.09489 \times 10^{-4}$ )	
	0.95	(0.83294, 0.009257, $9.64080 \times 10^{-4}$ )	
Common-cause failure	0.1	(0.11216, 0.006991, $6.98479 \times 10^{-4}$ )	
	0.45	(0.04426, 0.005889, $6.17539 \times 10^{-4}$ )	
	0.75	(0.04117, 0.005846, $6.09862 \times 10^{-4}$ )	
	0.95	(0.80241, 0.009278, $9.64137 \times 10^{-4}$ )	

TABLE 13: Digital characteristic values of the reliability of the steering hydraulic system of the pipelayer.

Failure condition	Reliability digital characteristic value
Independent failure	(0.83294, 0.009257, $9.64080 \times 10^{-4}$ )
Common-cause failure	(0.80241, 0.009278, $9.64137 \times 10^{-4}$ )

randomness of the system. Taking the expected value  $Ex$  of each state separately, the state space of the system and unit is {0.1, 0.45, 0.75, 0.95}, referring to complete failure, severe failure, mild failure, and complete state, respectively.

Assuming that each root node has 500 information samples of the failure probability of each state, the state failure probability comes from historical data, test data, expert experience, and field experience. All state probabilities form a sample set  $Z = \{z_1, z_2, \dots, z_{500}\}$ . According to the algorithm in Section 2.2 (2), the quantitative data in the sample set of each unit are substituted into the inverse normal cloud generator to obtain the mean value  $\bar{X}$ , the center distance  $M$ , and the variance  $S^2$  to get the digital feature parameter value of the unit probability cloud. In accordance with the algorithm in Section 2.2 (1), substitute into the positive normal cloud generator to obtain the cloud drop of the unit's probability cloud. MATLAB was used to draw the normal cloud diagram. With it, the ambiguity of the state probability of each unit can be reflected. The numerical characteristic parameter values of the specific probability cloud are shown in Table 5, and the normal cloud diagram is shown in Figures 8(a)–8(j).

According to Figure 6 and logical relationship equations (4) and (5) between the nodes, the conditional probability tables of the intermediate nodes  $y_1, y_2, y_3$ , and  $y_4$  and the leaf node  $T$  are obtained (Tables 6–10). According to the logical relationship of each unit in the engineering practice, objective knowledge, and the experience of field engineers and experts, the conditional probability table is obtained. For

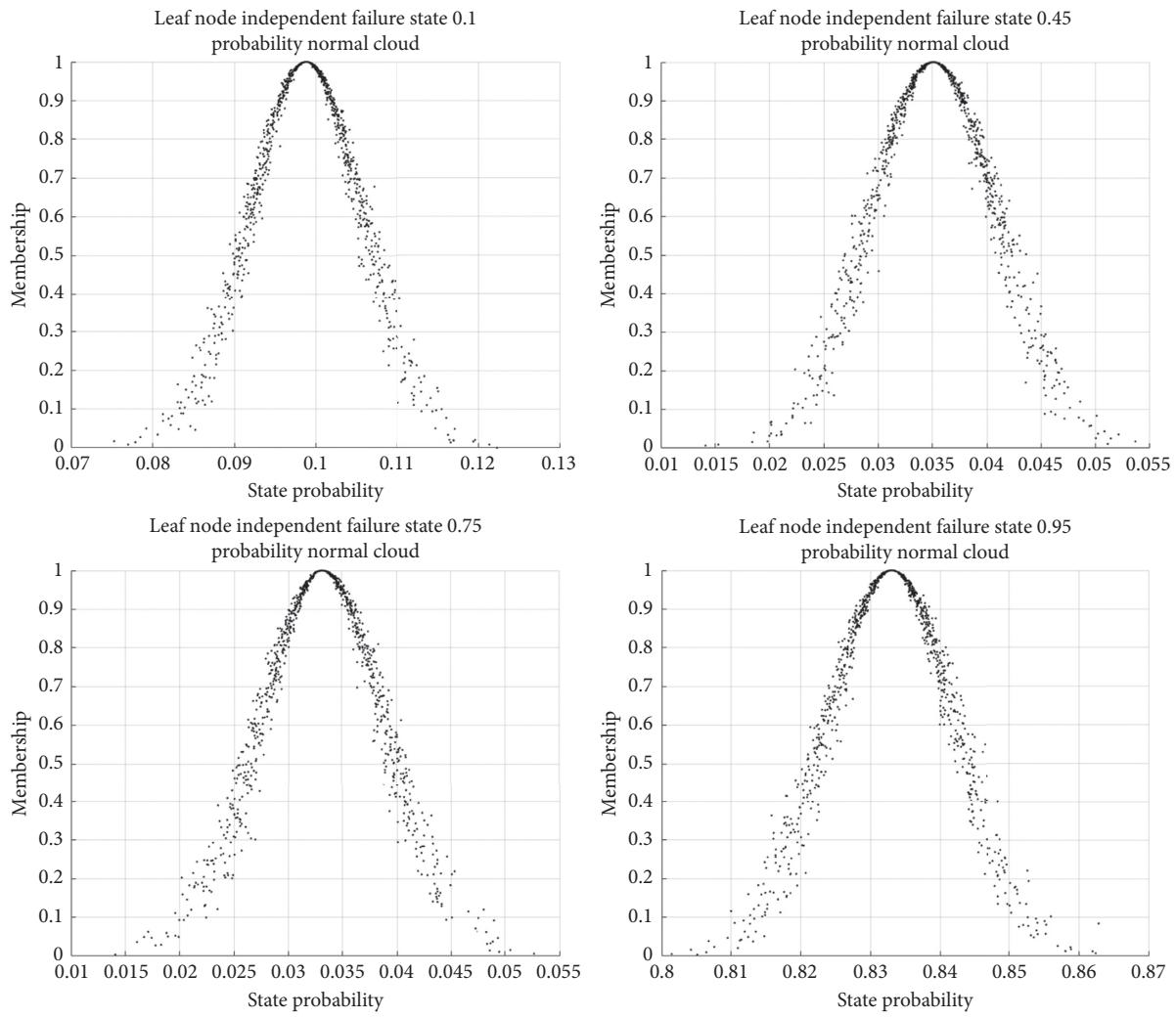


FIGURE 11: Continued.  
(a)

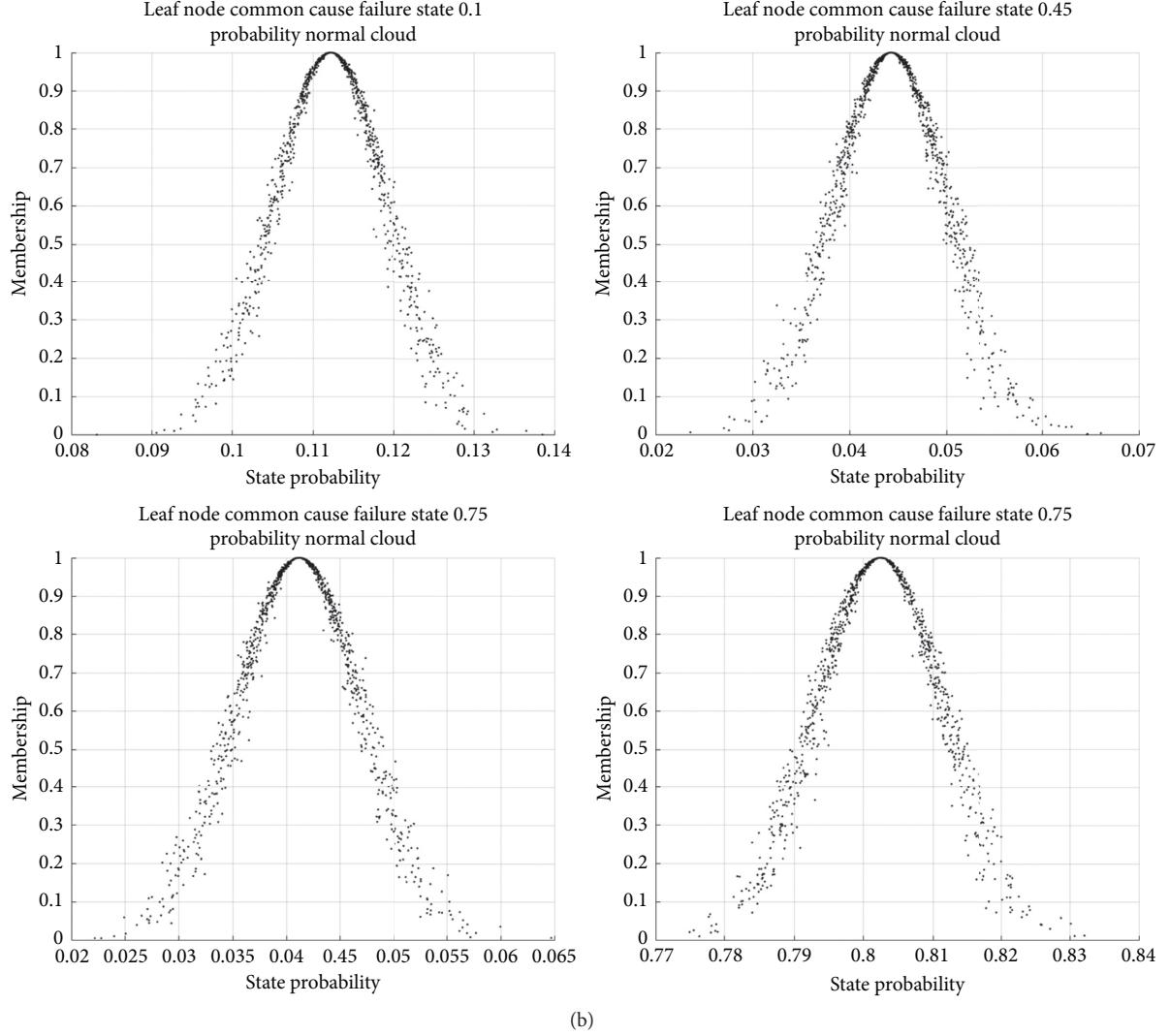


FIGURE 11: The normal cloud of each state of the steering hydraulic system of the pipelayer. (a) Independent failure of the steering hydraulic system of the pipelayer. (b) Common-cause failure of the steering hydraulic system of the pipelayer.

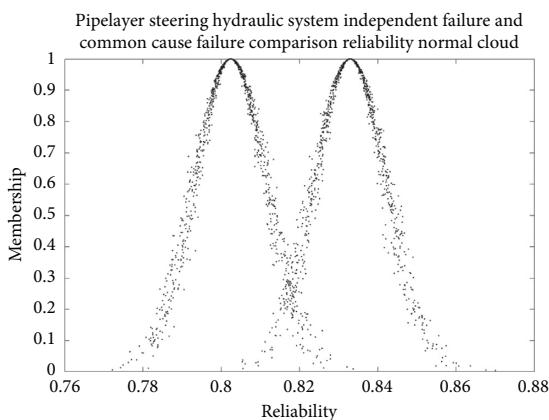


FIGURE 12: Normal reliability cloud of independent failure and common-cause failure of the steering hydraulic system of the pipelayer.

example, 0.1, 0.45, 0.75, and 0.95 in Table 6, respectively, represent that units  $x_1-x_4$  are intact, mild failure, severe failure, and complete failure. Because the units  $x_1-x_4$  or gates are connected, the probability cloud digital feature parameter takes the unit probability cloud digital feature parameter corresponding to the minimum of the four states and then calculates according to the Bayes formula. The same applies to Tables 7–10.

Since the root node steering valve  $x_6$  and the control valve  $x_7$  in the steering hydraulic system of the pipelayer constitute a common-cause failure group, it is very likely that the steering valve and the brake valve will fail at the same time due to a certain reason; that is,  $C = \{x_6, x_7\}$ . Owing to the subjective differences among experts,  $\beta$  is also uncertain. According to the experience of many experts, the  $\beta$  digital characteristic value is  $\beta = (0.15, 2.574e^{-4}, 2.6408e^{-5})$ . According to the numerical characteristic value of  $\beta$ , Table 7, equations (11) and (12), and the cloud computing rule in

Table 1, the probability cloud of common-cause failure is  $C_6 = (0.005417, 5.5843e^{-5}, 4.4350e^{-6})$  and  $C_7 = (0.005421, 5.5856e^{-5}, 4.4383e^{-6})$  of unit  $x_6$  and  $x_7$ . According to Borcsok et al. [62], the common-cause failure probability among components was selected to be a smaller value, so the probability cloud of common-cause failure is  $C = (0.005417, 5.5843e^{-5}, 4.4350e^{-6})$ . Figure 9 is a Bayesian network diagram of common-cause failure of the steering hydraulic system of the pipelayer. Figure 10 is a Bayesian network diagram of common-cause failure events at the root node.

According to formula (4), the conditional probability table of root nodes  $x'_6$  and  $x'_7$  of common-cause failure is shown in Table 11.

Using Table 1, Tables 5–11, and formula (3), the Bayesian calculation formula of the leaf nodes (system) and the probability cloud digital characteristic value table of each state under independent failure and common-cause failure of the steering hydraulic system of the pipelayer are obtained (see Table 12). The normal cloud diagrams are shown in Figures 11(a) and 11(b). Table 13 shows the numerical characteristic values of the reliability of the steering hydraulic system of the pipelayer during independent failures and common-cause failures. Figure 12 shows the normal cloud diagram of the reliability of the steering hydraulic system of the pipelayer comparing independent failures and common-cause failures.

To illustrate the effectiveness of the method, we compare the method with the evidence Bayesian network algorithm in [42]. According to the value range of the failure rate of each root node in Table 3, which is the upper and lower limit of the failure rate of each root node, the state probability of each root node is obtained, and then, according to the evidence Bayesian network method in the literature [42], we get the reliability intervals of each unit of the steering hydraulic system of the pipelayer in independent failure and common-cause failure as  $R_I = [0.803216, 0.860897]$  and  $R_C = [0.774544, 0.830291]$ , respectively. According to the cloud theory, the cloud drops that contribute to the concept in the universe mainly fall in the interval  $[Ex - 3En, Ex + 3En]$ , accounting for 99.74%. Therefore, according to this principle, the reliability of the steering hydraulic system of the pipelayer in the interval  $[Ex - 3En, Ex + 3En]$  using the cloud Bayesian network method is  $R'_I = [0.805169, 0.860711]$  and  $R'_C = [0.774576, 0.830244]$ . It can be seen from the calculation results that  $R'_I \subseteq R_I$  and  $R'_C \subseteq R_C$ . Therefore, the reliability of the pipelayer steering hydraulic system calculated by the cloud Bayesian network method is more accurate than the evidence Bayesian network algorithm in the literature [42] and is consistent with the actual situation.

From Table 11 and Figure 12, it can be seen that according to this method, the reliability of the pipelayer steering system presents a normal distribution range, which is mainly caused by insufficient cognition and lack of data, which also reflects the expression of the cloud model. The characteristic of uncertainty is more in line with the actual situation of the project. The reliability of the steering hydraulic system of the pipelayer is compared between the independent failures of each unit and the common-cause failure between the units. It can be seen from Figure 12 that

each unit of the steering hydraulic system of the pipelayer is in the event of common-cause failure. The reliability digital characteristic parameter value is lower than the reliability digital characteristic parameter value when each unit of the steering hydraulic system of the pipelayer fails independently. Owing to the common-cause failure of the steering control valve in the steering hydraulic system of the pipelayer, the expected value of the reliability digital characteristic parameter value  $Ex$  decreased by 0.03053. If the common-cause failure is ignored, the calculated reliability will have a large error, so it is essential to consider common-cause failures for analysis to be more consistent with actual engineering. The uncertainty of the reliability of the steering hydraulic system of the pipelayer is determined by the entropy and superentropy in the reliability digital characteristic parameter value. When the entropy and superentropy of the reliability digital characteristic parameter value increase, the range of the curve will become wider. Otherwise, the range of the curve will be narrow.

In the actual working process of the pipelayer, to reduce the failure of the unit and improve the reliability of the steering hydraulic system on the car, the important units in the system should be formulated with corresponding maintenance and other protective measures. First, keep the hydraulic oil in the system clean. Generally, the hydraulic oil needs to be replaced once a year or after 1,500 hours of work. When changing the hydraulic oil, ensure a dustless environment to prevent mixing of contaminated hydraulic oil. The climatic environment of the pipelayer is constantly changing when working on site. Sometimes, the climatic environment is extremely harsh, so different types of hydraulic oil should be used in different seasons: L-HM46 antiwear hydraulic oil and L-HM32 antiwear hydraulic oil should be used, respectively, in summer and winter. When the ambient temperature is lower than  $-20^{\circ}\text{C}$ , it should be replaced with L-HM22 low-temperature hydraulic oil or No. 12 aviation hydraulic oil. When the ambient temperature is higher than  $35^{\circ}\text{C}$ , L-HM68 hydraulic oil should be used. Hydraulic oils of different brands should not be mixed. When the pipelayer has been working for 250 hours, the oil should be replenished in time the oil suction filter, the oil return filter, and the liquid level of the battery pack should be checked and the vent holes of the ventilation device should be cleaned. When the pipelayer has worked for 1,000 hours, the oil in the oil tank should be replaced, and the filter element of the oil tank or oil filter should be cleaned. If the filter element is blocked, replace it in time. Focus on formulating corresponding maintenance measures for the special units in the steering hydraulic system of the pipelayer, such as the steering clutch. The steering clutch oil volume and steering rod stroke should be maintained and checked daily. When the pipelayer has worked for about 250 hours, the steering clutch components should be cleaned and replaced. When the pipelayer has worked for about 1,000 hours, the oil in the steering clutch should be replaced. In addition, the stroke of the steering rod should be adjusted from time to time to prevent the steering rod from becoming inflexible. By adjusting the steering clutch and the steering lever, poor contact can be prevented and occurrence of

failure can be reduced. Through the above protective measures, failures are reduced, thereby improving the reliability of the system.

## 6. Conclusion

This study analyzed the reliability of a multistate system with mixed uncertainty in the state probability information of each unit under common-cause failure. A cloud model was used to represent randomness and ambiguity in the probability of each unit state, and the cloud model was used to convert the language description of each state into a quantitative interval value or numerical value. The Bayesian network was thus expanded based on the cloud model theory. The cloud model and the Bayesian network were combined to utilize their respective advantages, and the cloud Bayesian network method was used to control independent and common-cause failure. Reliability analysis was conducted under failure conditions. The results show that effectiveness, feasibility, and common-cause failure have a certain impact on the reliability of a pipelayer's steering hydraulic system. The cloud Bayesian network method integrated the system's multistate characteristics, state ambiguity and randomness, uncertainty of state probability information, and common-cause failure of each unit. In this way, reliability analysis is more aligned with the actual situation of a project; the reliability of calculation is accurately higher; and large errors are avoided in the actual project. This cloud Bayesian network method can provide new ideas and methods for processing information or data randomness and ambiguity in multistate system reliability analysis. This study examined limited system on the basis of static and nonrepairable unit assumptions. We did not conduct reliability analysis on the dynamic sequence of the multistate system in the working process and the maintainability of the unit. The next step will be the dynamic reliability analysis of the maintainability of the multistate system in the working process so that the actual situation of the project is more consistent.

## Abbreviations

MSS:	Multistate system
CCF:	Common-cause failure
BN:	Bayesian network
CBN:	Cloud Bayesian network
DS:	Dempster-Shafer
TS:	Takagi and Sugeno
CNC:	Computer numerical control
DGY70H	Crawler-type pipelayer with the hydraulic drive and rated lifting capacity of 70 t.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request. These data include historical data, test data, expert experience, and usage experience.

## Conflicts of Interest

There are no conflicts of interest regarding the publication of this article.

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## References

- [1] N. Khakzad, F. Khan, and P. Amyotte, "Safety analysis in process facilities: comparison of fault tree and Bayesian network approaches," *Reliability Engineering and System Safety*, vol. 96, no. 8, pp. 925–932, 2011.
- [2] X. W. Yin, "Reliability evaluation of mechanical system based on bayesian network," Ph.D. Thesis, Northeastern University, Shenyang, China, 2007.
- [3] J. Pearl, "Fusion, propagation, and structuring in belief networks," *Artificial Intelligence*, vol. 29, no. no 3, pp. 241–288, 1986.
- [4] B. Cai, Y. Liu, Z. Liu, X. Tian, X. Dong, and S. Yu, "Using Bayesian networks in reliability evaluation for subsea blowout preventer control system," *Reliability Engineering and System Safety*, vol. 108, no. 8, pp. 32–41, 2012.
- [5] M. C. Gerstenberger, A. Christoffersen, R. Buxton, and A. Nicol, "Bi-directional risk assessment in carbon capture and storage with Bayesian Networks," *International Journal of Greenhouse Gas Control*, vol. 35, no. 3, pp. 150–159, 2015.
- [6] Q. Miao, X. Zhang, Z. Liu, and H. Zhang, "Condition multi-classification and evaluation of system degradation process using an improved support vector machine," *Microelectronics Reliability*, vol. 75, no. 8, pp. 223–232, 2017.
- [7] K. Wang, Y. Yang, J. Zhou, and M. Goh, "Fuzzy belief propagation in constrained Bayesian networks with application to maintenance decisions," *International Journal of Production Research*, vol. 58, no. 9, pp. 2885–2903, 2020.
- [8] C. Su and Y. Q. Fu, "Reliability assessment for Wind turbines Considering the influence of Wind speed using bayesian network," *Maintenance and Reliability*, vol. 16, no. 1, pp. 1–8, 2014.
- [9] S. Chen, Z. Qin, D. H. Chen et al., "Investigation of Bayesian network for reliability analysis and fault diagnosis of complex systems with real case applications," *Advances in Mechanical Engineering*, vol. 9, no. 10, pp. 1–18, 2017.
- [10] K. Sanjay, T. Barjeev, K. Vishal, and C. Sunita, "Incremental PMU placement considering reliability of power system network using analytical hierarchical process," *IET Generation Transmission and Distribution*, vol. 12, no. 16, pp. 3900–3909, 2018.
- [11] F. Mohammadi, P. Pascual-Ortigosa, E. Sáenz-de-Cabezón, and H. P. Wynn, "Polarization and depolarization of monomial ideals with application to multi-state system reliability," *Journal of Algebraic Combinatorics*, vol. 51, no. 4, pp. 617–639, 2020.
- [12] P. Gehl and D. D'Ayala, "Development of Bayesian Networks for the multi-hazard fragility assessment of bridge systems," *Structural Safety*, vol. 60, pp. 37–46, 2016.

- [13] X. F. Liang, H. D. Wang, H. Yi, and D. Li, "Warship reliability evaluation based on dynamic bayesian networks and numerical simulation," *Ocean Engineering*, vol. 136, pp. 129–140, 2017.
- [14] X. Li and W. Tang, "Structural risk analysis model of damaged membrane LNG carriers after grounding based on Bayesian belief networks," *Ocean Engineering*, vol. 171, pp. 332–344, 2019.
- [15] I. Tien and A. Der Kiureghian, "Algorithms for bayesian network modeling and reliability assessment of infrastructure systems," *Reliability Engineering and System Safety*, vol. 156, pp. 134–147, 2016.
- [16] U. Ozgur and B. Taner, "Performance analysis of an aggregation and disaggregation SolutionProcedure to obtain a maintenance plan for a partially observable multi-component system," *Reliability Engineering and System Safety*, vol. 167, pp. 652–662, 2017.
- [17] X. Chen, Q. Wang, Q. S. Wang, and D. Wang, "A high-reliability relay algorithm based on network coding in multi-hop wireless networks," *Wireless Networks*, vol. 25, no. 11, pp. 1557–1566, 2019.
- [18] L. Zhang, F. Restuccia, T. Melodia, and S. M.蒲列夫斯基, "Taming cross-layer attacks in wireless networks: a bayesian learning approach," *IEEE Transactions on Mobile Computing*, vol. 18, no. 7, pp. 1688–1702, 2019.
- [19] L. M. Huo, Y. L. Zhu, and G. F. Fan, "A new method of power system reliability evaluation based on bayesian network," *Automation of Electric Power Systems*, vol. 275, pp. 36–40, 2003.
- [20] H. Zheng, Q. Z. Wu, P. L. Wang et al., "The application of bayesian network in the safety evaluation of pyrotechnic system," *Acta Armamentarius*, vol. 27, no. 6, pp. 988–993, 2006.
- [21] D. L. Qin and D. J. Yu, "Bayesian network for machine fault diagnosis based on ontology," *China Mechanical Engineering*, vol. 24, no. 9, pp. 1195–1200, 2013.
- [22] A. G. Wilson and A. V. Huzurbazar, "Bayesian networks for multilevel system reliability," *Reliability Engineering and System Safety*, vol. 92, no. 10, pp. 1413–1420, 2007.
- [23] T. L. Graves, M. S. Hamada, R. Klamann, A. Koehler, and H. F. Martz, "A fully bayesian approach for combining multi-level information in multi-state fault tree quantification," *Reliability Engineering and System Safety*, vol. 92, no. 10, pp. 1476–1483, 2007.
- [24] Z. B. Zhou, C. Q. Ma, and J. L. Zhou, "Application of Bayesian network in reliability analysis of multi-state system," *Journal of Harbin Institute of Technology*, vol. 41, no. 6, pp. 232–235, 2009.
- [25] S. Zhai and S. Z. Lin, "Bayesian networks application in multi-state system reliability analysis," *Applied Mechanics and Materials*, vol. 347–350, pp. 2590–2595, 2013.
- [26] Y. J. Tong and I. Tien, "Algorithms for bayesian network modeling, inference, and reliability assessment for multistate flow networks," *Journal of Computing in Civil Engineering*, vol. 31, no. 5, pp. 1–04017051, 2017.
- [27] H. Boudali and J. B. Dugan, "A discrete-time Bayesian network reliability modeling and analysis framework," *Reliability Engineering and System Safety*, vol. 87, no. 3, pp. 337–349, 2005.
- [28] H. Boudali and J. B. Dugan, "A continuous-time bayesian network reliability modeling, and analysis framework," *IEEE Transactions on Reliability*, vol. 55, no. 1, pp. 86–97, 2006.
- [29] K. Nima, K. Faisal, and A. Paul, "Risk-based design of process systems using discrete-time Bayesian networks," *Reliability Engineering and System Safety*, vol. 109, pp. 5–17, 2013.
- [30] X. Wu, H. Liu, L. Zhang, M. J. Skibniewski, Q. Deng, and J. Teng, "A dynamic Bayesian network based approach to safety decision support in tunnel construction," *Reliability Engineering and System Safety*, vol. 134, pp. 157–168, 2015.
- [31] D. Z. Ma, Z. Zhou, and X. Y. Yu, "Reliability analysis of multi-state Bayesian network based on fuzzy probability," *System Engineering and Electronic Technology*, vol. 34, no. 12, pp. 2607–2611, 2012.
- [32] D. Chen and C. Y. Yao, "Reliability analysis of multi-state system based on fuzzy bayesian networks and application in hydraulic system," *Journal of Mechanical Engineering*, vol. 48, no. 16, pp. 175–183, 2012.
- [33] D. N. Chen, C. Y. Yao, and Z. Dang, "Reliability analysis of multi-state hydraulic system based on T-S fault tree and Bayesian network," *China Mechanical Engineering*, vol. 24, no. 7, pp. 899–905, 2013.
- [34] C. Yao, D. N. Chen, and B. Wang, "Fuzzy reliability assessment method based on T-S fault tree and Bayesian network," *Journal of Mechanical Engineering*, vol. 50, no. 2, pp. 193–201, 2014.
- [35] L. Zhang, X. Wu, M. J. Skibniewski, J. Zhong, and Y. Lu, "Bayesian-network-based safety risk analysis in construction projects," *Reliability Engineering and System Safety*, vol. 131, no. 3, pp. 29–39, 2014.
- [36] R. J. Zhang, L. L. Zhang, N. N. Wang et al., "Reliability evaluation of a multi-state system based on interval-valued triangular fuzzy Bayesian networks," *International Journal of Systems Assurance Engineering and Management*, vol. 7, pp. 16–25, 2016.
- [37] D. N. Chen and C. Y. Yao, "Hyper-ellipsoidal Bayesian network and its sensitivity method for system reliability evaluation," *China Mechanical Engineering*, vol. 26, no. 4, pp. 529–552, 2015.
- [38] W. Qiao, Y. Liu, X. Ma, and Y. Liu, "Human factors analysis for maritime accidents based on a dynamic fuzzy bayesian network," *Risk Analysis*, vol. 40, no. 5, pp. 957–980, 2020.
- [39] S. Q. Zhao, H. W. Wang, and D. C. Cheng, "Power distribution system reliability evaluation by D-S evidence inference and bayesian network method," in *Proceedings of the 2010 IEEE 11th International Conference on Probabilistic Methods Applied to Power Systems*, Singapore, June 2010.
- [40] B. Suo, C. Zeng, and Y. S. Chen, "Reliability analysis method combining evidence theory and Bayesian network," *System Engineering and Electronic Technology*, vol. 33, no. 10, pp. 2343–2347, 2011.
- [41] D. N. Chen, H. S. Li, and C. Y. Yao, "Reliability analysis of hydraulic drive system based on evidence theory and Bayesian network," *Hydraulic and Pneumatic*, vol. 4, pp. 8–14, 2017.
- [42] G. Y. Liu and C. Y. Zhang, "Reliability analysis of improved bayesian network hydraulic system based on evidence theory," *Machine Tool and Hydraulics Hydromechatronics Engineering*, vol. 47, no. 24, pp. 17–23, 2019.
- [43] Y. Pan, L. M. Zhang, Z. W. Li, and L. Y. Ding, "Improved fuzzy bayesian network-based risk analysis with interval-valued fuzzy sets and D-S evidence theory," *IEEE Transactions on Fuzzy Systems*, vol. 99, pp. 1–14, 2019.
- [44] D. Y. Li, H. J. Meng, and X. M. Shi, "Affiliated cloud and affiliated cloud generator," *Computer Research and Development*, vol. 32, no. 6, pp. 15–20, 1995.

- [45] D. Y. Li and C. Y. Liu, "On the universality of the normal cloud model," *Chinese Engineering Science*, vol. 6, no. 8, pp. 28–33, 2004.
- [46] D. Y. Li and Y. Du, *Uncertainty Artificial Intelligence*, National Defense Industry Press, Beijing, China, 2005.
- [47] K. N. Fleming, "A reliability model for common cause failures in redundant safety systems," in *Proceedings of the 6th Annual Pittsburgh Conference on Modeling and Simulation*, Pittsburgh, USA, August 1975.
- [48] J. K. Vaurio, "Availability of redundant safety systems with common-mode and undetected failures," *Nuclear Engineering and Design*, vol. 58, no. 3, pp. 415–424, 1980.
- [49] K. N. Fleming, A. Mosleh, and A. P. Kelley, "On the analysis of dependent failures in risk assessment and reliability evaluation," *Nuclear Safety*, vol. 24, no. 5, pp. 637–657, 1983.
- [50] A. Mosleh and N. O. Siu, "A multi-parameter event-based common-cause failure model," in *Proceedings of the 9th International Conference on Structural Mechanics in Reactor Technology*, Lausanne, Switzerland, August 1987.
- [51] X. Jin, Y. J. Hong, and H. M. Du, *Reliability Analysis Method of Common Cause Failure System*, National Defense Industry Press, Beijing, China, 2008.
- [52] X. W. Yin, W. X. Qian, and L. Y. Xie, "A common cause failure model of system reliability based on bayesian network," *Journal of Mechanical Engineering*, vol. 20, no. 1, pp. 90–94, 2009.
- [53] J. H. Mi, Y. F. Li, H. Z. Huang et al., "Reliability analysis of multi-state system with common cause failure based on Bayesian networks," *Maintenance and Reliability*, vol. 15, no. no. 2, pp. 169–175, 2013.
- [54] A. O. Connor and A. Mosleh, "A general cause based methodology for analysis of common cause and dependent failures in system risk and reliability assessments," *Reliability Engineering and System Safety*, vol. 145, pp. 341–350, 2015.
- [55] Z. Q. Li, Y. X. Xu, J. An et al., "Dynamic bayesian network modeling of common cause failure of redundant system," *Journal of Instrumentation*, vol. 39, no. 3, pp. 190–198, 2018.
- [56] Y. K. Gu, Y. J. Shen, Q. X. Zhang et al., "Reliability analysis of multi-state common cause failure system based on bayesian network," *Mechanical Design and Research*, vol. 34, no. 2, pp. 1–9, 2018.
- [57] J. Mi, Y.-F. Li, W. Peng, and H.-Z. Huang, "Reliability analysis of complex multi-state system with common cause failure based on evidential networks," *Reliability Engineering and System Safety*, vol. 174, no. 6, pp. 71–81, 2018.
- [58] C. Y. Liu, M. Feng, X. J. Dai et al., "A new algorithm of backward cloud," *Journal of System Simulation*, vol. 16, no. 11, pp. 2417–2410, 2004.
- [59] C. Zhang, Q. Shi, and T. L. Liu, "Application of cloud center of gravity evaluation method in target damage effect evaluation," *Computer Simulation*, vol. 29, no. 9, pp. 28–31, 2012.
- [60] J. Z. Jia, Z. Li, P. Jia, and Z. G. Yang, "Reliability analysis of common cause failure multistate system based on CUGF," *Mathematical Problems in Engineering*, 2020.
- [61] Y. Y. Zhang, B. C. Li, and J. W. Cui, *Computer Science*, vol. 40, no. 10, pp. 127–131, 2013.
- [62] J. Borcsok, S. Schaefer, and E. Ugljesa, "Estimation and evaluation of common cause failures," in *Proceedings of the Second International Conference on Systems(ICONS'07)*, vol. 41, pp. 22–28, Martinique, France, April 2007.