

Research Article

Evaluation of Resilience of Battle Damage Equipment Based on BN-Cloud Model

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In order to solve the problem of a lack of supportive means for evaluating the resilience of battle damage equipment, a Bayesian network cloud model is proposed to evaluate the resilience of battle damage equipment. The equipment functional features are analyzed to establish the equipment functional state evaluation model. Moreover, the samples of Bayesian network parameters training are obtained by inserting the results of battle damage simulation into the functional evaluation model. The simulation flow of parts state recovery probability is designed to determine the relationship between parts' functional state and time. Based on the cloud model, the transformation model of functional state level probability to functional index is established. Hence, the equipment functional state level probability obtained by Bayesian network reasoning is transformed into a functional index and the transformation from uncertainty to certainty is realized. Considering self-propelled artillery as the object of resilience evaluation, the results of numerical examples show that by this method, the problem of equipment resilience evaluation can be effectively solved, and more information can be obtained by the accurate representation method compared to the traditional Bayesian network probabilistic evaluation results. This is greatly significant to the wartime maintenance support decision.

1. Introduction

The evaluation of the resilience of battle damage equipment refers to evaluating the capability of the equipment to recover the specified functions after being damaged by a specific threat under specific battlefield conditions. The key to assess the resilience of battle damage equipment is to determine the relationship between recovery status and recovery time. In the previous researches on equipment damage assessment, the damage degree of equipment after hitting is assessed mainly reflecting the state of equipment not recovered after hitting. At present, the recovery time evaluation research is mainly the equipment state classified into two intact and damaged discrete states determining the recovery time probability curve of the equipment form damage to good condition. However, this does not reflect the function of the equipment characteristics of diversity. Therefore, it is necessary to study the relationship between the functional state of the equipment and the recovery time.

In the assessment of equipment resilience, it is essential to consider the effects of equipment damage, support resources, environment, combat mission, and human subjective. Compared with the assessment of equipment damage status and recovery time, the randomness is stronger with a more complex assessment. Regarding the evaluation of functional status and recovery time, the studies [1–5] used cloud model to evaluate the status of equipment considering the fuzziness and randomness of data. In the literature [6–9], the status of equipment was evaluated by combining fuzzy theory with analytic hierarchy process and other methods. Although these two methods can take into account the fuzziness and uncertainty of the functional state of damaged equipment, it is difficult to take into account the changing relationship of the functional state of equipment with time. In the studies [10–12], the damage state of equipment is determined by damage mode effect analysis (DMEA) and damage tree analysis. The assessment result is accurate and can be closely related to the reality; however, it cannot be

accurately quantified; hence, it is difficult to judge the state change with time. In other studies [13–17], based on Markov model, the discrete states of components are analyzed and then mapped to the system level, so as to obtain the state evaluation results of the system. This model has a great advantage in showing the correlation between time and state; however, when existing more parts, there is the problem of state space explosion [18]. The study in [19–22] obtained the maintenance time distribution of equipment by collecting the maintenance time data of equipment through mathematical statistics. This method needs a large amount of equipment repair time data to support; however, at present, our team encounters the problem of lacking the recovery time data of war-wounded equipment. The study in [23–27] uses Bayesian network to determine the state of the system, which can deal with uncertainty and timing problems. Simultaneously, the obtained information is the evidence to update the model in real time. Although the assessment results are more accurate and reliable, the time-invariant hypothesis and the Markov hypothesis must be satisfied. In addition, the evaluation results are expressed as the probability with great uncertainty and insufficient accuracy.

According to the above analysis, it is found that Bayesian network does not have the problem of state space explosion, and the model can be updated in real time, with strong operability. Therefore, it has more obvious advantages compared with other assessment methods to solve the problem of resilience assessment of complex equipment. Cloud model is a qualitative and quantitative uncertainty transformation model, which has certain advantages in dealing with the problems of randomness and fuzziness. Through this model, the state probabilistic uncertainty results obtained by Bayesian network can be accurately expressed to compensate the lack of accuracy of Bayesian network evaluation results. For this reason, this paper proposes a resilience evaluation method for battle damage equipment based on Bayesian network cloud model. Firstly, the functional states of parts and functional states of equipment are linked probabilistically by establishing Bayesian network. Then, the change process of the parts state probability with time is used as the prior information to update the functional state of the equipment, and the relationship between the functional state of the equipment and time is obtained. Finally, on the basis of the Bayesian network evaluation results, the transformation model from the probability to the function index of the equipment's functional status level is established using the cloud model theory to achieve the accuracy of the evaluation results.

The main contribution of this paper is embodied in the following three aspects. First, in previous studies, the dynamic change process of equipment function state with recovery time was not included, while it was studied in this paper. Secondly, a recovery capability assessment method of Bayesian network cloud model is proposed. Compared with Markov, DMEA, and damage tree methods, this combination method does not have the problem of state space explosion, and the model can be updated in real time. In comparison to the mathematical statistics method, this

method requires less data and the evaluation result is more accurate. The proposed method has few assumptions and overcomes the problem of large uncertainty of Bayesian network evaluation results. Third, in the traditional Bayesian network state evaluation research, the conditional probability is often determined according to experience; this method has a large error. The simulation method proposed in this paper makes up for this defect and makes the evaluation result more accurate.

In the first section, the research status of equipment damage status assessment and recovery time are introduced. In the second section, the basic theories of Bayesian network and cloud model are described. In the third section, a combination of Bayesian network and cloud model is used to define the assessment steps of the resilience of battle damage equipment, and three key problems are analyzed in detail. In the fourth section, self-propelled artillery is used as the recovery capability evaluation object, and the method proposed in this paper is applied. The result shows that this method is reasonable. The fifth section deals with the research conclusion.

2. Basic Theory of Bayesian Network and Cloud Model

2.1. Bayesian Network Model. Bayesian network is an uncertain knowledge representation and inference model as a graphical network based on probabilistic inference. The Bayesian network model can be expressed as $B(G, P)$. As shown in Figure 1, G represents a directed acyclic graph structure composed of multiple nodes. Each node X in the graph represents a variable, and the directed arcs between nodes reflect the dependencies between variables. P represents the conditional probability associated with each node and represents the probabilistic dependence among variables in a quantitative way.

Based on the direction of reasoning, the Bayesian network is classified into three main inference modes of causal reasoning, diagnostic reasoning, and explanatory reasoning [28]. The causal reasoning also known as top-down reasoning is a positive reasoning process starting from prior probability. Diagnostic reasoning is bottom-up reasoning probably leading to the conclusion on the premise of a known conclusion. Explanatory reasoning can be summarized as the use of causal reasoning in diagnostic reasoning. However, regardless of the type of reasoning mode, its reasoning is oriented by the Bayes formula. One has

$$p(x|l) = \frac{p(l|x)p(x)}{\sum_x p(l|x)p(x)}, \quad (1)$$

where $p(x|l)$ is the posterior probability of the variable x after obtaining the evidence information l , $p(l|x)$ shows the likelihood function, and $p(x)$ represents the prior probability of the variable.

To establish a complete Bayesian network, two kinds of parameters need to be determined, namely, the distribution of initial state $P(X_0)$ and the distribution of observation conditions $P(X_i | \pi(X_i))$. $\pi(X_i)$ represents the parent of X_i .

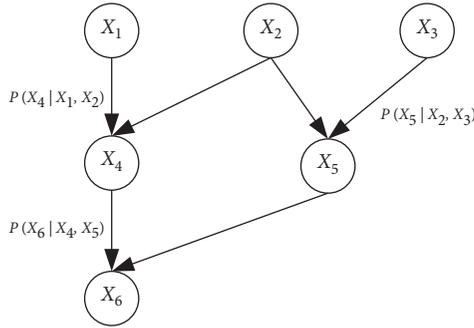


FIGURE 1: Bayesian network.

After determining the parameters, the Bayesian update can be carried out according to the evidence information.

2.2. Cloud Model. The cloud model is a qualitative and quantitative uncertainty transformation model proposed based on the traditional fuzzy set theory and probability statistics. Its definition can be expressed as follows. Let U be a quantitative domain expressed numerically. C is the qualitative concept in this quantitative domain U . Let the quantitative value $x \in U$ be a random implementation of the qualitative concept C , and the certainty degree $\mu(x) \in [0, 1]$ of x to C is a random number with stable tendency: $\mu: U \rightarrow [0, 1], \forall x \in U, x \rightarrow \mu(x)$; then the distribution of x in the concept U is called the cloud, denoted as the cloud $C(x)$. Each x is called a cloud drop and is represented as drop $(x, \mu(x))$. A cloud is composed of numerous cloud droplets. A cloud droplet is a transformation from a qualitative concept to a quantitative value.

Cloud $C(x)$ is represented by expectation Ex , entropy En , and hypertrophy He . The expectation Ex represents the point where cloud droplets represent qualitative concepts in the domain space. It is a typical sample of concept quantification and the most representative numerical feature. On the one hand, the randomness of the qualitative concept is measured by entropy En and the degree of cloud drop dispersion of the qualitative concept is reflected. On the other hand, the fuzziness of qualitative concepts is measured and the value range of cloud drop accepted by the concept can be reflected. Hypertrophy He is the uncertainty measure of entropy, which is determined by the uncertainty and fuzziness of entropy En . A normal cloud model of expectation $Ex = 20$, entropy $En = 2$, and hyperentropy $He = 0.4$ is represented in Figure 2. The universality of normal distribution and normal membership function jointly lays the foundation for the universality of the normal cloud mode [4].

2.3. Cloud Generator Algorithm Implementation. Two key algorithms in the cloud model are forward cloud generator and reverse cloud generator. Through the forward cloud generator, the range and distribution law of the quantitative data can be obtained from the qualitative information, which is the forward mapping from qualitative to quantitative. A certain number of precise values can be converted by the

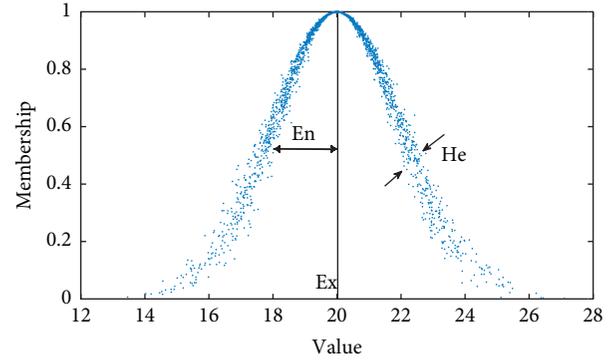


FIGURE 2: Normal cloud model.

reverse cloud generator effectively into proper qualitative language values as a reverse mapping from quantitative to qualitative values. The qualitative concept is mainly transformed by this appropriate mode into quantitative value. Algorithm 1 is described as follows [3].

3. Description of the Equipment Resilience Evaluation Method

Regarding the strong reasoning ability of the Bayesian network model in processing uncertain information and the transformation ability of the cloud model between qualitative concept and quantitative value, a Bayesian network cloud (BN-cloud) model is proposed in this paper to solve the problem of evaluating the resilience of battle damage equipment. The basic steps are as follows [7]:

Step 1: according to the equipment functional structure model, the corresponding network node variables and the Bayesian network topology diagram are determined.

Step 2: based on the battlefield environment, equipment characteristics and sources of threat and other pieces of information are obtained through the battle damage simulation platform to damage simulation of equipment, function state, and damage probability of the equipment parts. To attain the equipment discrete state training samples, the parts functional state data obtained from each simulation are inserted into the equipment functional state evaluation model. Then, it is trained by the parameter learning algorithm of the Bayesian network to obtain the conditional probability distribution of each node.

Step 3: based on the probability density function of parts' emergency repair time and the damage probability of parts, the state probability information of parts at each moment is predicted. Then, they are inserted into the Bayesian network model as evidence information to obtain the state probability of equipment at each moment.

Step 4: the transformation model of function state level probability is established to function index based on the cloud model and obtain the relationship of function

index of equipment with time to solve the problem of insufficient accuracy of Bayesian network.

Step 5: if the available information is obtained during the actual repair process, the parts state probability can be updated by adjusting the parts emergency repair parameters, and then it can be reentered into the Bayesian network model as evidence information for reasoning to obtain the updated equipment functional state evaluation result.

Figure 3 represents the overall process. Generally, three problems exist in evaluating the resilience: first, the conditional probability determination of Bayesian network nodes, second, determination of part state recovery probability, and third, establishing the transition model from the probability of functional state level to the functional index based on the cloud model.

3.1. Determination of Conditional Probability of Bayesian Network Nodes. The parameter learning of Bayesian network requires numerous samples, and through random experiment and simulation, a large number of relatively accurate battle damage data can be obtained using Monte Carlo simulation method. Since numerous discrete state samples are required for parameter learning in this paper, the damage data is processed within this work by establishing a functional state evaluation model, to obtain a complete and reliable parameter learning sample of the Bayesian network. The methods to determine the conditional probability of Bayesian network nodes are as follows:

- (1) The equipment function block diagram is drawn according to the equipment structure. Then, in combination with the current task, the importance ranking of each element in the equipment functional block diagram is determined according to the expert opinion. Table 1 represents the judging standard. p_{ij} represents the relationship of importance between elements, and a_i shows the elements in the block diagram.
- (2) The index judgment matrix $R_w = (r_{ij})_{q \times q}$ is obtained according to the importance degree of elements and the criterion of judgment scale, where

$$\left\{ \begin{array}{l} r_{ij} = \frac{(r_i - r_j)}{[2(n-1)]} + 0.5, \\ r_i \sum_{t=1}^q p_{it}, \\ r_j \sum_{t=1}^q p_{jt}. \end{array} \right. \quad (2)$$

- (3) Normalize the column vectors of the matrix R_w , and then calculate the average of the sum of the rows to obtain the combined weight value $\omega = \{\omega_{F_1}, \dots, \omega_{F_k}, \omega_{m_1}, \dots, \omega_{m_d}\}$ of each element relative to the target.

- (4) Obtain the damage probability λ_k of each part and the function index of the damaged part v_k based on the battlefield information to simulate the equipment in the battle damage simulation system. One has

$$\lambda_k = \frac{N_k}{Ns}, \quad (3)$$

where Ns shows the simulation times; N_k is the number of times the hit k th part.

The function index of parts is calculated as follows:

$$b_f = \begin{cases} 0, & h_{f_i} < h_1, \\ \frac{h_{f_i} - h_1}{N(h_c - h_1)}, & h_1 \leq h_{f_i} < h_c, \\ 1, & h_{f_i} \geq h_c, \end{cases} \quad (4)$$

$$v_k = \prod_i^s (1 - b_{f_i}),$$

where b_{f_i} shows the damage probability of a single fragment f to the part. h_f is the penetration depth of the fragment to the part. When the penetration depth h_f is less than a certain threshold h_1 , the function of the part is basically unaffected. When the penetration depth is greater than h_1 and less than the thickness of the part h_c , the damage degree of the part is a linear function of the penetration depth. When the penetration depth is greater than h_c , the impact of fragments on the function of parts reaches the maximum. v_k represents the functional index of the damaged part. s shows the number of fragments hit on the part.

- (5) The functional damage information of each part obtained in each simulation is inserted into the functional evaluation model, and the equipment is evaluated based on the weight value obtained in step (3). When solving the functional exponential for the parts in parallel relation, the weighted summation method is used, and the power exponential method is utilized when solving the functional exponential for the parts in series relation [29]. The function index of each level element ($v_w, v_{F_1}, \dots, v_{M_d}$) is calculated, and the function state level of each element of equipment is determined according to the function level classification standard; therefore, the state vector of elements ($S_w, S_{F_1}, \dots, S_{M_d}$) is obtained.
- (6) The obtained state vectors of each element are taken as training samples, and the parameter learning algorithm in the Bayesian network is used to train the samples and obtain the conditional probability of each node.

3.2. Recovery Probability Determination of Parts State.

The recovery probability of parts state is determined as the probability that the part is in good or lost state at any time. The recovery probability of parts at any time is affected by

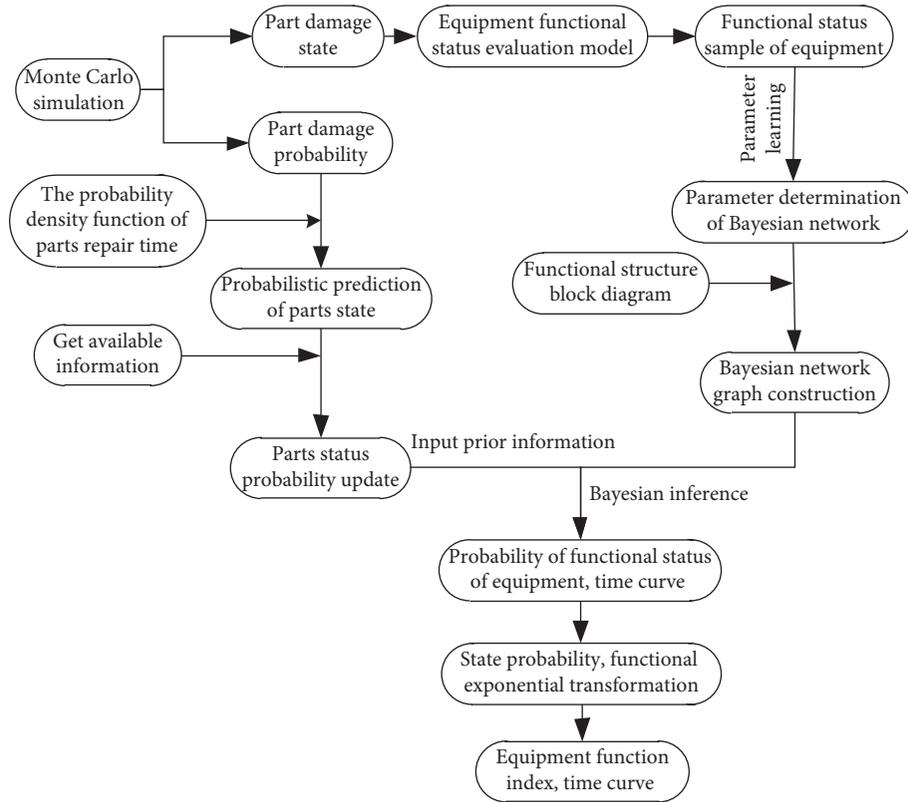


FIGURE 3: Procedure for evaluating the resilience of battle damage equipment.

Input: three numerical characteristics representing qualitative concept Q expectation Ex , entropy En , hyperentropy He , and cloud drop number N
 Output: the quantitative value x of N cloud droplets and the certainty degree y that the qualitative concept Q represented by each cloud droplet

- (1) Generate a normal random number $En1$ with En as expectation and He as a standard deviation
- (2) Generate a normal random number x with expectation $En1$ and standard deviation Ex
- (3) Calculate the certainty degree $y = \exp(-(x - Ex)^2 / 2(En1)^2)$ corresponding to x
- (4) Repeat steps (1)~(3) N times to obtain the normal cloud model composed of N random cloud droplets (x, y)

ALGORITHM 1: Forward cloud generator.

resources, personnel, equipment damage result, equipment structure, and mission requirements. When determining the probability, it is necessary to take the distribution function of the parts' emergency repair time as the basis, take the waiting time before the parts' emergency repair and the repair time of the parts into comprehensive consideration, and judge the change process of the probability of the parts' intact or lost state with time. The time consumed by damage assessment and resource preparation before the emergency repair is t_d . Then, the probability that the part i function is intact at the time of t can be expressed as

$$\begin{aligned}
 T_i &= t_d + \sum_{j \in \Omega_i} t_j \\
 P_i(t) &= P_i(T_i + t_i \leq t, \text{repairable parts damage}) \\
 &\quad + P_i(\text{parts not damaged}) \\
 &= 1 - \lambda_i + \lambda_i \eta_i P_i(T_i + t_i \leq t),
 \end{aligned} \tag{5}$$

where Ω_i represents the set of parts with higher priority than i . t_j represents the repair time of the part j . T_i represents the time from the start of equipment repair to the start of the part i repair. $P_i(t)$ represents the probability that the part i is in good condition at the time t . t_i represents the time of

emergency repair of the part i . η_i is the probability that parts i can be repaired after being damaged. λ_i is the part i damage probability. $P_i(T_i + t_i \leq t)$ represents the probability that the repair time of the part i is less than t , when the part i is damaged and repairable.

Considering the complexity of the analytical calculation of $P_i(t)$, the simulation method is adopted for calculation, for which the recovery probability simulation process of the part state is shown in Figure 4.

The specific implementation steps are as follows:

- (1) The probability density function of part repair time $f_k(t)$, part repairable probability λ_k , number of parts m , and priority of parts repair are obtained. The total number of simulation runs is Ns , and the serial number of simulation runs is j , so $j = 1, 2, \dots, Ns$.
- (2) Sort the parts from high priority to low priority and get the new parts sort label.
- (3) According to the probability density function of parts emergency repair time, parts emergency repair time data group $T_m = (t_1, t_2, \dots, t_m)$ is generated.
- (4) Generate random numbers x and h that are uniformly distributed $[0, 1]$.
- (5) For each part in Ω_i , judge whether it is $x \leq \lambda_k$ or not. If it is not true, it is considered that the part k is not damaged; then let $t_k = 0$. Rather, the part k is considered damaged, and the continued damaged parts are judged. If $h \leq \eta_k$ is established, the part is considered repairable. If not, the part is considered unreparable; then let $t_k = 0$, which is ordered to prevent the impact of the repair time of the estimated parts. Update the data group T_m .
- (6) Calculate the recovery time $Z(j)$ under the repairable condition, when the i th part is damaged in the j th simulation. One has

$$Z(j) = \text{sum}(T(1:i-1)) + t_i + t_d. \quad (6)$$

- (7) To see whether $0 < Z(j) \leq t$ is true, it is believed that, in the j th simulation, the part i can be repaired at the time t under the damaged and repairable condition; then, let $n_i = n_i + 1$. If it is not true, it is believed that the damaged part i in this simulation cannot be repaired within time t ; let $n_i = n_i$.
- (8) Repeat steps (3~7) for a total of Ns times, and calculate the probability $p_i(t)$ that the part i is in good condition at the time t . One has

$$p_i(t) = \lambda_i \eta_i \frac{n_i}{Ns} + 1 - \lambda_i. \quad (7)$$

Obtaining some available information in practical application, such as the complete recovery of communication function or basic recovery of motor function at t_0 moment, it is used as evidence to conduct Bayesian diagnostic reasoning to obtain the $P_{ip}(t_0)$ of part recovery probability after

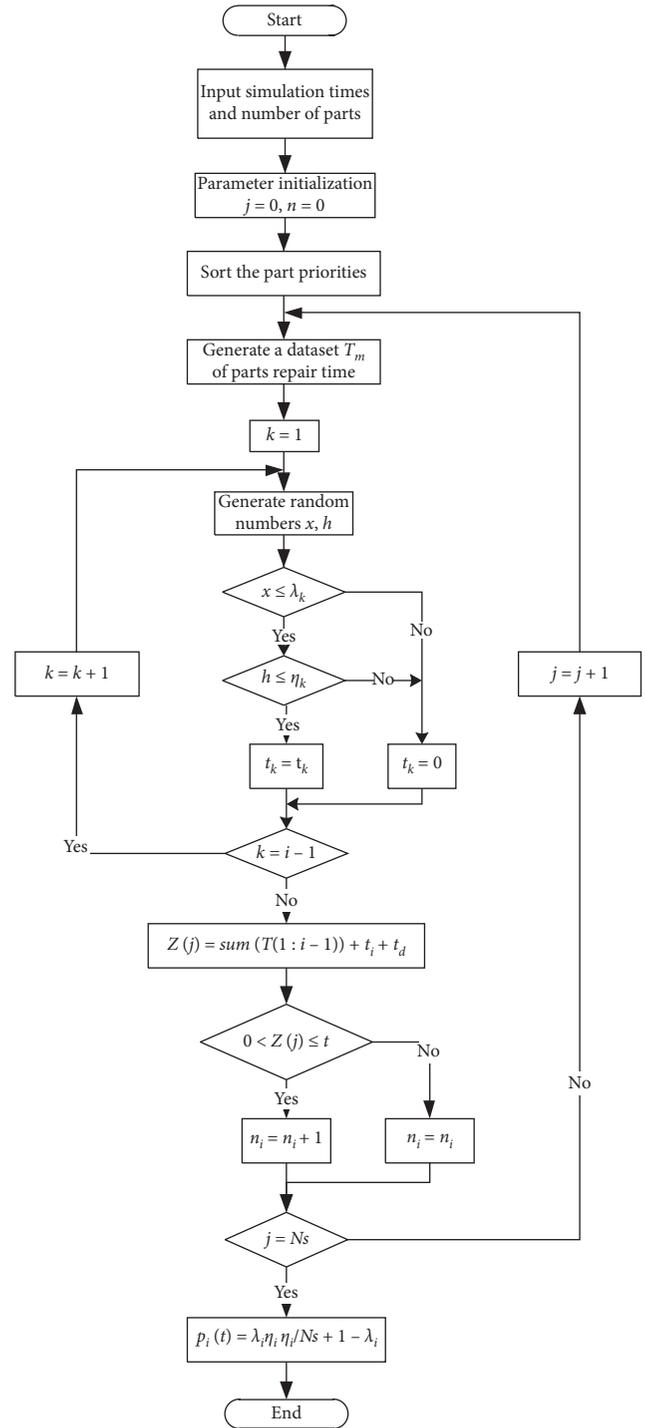


FIGURE 4: The recovery probability simulation flowchart of parts state.

reasoning. Then, based on the recovery probability $P_{ip}(t_0)$ of the part, the recovery parameters of the part are modified to meet the condition, where the recovery probability of the part is $P_{ip}(t_0)$ at t_0 moment.

Changing the parameters such as the repairable probability, the probability density function of the repair time and the damage probability of the part will result in changing the part state recovery probability. When updating the part

parameters, the parameter with the greatest possibility of change can be rationally adjusted according to the changes before and after the probability. If the adjustment of this parameter cannot support the result, the next probably changing parameter can be selected for analysis until the part probability meets the requirements. After obtaining the changed parameters, the state probability of the part at each moment is simulated again accordingly, and the probability information is inserted into the Bayesian network model; finally, the updated evaluation result of the equipment's functional state is obtained.

3.3. Establishment of the Transition Model from Functional State Level Probability to Functional Index Based on the Cloud Model. The transformation from the functional state level probability to the functional index mainly includes the transformation from the functional state level to the cloud model and the transformation from the state level probability to the functional index. The transformation from the functional state level to the cloud model aims at quantifying the qualitative language of the equipment functional state by using the three digital features (Ex, En, He) of the cloud model, which is the foundation of the transformation model of the equipment functional state level probability to functional index. Let U be the theory domain of equipment function state, and $U = [0, 1], U_1, U_2, \dots, U_k$ is the division of the theory domain U , which shall meet the following requirements: (1) $\cup_{i=1}^k U_i = U$; (2) $\cap_{i=1}^k U_i = \emptyset$; (3) $\forall u_i \in U_i, \forall u_j \in U_j$. If $i < j$, $u_i < u_j$. Let W_1, W_2, \dots, W_k be the qualitative language of equipment's functional state level, $\forall W_i, u_{W_i}(w)$ represent the degree of certainty of w with respect to W_i , and $u_{W_i}(w) \in [0, 1]$. The distribution of w over W_i is called state level cloud C_{W_i} , each w is a cloud droplet, represented by $\text{drop}(w, \mu_{W_i}(w))$, and the value of w represents the equipment function index in this article.

According to the classification criteria of functional damage in [30] as well as expert opinions, this paper divides the overall functional status of equipment into three grades: functional intact (FI), functional weakened (FW), and functional lost (FL). The evaluation criteria are shown in Table 2. For parts, the evaluation method of equipment resilience is based on the probability density function of parts' emergency repair time. In this paper, the functional status of parts is divided into two grades of functional intact (FI) and functional loss (FL). Due to the great differences in the structure and tasks undertaken by the parts, the functional classification criteria of the parts are different. In practical application, the specific analysis should be made according to the characteristics of parts and the undertaken tasks.

By using the transformation relation between interval number and cloud model, the interval of equipment function state is transformed into the cloud model. If a function index interval is $[a_i, a_j] | 0 < a_i < a_j < 1$, then the characteristic parameters of the cloud model can be determined according to the index approximation method:

$$\begin{cases} \text{Ex} = \frac{(a_i + a_j)}{2}, \\ \text{En} = \frac{(a_j - a_i)}{6}, \\ \text{He} = 0.15\text{En}. \end{cases} \quad (8)$$

When the function index interval is $[0, a_i]$, since the ideal function index is 0, $\text{Ex} = 0$ and $\text{En} = a_i/3$ are taken. When the function index interval is $(a_j, 1]$, since the ideal function index is 1, $\text{Ex} = 1$ and $\text{En} = (1 - a_j)/3$ are taken. Then, the three clouds in the functional state domain in this paper, respectively, represent the functional intact cloud $C_{FI}(1, 0.05, 0.0075)$, the functional weakened cloud $C_{FW}(0.4, 0.1, 0.015)$, and the functional lost cloud $C_{FL}(0, 0.0333, 0.005)$ (Figure 5). The blue image represents functional loss cloud C_{FL} , the red image represents functional weakening cloud C_{FW} , and the yellow image represents a functional intact cloud C_{FI} .

The purpose of this model is to convert the probabilistic value of the equipment function state obtained by Bayesian network reasoning into the accurate description value of the function state. In the cloud model, the closer the membership degree to 1, the higher the degree that the functional index x belongs to C_W ; the closer the membership degree to 0, the lower the degree that the functional index x belongs to C_W . The established transformation model is as follows:

$$\begin{cases} u_i = \sum_{i=1}^k p_{W_i} w_i, \\ w_i = \text{Ex}(i) + \sqrt{-2(\text{En}1(i))^2 \ln(p_{W_i})}, & \text{if } p_{W_1} \geq p_{W_3} \text{ or } i = 3, \\ w_i = \text{Ex}(i) - \sqrt{-2(\text{En}1(i))^2 \ln(p_{W_i})}, & \text{if } p_{W_1} < p_{W_3} \text{ or } i = 1, \end{cases} \quad (9)$$

where u_i represents the equipment function index, p_{W_i} represents the probability that the device is in the i th functional state class, and w_i represents the function index of an item at the i th functional status level.

4. Analysis of Examples

A type of self-propelled artillery is taken for the resilience evaluation. Figure 6 illustrates the functional state diagram of this self-propelled artillery [6]. The equipment functional state diagram should contain all the functions of the equipment and all the key parts related to the equipment functions. However, considering the complexity of the self-propelled artillery equipment system, this paper simplifies the description of self-propelled artillery equipment system, divides the function of self-propelled artillery into firepower function, maneuvering function, protection function, and communication function, and takes the key part of the function as the three-level indicator.

TABLE 1: Criteria for judging the importance.

P_{ij}	Criteria instructions
0.5	The element a_i has the same importance as a_j
0.6	Element a_i is one level higher than the element a_j
0.7	Element a_i is two levels higher than the element a_j
0.8	Element a_i is three levels higher than the element a_j
0.9	Element a_i is four levels higher than the element a_j
0.1, 0.2, 0.3, 0.4	The results of the reverse comparison and positive comparison are complementary

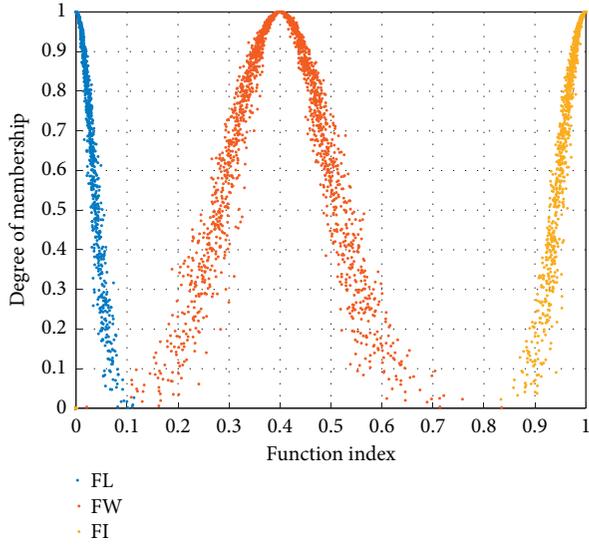


FIGURE 5: The cloud model of equipment functional state level.

In the battle damage simulation platform, the equipment and threat model are inserted, Monte Carlo simulation is conducted, each simulation result is inserted into the functional state evaluation model, and the functional index of the equipment is calculated. In the evaluation model, according to the functional characteristics of self-propelled artillery, the functional index relationship of each node can be described by the following formula:

$$\begin{cases} F_W = \omega_{F_1} F_{F_1} \times \omega_{F_2} F_{F_2} \times \omega_{F_3} F_{F_3} \times \omega_{F_4} F_{F_4}, \\ F_{F_1} = F_{M_1}^{\omega_{M_1}} \times F_{M_2}^{\omega_{M_2}} \times F_{M_3}^{\omega_{M_3}}, \\ F_{F_2} = F_{M_4}^{\omega_{M_4}} \times F_{M_5}^{\omega_{M_5}} \times F_{M_6}^{\omega_{M_6}}, \\ F_{F_3} = \omega_{M_7} F_{M_7} + \omega_{M_8} F_{M_8} + \omega_{M_9} F_{M_9} + \omega_{M_{10}} F_{M_{10}}, \\ F_{F_4} = \omega_{M_{11}} F_{M_{11}} + \omega_{M_{12}} F_{M_{12}} + \omega_{M_{13}} F_{M_{13}}, \end{cases} \quad (10)$$

where F_G represents the function index of the node $G \in \{W, F_1, F_2, \dots, M_{12}, M_{13}\}$ and ω_G represents the weight of the node G .

The elements in the functional state diagram of this type of self-propelled artillery are set as the nodes in the Bayesian network, and the discrete state of each node is given at the same time. The part layer is divided into two status grades of functional integrity (FI) and functional loss (FL), and the equipment's integrated function and subfunction are divided into three status grades of functional integrity (FI), functional weakened (FW), and

functional loss (FL). Then, according to the interlayer relationship of each element and the upper and lower relationships, Netica software is used to establish the directed acyclic graph of the static Bayesian network, as shown in Figure 7.

Based on the establishment of the Bayesian network topology, the state information of each node of the equipment obtained through the functional evaluation model is taken as the sample of parameter learning, and the EM algorithm in the parameter learning of Bayesian network is adopted to train it. The obtained conditional probability of each node is inserted into the Bayesian network topology diagram to obtain the complete Bayesian network structure diagram.

According to the previous emergency repair data and expert experience, the consumption time before the emergency repair of this type of self-propelled artillery is $t_d \approx 5$. The probability density function of emergency repair time and the repairable probability of each part under the current maintenance supportive condition are shown in Table 3. According to the probability calculation method of part state in Section 2.2, the probability value of the functional state of the part at t time can be calculated and input it as a prior probability into the Bayesian network model for Bayesian reasoning to obtain the probability value of some functional state of the equipment at t time. Let $\Delta t = 5$, with Δt being the time interval; list the variation trend of the probability value of each functional state rating of the equipment in $t = [0, 100]$, as shown in Figure 8.

To verify the usability of Bayesian model, three axioms proposed in literature [31] should be satisfied. At this point, the initial integrity probability of node M_1 is set from 0.553 to 0.653. The integrity probability of the system increased from 0.296 to 0.315. Continue to set the initial integrity probability of node M_2 from 0.761 to 0.861; then the system's integrity probability increases to 0.334. Continue to set the initial integrity probability of node M_3 from 0.833 to 0.933; then the system's integrity probability increases to 0.353. Then, improve the integrity probability of M_4 , M_5 , and M_6 by 0.1 and the system integrity probability to 0.353. It can be seen that the Bayesian model in this paper satisfies the three axioms of literature [31], and the usability of the model is verified.

If the moment $t = 20$, then the self-propelled artillery firepower function is in good condition; at this time through the Bayesian diagnosis reasoning, the state probability of M_1 , M_2 , and M_3 parts is changed. By the information on various aspects to analyze the data, the experts consider the

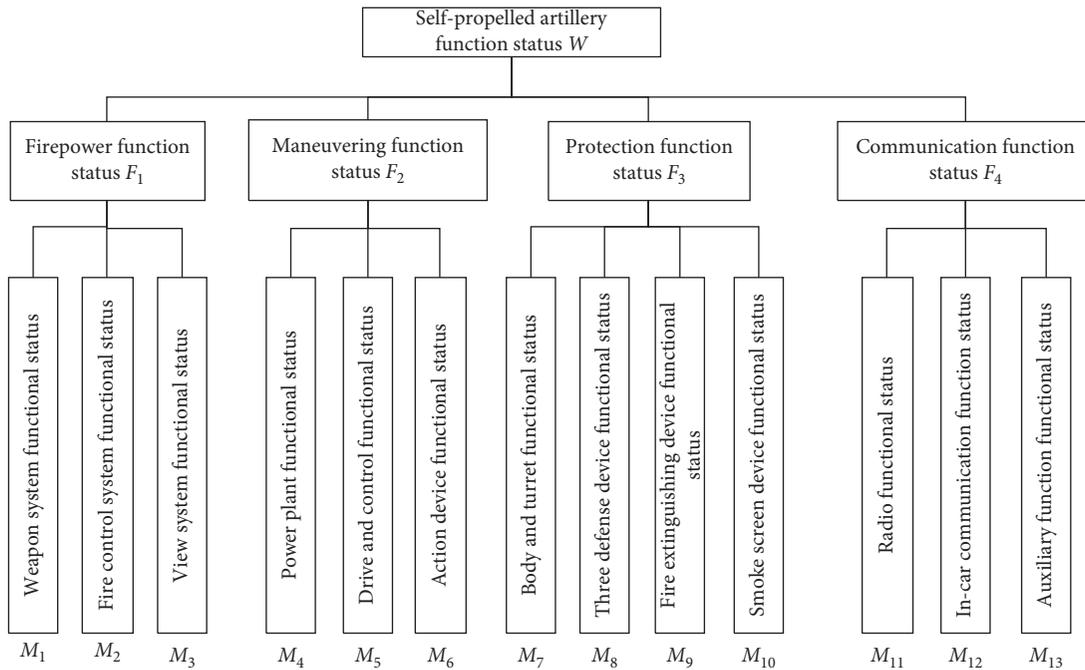


FIGURE 6: Functional state diagram of self-propelled artillery.

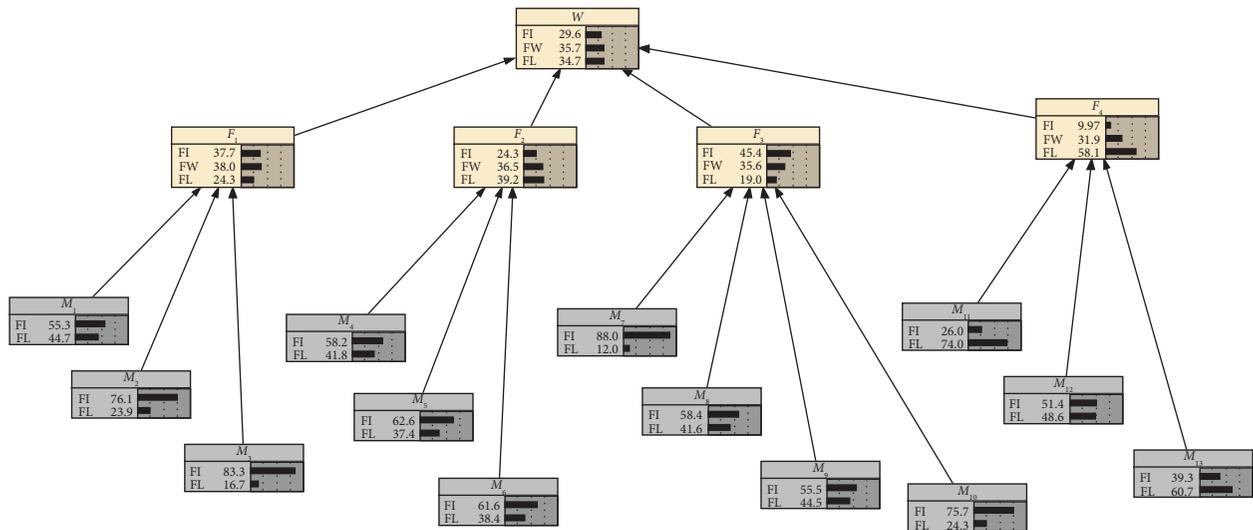


FIGURE 7: Bayesian network structure of self-propelled artillery.

TABLE 2: Classification criteria of equipment functional status.

State level	Functional exponential interval	Functional description
Functional intact	0.7~1.0	The completion of the intended function is barely affected
Functional weakened	0.1~0.7	The completion of the intended function is affected
Functional lost	0~0.1	The completion of the intended function cannot be completed

three-part repairable probability as most likely changed and the possibility of damage probability change as minimal. Then, the part parameter information is adjusted, and the

updated state level probability information of each part is shown in Table 4. The updated probability change curve of the equipment's functional state rating is shown in Figure 9.

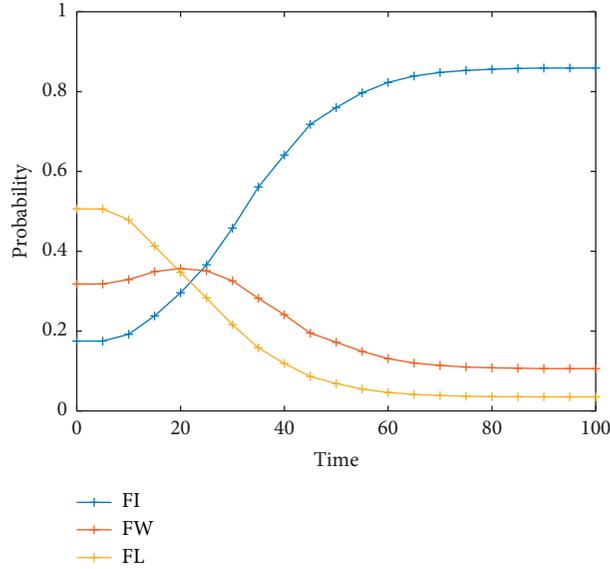


FIGURE 8: Probability change curve of functional state level.

TABLE 3: Emergency repair information table for each node element.

Functional level	Variable G	Damage probability λ	Weight value ω_G	Repairable probability η_G	Probability density function of emergency repair time $f_i(u)$
Self-propelled artillery W	F_1	—	0.3012	—	—
	F_2	—	0.2671	—	—
	F_3	—	0.1988	—	—
	F_4	—	0.2329	—	—
Firepower function F_1	M_1	0.559	0.4038	0.8	$U(10, 30)$
	M_2	0.464	0.2276	1	$N(8, 0.26)$
	M_3	0.359	0.3686	1	$E(6.5)$
Maneuvering function F_2	M_4	0.532	0.3668	0.56	$LN(1.8, 0.46)$
	M_5	0.458	0.3166	1	$U(6, 16)$
	M_6	0.502	0.3166	1	$E(5.5)$
Protection function F_3	M_7	0.128	0.3012	0.6	$N(2, 0.34)$
	M_8	0.436	0.1988	0.95	$LN(1.32, 0.25)$
	M_9	0.487	0.2671	1	$E(4)$
	M_{10}	0.251	0.2329	0.95	$U(4, 10)$
Communications functions F_4	M_{11}	0.889	0.3841	0.76	$N(3, 0.52)$
	M_{12}	0.557	0.3333	1	$N(5, 0.24)$
	M_{13}	0.648	0.2826	0.68	$LN(1.58, 0.43)$

According to Figures 8 and 9, it is indicated that, over a longer duration of the repair, the probability of equipment in functions integrity state (FI) decreases gradually in a state of function weakened (FW) state and function loss (FL) state probability. After obtaining the information of intact firepower function, the probability of the whole equipment in the intact function state increases, while the time of approaching steady state is shortened, and the evaluation result is reasonable. However, it is found that, within the period of 0–20 before and 0–30 after the update, the probability of the equipment in each functional state is making problems for evaluation decisions. Therefore, according to the transformation model of equipment function state rating probability to function index in Section 2.3, the obtained result is converted into quantitative form, and the curve shown in Figure 10 can be

obtained. The initial point of the function recovery curve represents the function index of the equipment after being hit reflecting the damage degree of the equipment. The slope of the curve represents the recovery rate of the function. Since the equipment adopts the strategy of repairing important parts before repairing minor parts in rush repair, the recovery rate of equipment function is large at the initial moment and gradually decreases with the extension of time. Moreover, it gradually decreases with the extension of time. The ultimate steady-state value reached by the curve represents the maximum function index that can be restored under the current guarantee conditions after the equipment is damaged.

As can be seen from Figure 10, with the extension of time, the function of the equipment gradually recovers the function weakened state (FW) to the function intact state

TABLE 4: Update information of component state probability.

Part number M_i	$P_i(20)$	$P_{ih}(20)$	Repairable probability η_i	Probability density function $f_i(t)$	Damage probability λ_i
1	0.5529	0.9494	1.00	$U(8, 16)$	0.406
2	0.7611	0.9953	1.00	$N(1, 0.14)$	0.046
3	0.8334	0.9945	1.00	$E(1.5)$	0.042
4	0.5821	0.6614	0.56	$LN(1.8, 0.46)$	0.532
5	0.6259	0.7378	1.00	$U(6, 16)$	0.458
6	0.6158	0.7139	1.00	$E(5.5)$	0.502
7	0.8800	0.8897	0.60	$N(2, 0.34)$	0.128
8	0.5836	0.6095	0.95	$LN(1.32, 0.25)$	0.436
9	0.5550	0.6029	1.00	$E(4)$	0.487
10	0.7568	0.7673	0.95	$U(4, 10)$	0.251
11	0.2598	0.3908	0.76	$N(3, 0.52)$	0.889
12	0.5136	0.5914	1.00	$N(5, 0.24)$	0.557
13	0.3929	0.4374	0.68	$LN(1.58, 0.43)$	0.648

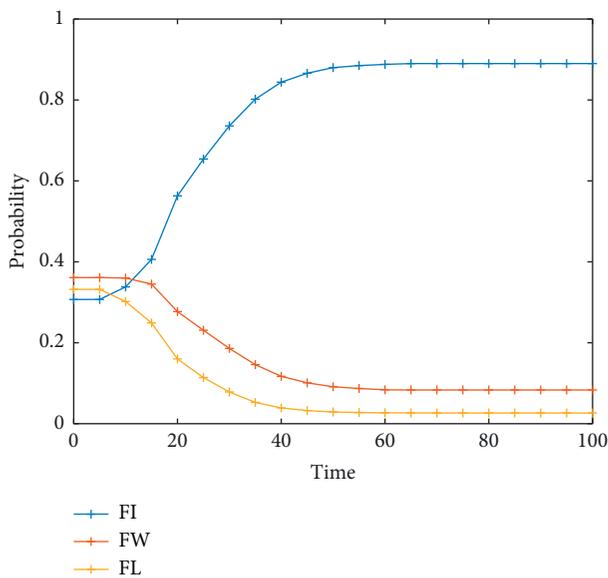


FIGURE 9: Probability change curve of the functional status level after updating.

(FI). Before obtaining the information of intact firepower function, the function index of the equipment is 0.2684 after being damaged, and the equipment function is seriously damaged; nevertheless, it is still in the state of function weakening (FW). Before $t = 5$, since the equipment is not officially started to repair, therefore, its function index is not changed. After $t = 35$, the functional state of the equipment changes from the function weakened state (FW) to the function intact state (FI), and at $t = 90$, the function index tends to be stable. However, due to the equipment damage, some parts are difficult to be repaired under the current supporting conditions; hence, the function cannot be fully restored and only be restored to 0.9032.

After updating the equipment function status, the initial function index of the equipment is 0.3906, which increased by 0.1222. At $t = 20$, the equipment functions are gradually recovered from the weakened state (FW) to the intact state (FI). It is about 15 min earlier than previously. The ultimate functional index limit for the device recovering is 0.9228,

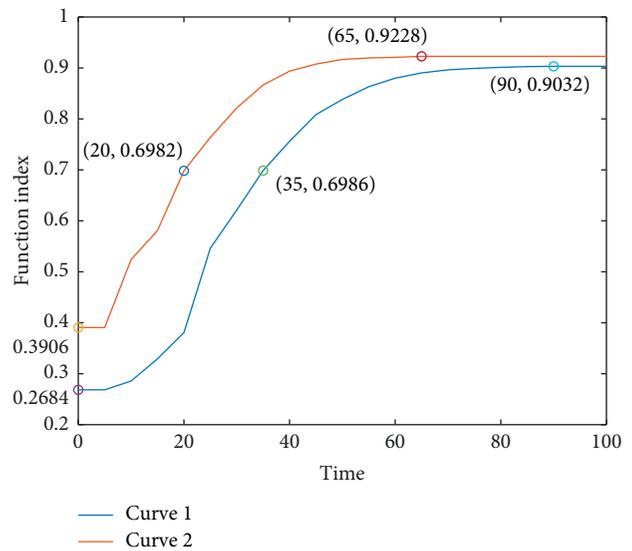


FIGURE 10: Functional index recovery curve. Curve 1 represents the functional recovery curve before the update, and curve 2 shows the functional recovery curve after the update.

which is 0.0196 higher than the original one, and the time of equipment recovering to a stable state is 25 min less than the original one.

Since the calculation of part state recovery probability is not an independent process, parts with a high priority will have a certain impact on the part state probability with low priority; therefore, when the obtained firepower function information is inserted as evidence, it will influence the part state recovery probability of maneuvering function, communication function, and protection function. For the convenience of analysis, the recovery curve of the equipment maneuvering function index is drawn as shown in Figure 11. As it is observed in Figure 11, after obtaining the intact information of the firepower function, the recovery time of the maneuvering function of the equipment is shortened, and the time to reach the steady state is shortened by about 25 min. Based on the evidence information observed before and after the input simultaneously, there is no translational change in the recovery curve of

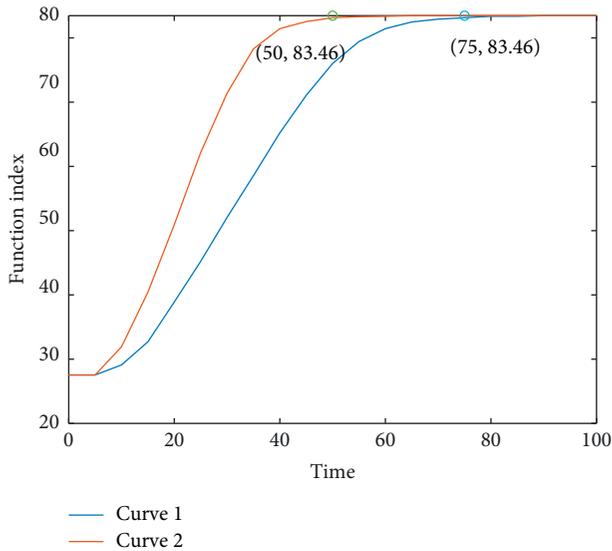


FIGURE 11: Recovery curve of maneuvering function. Curve 1 represents the maneuvering function index recovery before the update. Curve 2 represents the maneuvering function index recovery after the update.

equipment function index; nonetheless, the recovery curve still starts from $t = 5$ and gradually tends to the steady state since the function index in this paper is transformed based on the probability. Therefore, the changing process must be a continuous process from the beginning of equipment repair to a steady state.

5. Conclusion

This paper proposed a resilience evaluation method for battle damage equipment based on the BN-cloud model. The model completely represented the strong reasoning ability of the Bayesian network model in dealing with uncertain information. It also made use of the transformation ability of the cloud model between qualitative concepts and quantitative values to compensate for the nonaccuracy of Bayesian network reasoning results. The assessment results expressed more information and were more valuable for decision-making.

This paper proposed a method to generate training samples using battle damage simulation and equipment functional state modeling compensating the lack of data support in the parameter learning of Bayesian network for battle damage equipment.

The proposed simulation method for calculating the recovery probability of parts could be used as the input of prior information of the Bayesian network; in addition, it could update the probability information of functional states of parts after obtaining the available information. Finally, an example was given to verify the effectiveness and practicability of the method.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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