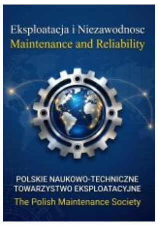

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Fault risk assessment of CNC machine tools based on DEA considering fault correlation

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Abstract

The classical Failure Mode, Effects and Criticality Analysis (FMECA) method for Computer Numerical Control (CNC) machine tools has difficulty in solving machine failure correlation, processing sparse fault information, and meeting the comprehensive risk evaluation criteria. To overcome the above problems, a novel risk assessment method is put forward. First, a complete risk evaluation index system is established including the failure impact degree, failure frequency, failure rate, failure maintenance time, failure maintenance difficulty, maintenance ergonomics requirements and maintenance cost. Second, Decision Making Trial and Evaluation Laboratory (DEMATEL), Interpretive Structural Modeling (ISM) and Analytic Network Process (ANP) are integrated with Bayesian theory and Copula function to model the failure correlation and address data sparsity. Finally, a cloud model is adopted to quantify qualitative expert judgments. Then, Data Envelopment Analysis (DEA) is employed for objective risk ranking. The proposed method is verified by a series of domestic machining centers, and the results also validate the effectiveness of the approach in improving objectivity, comprehensiveness and practical value for CNC machine tool improvement of reliability and maintenance decision-making.

Keywords: *CNC machine tools, DEA, fault correlation, fault risk assessment*

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Highlights

- An integrated framework combining FMECA, DEMATEL, ISM, ANP, Bayesian inference, Copula, cloud model, and DEA is proposed for fault risk assessment of CNC machine tools.
- Fault correlation and sparse data issues are effectively addressed.
- A cloud model quantifies subjective expert judgments.
- Validation on domestic machining centers confirms the method’s effectiveness in improving reliability and maintenance decisions.

1. Introduction

The common method of fault risk assessment is Failure Mode, Effects and Criticality Analysis(FMECA). Based on Failure Mode and Effects Analysis (FMEA), this method further quantitatively describes the consequences caused by failure modes, which is its core expansion content [1–4]. Carrying out fault mode hazard analysis of Computer Numerical Control (CNC) equipment can accurately identify key components that restrict its reliability, so as to improve reliability in a targeted manner. Knowing the function of the fault subsystem of CNC equipment in the whole system and identifying the weak links is the key to fault location and system reliability growth.

In recent years, with the rapid development of fault mode, impact degree and hazard analysis technology, FMECA has been widely used in the reliability research of numerical control equipment [5]. However, because CNC equipment is a complex mechatronics product, its fault nodes are coupled, which leads to the characteristics of non-isolated and mutual influence of system fault modes: a certain fault often becomes the inducement of subsequent faults. If a single point is still used to evaluate each fault mode, the evaluation results will significantly deviate from the real risk. These complex relationships have a great impact on the whole machine, so they should be fully considered. Sun YZ et al. [6] pointed out that ignoring fault correlation can lead to misjudgment of critical failure modes, thereby affecting the accuracy of subsequent reliability improvements. On the other hand, the calculation of fault mode hazard in existing studies mainly relies on mathematical statistics,which is estimated through the qualitative and quantitative of fault frequency and FMEA,but the analysis accuracy is limited. Bowles John B [7] pointed out that if the data collected in the field do not cover the fault modes with significant hazards in the prior information,the statistical method would cause its hazard degree to be mistakenly assigned to zero.With the effective use of prior information, Bayesian method can significantly improve the statistical accuracy under the condition of small samples, and it has become a common means to deal with scarce fault data. In addition, the traditional hazard degree is only calculated based on three parameters: the frequency ratio of failure modes, the degree of influence and the failure rate, and the influence of maintainability is not considered. However, factors such as repair time and repair costs following CNC equipment failures directly affect the reliability and lifecycle economy of the equipment,ignoring these metrics will lead to incomplete assessment results [8]. In a word, in the process of applying traditional FMECA to fault risk assessment, there are inevitably the following problems:

① Only consider the severity of the fault mode itself, without considering the relationship between fault modes, so that the influence degree and failure rate of the fault mode are not accurate enough.

② The frequency ratio of failure modes is regarded as a priori information, and it is not accurate enough to substitute it into the calculation of hazard degree.

③ The evaluation index is too simple and needs to be enriched.

In order to solve the above problems, in recent years, scholars at home and abroad have done a large number of exploratory researches. For fault correlation modeling, Sun et al. [9] combined Decision Making Trial and Evaluation Laboratory (DEMATEL), Interpretive Structural Modeling (ISM) and Analytic Network Process (ANP) to establish a hierarchical network structure model for the fault factors of CNC machines. For probabilistic modeling, Li H et al. [10] applied the method of Bayesian networks to fuse multi-source information to improve the fault probability prediction accuracy. For multi-criteria comprehensive evaluation, Yu L et al. [11] applied DEA method to complete the objective sorting of fault risk. Further, Tian HL et al. [4] proposed an improved FMECA method integrating Distance Grey Relational Analysis (D-GRA) and Data Envelopment Analysis (DEA), and overcome the disadvantages of the traditional FMECA regarding improper consideration of fault correlation and static evaluation; then introduced fault correlation and expert collaborative evaluation criteria to construct a dynamic FMECA method [6]. The Copula function has also been applied in reliability engineering to model the dependence among failure events [12]. It is a statistical tool for constructing joint probability distributions while preserving marginal characteristics. While correlation coefficient only measures the linear correlation among variables, Copula can capture all kinds of dependence among failure events including nonlinear dependence and tail dependence.Although the above research has made progress,still needs to make further breakthroughs: First, handling fault correlation mainly considers dependency at the structural level, failing to handle structural correlation and probabilistic dependency into a common modeling framework; second, estimation of failure mode frequency ratio is based on prior information, lacking a mechanism of posterior updating according to data information; third,the assessment of risk indicators is relatively singular, lacking a comprehensive evaluation method that incorporates various combined information.Therefore,this study proposes a DEA-based fault risk assessment method for CNC equipment considering fault correlation:

① DEMATEL-ISM method is used to obtain the fault correlation model, which is transformed into an ANP network model, and the fault impact degree is obtained by the ANP method. Based on the DEMATEL-ISM network model, Copula is used to obtain the comprehensive failure rate.

② The DEMATEL-ISM network model is transformed into a Bayesian model,and the posterior information of the failure mode frequency ratio is obtained by using the Bayesian method.

③ Construct the fault risk assessment index system, including fault impact degree,frequency of failure,failure rate,fault maintenance time, maintenance difficulty, meeting maintenance ergonomics requirements,repair cost,and apply

DEA for comprehensive risk evaluation. This study aims to provide a more scientific and systematic methodological support for the reliability analysis and maintenance decision-making of CNC equipment.

2. Theoretical basis of fault risk assessment of CNC equipment based on DEA considering fault correlation

This study first establishes a DEMATEL-ISM model based on fault data to reflect the hierarchical relationships among faults. Then, the fault correlation model is transformed into an ANP network model to obtain the fault influence degree. Meanwhile, the Bayesian method is introduced to transform the model into a Bayesian model, thereby obtaining the posterior information on the frequency of fault modes.Copula functions are introduced to obtain the comprehensive failure rate considering fault correlations. Subsequently,this paper constructs risk assessment indicators considering failure impact degree, failure frequency,failure rate, failure maintenance time,failure maintenance difficulty,maintenance ergonomics requirements and maintenance cost. Finally, the DEA method is adopted for fault risk assessment of CNC equipment.The methods are interconnected and closely linked, providing comprehensive methodological support for the risk assessment of CNC equipment faults. The flowchart is shown in Fig. 1.

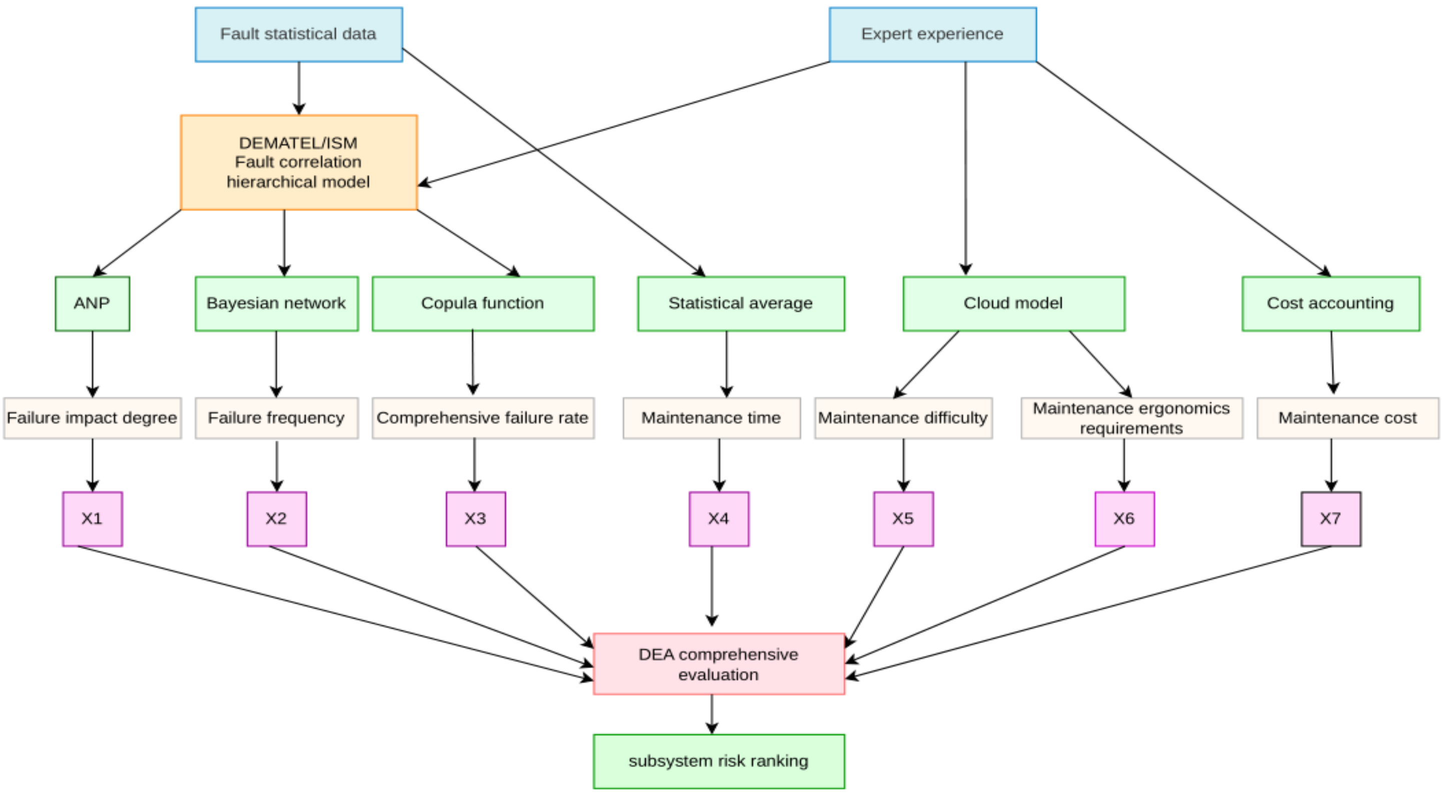

Figure 1. Flowchart of the proposed methodology.

2.1. CNC equipment failure risk assessment index system

Establishing the fault risk assessment index system of CNC equipment is the premise of evaluating the risk of CNC equipment, so the key is to select the appropriate risk assessment index [13]. Based on the current situation of CNC equipment fault assessment research and taking into account the fault correlation, select the indicators to build a fault risk assessment system.

(1) Failure impact degree (x1): Measures the ability of a certain failure mode to trigger other failure modes. The higher the value, the greater the risk.

(2) Failure frequency (x2): The proportion of the frequency of failure of component i in failure mode j, the higher the value, the greater the risk of failure in the study of failure mode.

(3) Comprehensive failure rate (x3): The failure rate of the system considering fault correlations, calculated using the

Copula function. A higher value indicates greater risk.

(4) Maintenance time (x4): The average repair time after a failure occurs. A higher value indicates greater risk. Shorter maintenance time is preferred.

(5) Maintenance difficulty (x5): The level of difficulty associated with repairing the subsystem after a failure.

(6) Maintenance ergonomics requirements (x6): Degree of compliance to the ergonomics of human factors engineering in maintenance tasks, for example, working posture, working space, manoeuverability.

(7) Maintenance cost (x7): The total cost incurred to restore normal function after a failure, namely labor and parts costs, and other costs.

2.2. DEMATEL/ISM/ANP method

Using DEMATEL [14–16] and ISM [17,18] methods,the fault correlation model is constructed. The DEMATEL method quantifies the direct and indirect influence relationships between fault subsystems using an comprehensive influence matrix, while ISM uses this impact matrix to construct

a reachable matrix to reveal the hierarchical structure of fault. The basic equations are summarized below. Let $Y = (y_{ij})_{n\times n}$ denote the direct influence matrix, y_{ij} means the number of times that fault subsystem i impacts fault subsystem j. Matrix X is normalized $X = Y/\,max\sum y_{ij}$ .Comprehensive influence matrix T is computed $T = X/(I - X)^{-1}$, where I is the unit matrix.The overall influence matrix $H = T + I$ is further derived, an overall reachable matrix M is built up. According to M, fault correlation model is built by partitioning the region and hierarchical division. The detailed steps of calculation are given in Section 2.1.

ANP was proposed by T. L.Saaty of the University of Pittsburgh in 1996 [19–21].It is a decision-making method developed on the basis of Analytic Hierarchy Process (AHP) and further incorporates the correlation between elements. Unlike AHP, which assumes that all elements are independent of each other and simplifies, or even ignores their correlations, ANP can better reflect the relationship of elements as well as their dependent hierarchical structure in a complex system [22–23]. However, AHP,due to its simplifying assumption,is difficult to apply to a complex electromechanical system such as CNC equipment, where coupling relationships among faults are prevalent and AHP cannot describe such coupling relationship. As ANP needs a network structure, the DEMATEL-ISM model constructed above is directly used as the network structure of ANP. In the network structure, fault impact degree is the control layer objective, and each fault subsystem is an element network layer cluster. The calculation process of ANP is as follows: (1) construct the pairwise comparison matrix of ANP according to the Saaty 1-9 grade by expert opinions; (2) establish the unweighted supermatrix; (3) obtain the weighted supermatrix; (4) acquire the limit supermatrix to obtain the steady-state weights, which are fault impact degrees of each subsystem.Due to computational complexity, Super Decision software is employed [24,25].

The process of ANP solving practical problems roughly includes the following basic steps:

(1) Construct an ANP network structure model.Clarify the decision-making objectives, establish a control layer and

a network layer, whose interior is composed of elements that affect each other.

(2) According to the relative importance of the comparison of the two factors, combined with literature and expert consultation, the judgment matrix is constructed by using the Saaty 1-9 scale: first, the influence relationship table of the evaluation indicators is sorted out, and then the element sets with dependency and feedback relationships and their internal elements are respectively constructed. Construct a judgment matrix, and test its consistency.

(3) Construct a supermatrix: first compare the elements of the network layer to form an unweighted supermatrix, and then obtain a weighted supermatrix after weight correction, so as to quantify the relative importance of the elements.

(4) By solving the limit supermatrix, the steady-state weights of each index set and index elements to the final goal can be obtained.

ANP is computationally complex and needs to be implemented using software in practical applications [25]. Therefore, the construction and solving of the ANP supermatrix are performed using the Super Decision software. In this study, Super Decision is used to generate the unweighted supermatrix, weighted supermatrix, and limit supermatrix (see Tables 1-3), from which the steady-state weights of each subsystem are derived for the subsequent DEA evaluation.

2.3. Bayesian network (BN)

A Bayesian network (BN) [26,27] is a probabilistic graph model that combines probability theory and graph theory to accurately quantify the uncertainty of complex systems and has become a core tool for fault diagnosis and risk analysis.Using BN to solve the posterior information of the occurrence frequency of fault modes can greatly improve the reliability of diagnosis.

In this paper, the DEMATEL-ISM fault correlation model is transformed into a Bayesian network to obtain the posterior probability of failure occurrence frequency. The transformation adheres to the mapping rules as follows:subsystems are mapped to BN nodes, causal relationships between fault modes are mapped to directed edges, and the hierarchical structure is preserved. The prior probability of the root node is defined based on historical failure data. Conditional probability tables of the BN model are obtained from the direct influence matrix and the joint reliability database. The top event,system failure, is added to the hierarchy, and the BN model is generated by GeNIe (Graphical Network Interface) software. Through BN causal and diagnostic reasoning, the posterior probability of each failure is obtained to update the prior failure frequency.

2.4. Data envelopment analysis (DEA)

Data Envelopment Analysis (DEA), proposed by Charnes, is a non-parametric method to evaluate the relative efficiencies of Decision-Making Units (DMUs) with multiple inputs and outputs [28,29]. Data Envelopment Analysis judges the efficiency by measuring how far each DMU deviates from the efficiency frontier.There is no need to preset weights or standardizing data, so it can ensure the objectivity evaluation. In this paper, every fault subsystem is considered as a DMU, and its seven indicators of risk as inputs, and output is the ranking results.

In this research, the efficiency assessment is conducted by utilizing the original input and output variables. At the same time, based on the assumption that returns to scale are variable, the input-oriented BCC model is used to measure, and the technical efficiency (TE), scale efficiency (SE), and pure technical efficiency (PTE) are finally calculated, where the product of scale efficiency and pure technical efficiency is equal to technical efficiency.

$$min\, \theta - \varepsilon(e^T S^- + e^T S^+)$$

$$s.t. \begin{cases} \sum_{i=1}^{l} X_j \lambda_j + S^- = \theta X_0 \\ \sum_{i=1}^{l} Y_j \lambda_j + S^+ = Y_0 \\ \lambda_i \geq 0, S^- \geq 0, S^+ \geq 0 \end{cases} \quad (1)$$

In formula (1):$i = 1,2,\cdots n$denotes the decision-making unit; X and Y represent input vector and output vector respectively; S^- and S^+ are the relaxation variables of input index and output index respectively; λ is the weight coefficient;θ is the effective value of the decision-making unit.

3. Example analysis

In this study, a series of machining centers is divided into 10 subsystems: spindle system S, tool magazine system M, feed J, numerical control NC, electric V, pneumatic G, lubrication L, cooling W, chip removal K and protective device Q.

3.1. Calculation of fault analysis indicators

(1) Construction of fault-related model based on DEMATEL-ISM

1) Determine the fault subsystem of the machining center According to the data of fault statistics, the set $S = \{S_i\}, i = 1,2,\cdots n$ of fault-related subsystems is determined, S_i represents the i-th subsystem that has relevant faults with other subsystems, and n represents the number of fault subsystems that have relevant faults. Let S_1 be a tool magazine system, S_2 be an electrical system, S_3 be a feed system, S_4 be a cooling system, S_5 be a chip removal system, S_6 be a pneumatic system, S_7 be a lubrication system, S_8 be a numerical control system, S_9 be a spindle system, and S_{10} be a protective device.

2) Directly affect the construction of the matrix

The direct fault propagation information is taken from the maintenance log database, in which any fault event carries information about failed components, fault mode, maintenance action and chain of causation if the fault of multiple subsystems were involved. These direct fault propagation relations are summarized from the maintenance records through cross examination and consultation with senior maintenance engineers to make sure that the cause effect attribution is accurate.

Constructing the Direct Influence Matrix Y between Fault Subsystems

$$Y = (y_{ij})_{n\times n} \quad (2)$$

In the formula: y_{ii} is the number of times that the subsystem S_i affects the subsystem S_j, when $i = j$, $y_{ii} = 0$, n represents the number of faulty subsystems with related faults.

$$Y = \begin{array}{c} S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ S_6 \\ S_7 \\ S_8 \\ S_9 \end{array} \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 4 & 0 & 2 & 2 & 0 & 0 & 0 & 2 & 2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 4 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 9 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 10 \\ 0 & 0 & 5 & 0 & 2 & 0 & 0 & 0 & 2 \\ 1 & 0 & 8 & 0 & 0 & 0 & 0 & 0 & 2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

3) Normalized matrix construction

The direct influence matrix Y between all fault subsystems is normalized, and the normalized matrix X is obtained

$$X = \frac{Y}{\max\limits_{1 \le i \le n}\left(\sum_{j=1}^{n} y_{ij}\right)} \qquad (3)$$

In the formula: y_{ij} is the number of times that the subsystem S_i affects the subsystem S_j, and n represents the number of faulty subsystems with related faults.

$$X = \begin{array}{c} S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ S_6 \\ S_7 \\ S_8 \\ S_9 \end{array} \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.211 & 0 & 0.105 & 0.105 & 0 & 0 & 0 & 0.105 & 0.105 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.211 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.474 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.526 \\ 0 & 0 & 0.263 & 0 & 0.105 & 0 & 0 & 0 & 0.105 \\ 0.053 & 0 & 0.421 & 0 & 0 & 0 & 0 & 0 & 0.105 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

4) Calculate the comprehensive influence matrix

$$T = \lim_{k \to \infty}(X + X^2 + \cdots X^k) = X(I - X)^{-1} \qquad (4)$$

In the formula: I is the identity matrix, X is the normalization matrix, X^k represents the indirect influence of subsystem S_i on the k stage of subsystem S_j, where S_i represents the i-th subsystem with related faults with other subsystems, S_j represents the j-th subsystem with related faults with other subsystems, $i = 1,2,\cdots n$, $j = 1,2,\cdots,n$, $k = 1,2,\cdots,n$.

$$T = \begin{array}{c} S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ S_6 \\ S_7 \\ S_8 \\ S_9 \end{array} \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.216 & 0 & 0.150 & 0.105 & 0.022 & 0 & 0 & 0.111 & 0.116 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.211 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.474 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.526 \\ 0 & 0 & 0.263 & 0 & 0.105 & 0 & 0 & 0 & 0.105 \\ 0.053 & 0 & 0.421 & 0 & 0 & 0 & 0 & 0 & 0.105 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

5) Calculate the reachable matrix

The comprehensive influence matrix can only clearly reflect the mutual influence relationship and degree between different fault subsystems, and does not consider the influence of fault subsystems on themselves, so it is necessary to calculate and reflect the overall influence relationship of fault subsystems.

Calculate the overall impact matrix H, the calculation formula of which is:

$$H = T + I = \left[h_{ij}\right]_{n \times n} \qquad (5)$$

In the formula: I is the identity matrix, h_{ij} represents the degree of direct and indirect influence of subsystem S_i on subsystem S_j after considering the influence of the faulty subsystem on itself, and n represents the number of faulty subsystems with related faults.

$$H = \begin{array}{c} S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ S_6 \\ S_7 \\ S_8 \\ S_9 \end{array} \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.216 & 1 & 0.150 & 0.105 & 0.022 & 0 & 0 & 0.111 & 0.116 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0.211 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0.474 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0.526 \\ 0 & 0 & 0.263 & 0 & 0.105 & 0 & 1 & 0 & 0.105 \\ 0.053 & 0 & 0.421 & 0 & 0 & 0 & 0 & 1 & 0.105 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Through the global influence matrix H, the reachable matrix M can be determined, make that

$$M = \left[m_{ij}\right]_{n \times n}, i,j = 1,2,\cdots n \qquad (6)$$

m_{ij} is valued according to the following equation, and in order to make the calculation more convenient, let the threshold value $\lambda = 0.150$.

$$m_{ij} = \begin{cases} 1 & h_{ij} > \lambda \\ 0 & h_{ij} \le \lambda \end{cases} (i = 1,\cdots,n, j = 1,\cdots,n) \qquad (7)$$

$$M = \begin{array}{c} S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ S_6 \\ S_7 \\ S_8 \\ S_9 \end{array} \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

6) Regional decomposition and hierarchical division. The reachable matrix M is decomposed into regions, and each decomposed region is divided into levels and bits to obtain each level set, including: defining the subsystem set affected by the subsystem S_i as the reachable set $R(S_i)$ of the subsystem S_i, and the subsystem set affecting the subsystem S_i as the antecedent set $A(S_i)$ of the subsystem S_i. By calculating the reachable set $R(S_i)$ and the antecedent set $A(S_i)$, the region decomposition and level division of M are carried out.

Domain decomposition: Define $Y = (y_{ij})_{n \times n}$ as a common set, define the elements of the common set $R(S_i) \cap A(S_i) = A(S_i)$ as the starting set $B(S)$. For S_i and S_j in $B(S)$, if $R(S_i) \cap A(S_j) = \Phi$, then S_i and $S_j$do not belong to the same region, if $R(S_i) \cap A(S_j) = \Phi$ is the same region, then Realize the decomposition of the region.

The result of domain decomposition, denoted $P(S) =$

$P_1, P_2, \cdots P_k$;

Where P_k is the set of subsystems in the kth relatively independent region, $k = 1,2,\cdots,n$;

Level division: For the same area P_1, subsystems satisfying $R(S_i) \cap A(S_i) = R(S_i)$ are obtained in turn, and each level set is found, expressed as:

$$L_1 = \{S_i/S_i \in P_1 - L_0, R(S_i) \cap A(S_i) = R(S_i), i = 1,2\cdots,n\}$$

$$L_2 = \{S_i/S_i \in P_1 - L_1, R(S_i) \cap A(S_i) = R(S_i), i < n\}$$

$$\cdots$$

$$L_k = \{S_i/S_i \in P_1 - L_1 - \cdots - L_{k-1}, R(S_i) \cap A(S_i) = R(S_i), i < n\} \quad (8)$$

Wherein: L_k is the set of each grade obtained by dividing the grades.

The whole system can be divided into two levels, $L_1 = \{S_1, S_3, S_5, S_9\}$, $L_2 = \{S_2, S_4, S_6, S_7, S_8\}$, by dividing the reachable matrix into regions and levels. Construct the hierarchical structure model of the relevant fault subsystem, as shown in Fig. 2.

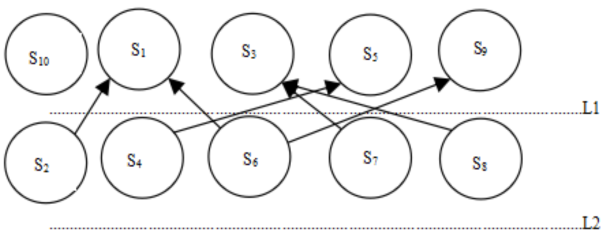

Figure 2. Hierarchical structure of fault correlation model.

As shown in Fig.2, the surface subsystems are S_1 (tool magazine system), S_3 (feed), S_5 (chip removal) and S_9 (spindle); the deep subsystems are S_2 (electrical), S_4 (cooling), S_6 (pneumatic), S_7 (lubrication) and S_8 (numerical control). S_2 electrical system and S_6 pneumatic system jointly affect S_1 tool magazine system; S_7 lubrication system and S_8 numerical control system jointly affect S_3 feed system; S_4 cooling system affects S_5 chip removal system; S_6 pneumatic system affects S_9 spindle system.

(2) ANP evaluation of machining center fault impact degree

1) Selection of the evaluation index of the machining center fault impact degree

In view of the hierarchical network structure of the machining center, the evaluation index of fault impact degree is decomposed layer by layer from top to bottom.In order to quantify the effect of fault propagation between nodes and get the influence of faults between faulty nodes in the machining center, each subsystem (faulty node) is directly set as the second-level evaluation index.

2) Construction of ANP Network Structure of Machining Center Fault Impact Degree

Based on the fault impact evaluation index system and the hierarchical directed graph generated by DEMATEL-ISM, an ANP network structure for machining center fault impact was established, taking "fault impact degree" as the control layer objective and each fault subsystem as the element layer evaluation unit.The machining center fault influence is regarded as the target decision-making factor in the control layer, and the fault influence of the fault subsystem is regarded as the element cluster in the element layer.

3) Evaluation of the impact degree of machining center failure

With the help of the Assess/Compare module of Super Decision software, the comparison matrices of each fault subsystem can be automatically generated by inputting the expert comparison data. After the analysis of the fault cause mechanism is completed, the judgment matrix is quantified by using the 1-9 scale method to score. Invite senior engineers with many years of experience to score the impact degree of each node, and get a pairwise comparison impact matrix after summarizing the results.

After calculation, the matrix in the following table can be obtained (Tables 1-4).

Resulting matrices are in Tables 1-3. Table 1 shows the unweighted supermatrix in which each column reflects the relative importance weights of elements affecting each element obtained from pairwise comparison. Table 2 gives the weighted supermatrix after normalization. Table 3 gives the limit supermatrix, which converges to a stable matrix after successive multiplication, giving the steady weights of each subsystem.

As can be seen from the Table 4, the subsystems with the greatest influence are the pneumatic system, cooling system, tool magazine system and feed system. These 4 subsystems are dominant fault propagation source subsystems of the machining center. The rest of the subsystems, that is, electrical system, lubrication system, numerical control system, chip removal system, spindle system, and guards all have small influence weights, so the faults of these subsystems are not easy to propagate to other subsystems. This ranking provides a clear basis for a reliability improvement.

Table 1. Unweighted super matrix.

	S_1 Tool magazine system	S_2 Electrical system	S_3 Feed system	S_4 Cooling system	S_5 Chip removal system	S_6 Pneumatic system	S_7 Lubrication system	S_8 Numerical control system	S_9 Spindle system	S_{10} Guards
S_1 Tool magazine system	0.52784	0	0.0000	0	0.0000	0	0	0	0.0000	0
S_2 Electrical system	0.33252	0	0.0000	0	0.0000	0	0	0	0.0000	0
S_3 Feed system	0.0000	0	0.49339	0	0.0000	0	0	0	0.0000	0
S_4 Cooling system	0.0000	0	0.0000	0	0.75000	0	0	0	0.0000	0
S_5 Chip removal system	0.0000	0	0.0000	0	0.25000	0	0	0	0.0000	0
S_6 Pneumatic system	0.13965	0	0.0000	0	0.0000	0	0	0	0.75000	0
S_7 Lubrication system	0.0000	0	0.31081	0	0.0000	0	0	0	0.0000	0
S_8 Numerical control system	0.0000	0	0.19580	0	0.0000	0	0	0	0.0000	0
S_9 Spindle system	0.0000	0	0.0000	0	0.0000	0	0	0	0.25000	0
S_{10} Guards	0.0000	0	0.0000	0	0.0000	0	0	0	0.0000	0

Table 2. Weighted supermatrix.

	S_1 Tool magazine system	S_2 Electrical system	S_3 Feed system	S_4 Cooling system	S_5 Chip removal system	S_6 Pneumatic system	S_7 Lubrication system	S_8 Numerical control system	S_9 Spindle system	S_{10} Guards
S_1 Tool magazine system	0.52784	0	0.0000	0	0.0000	0	0	0	0.0000	0
S_2 Electrical system	0.33252	0	0.0000	0	0.0000	0	0	0	0.0000	0
S_3 Feed system	0.0000	0	0.49339	0	0.0000	0	0	0	0.0000	0
S_4 Cooling system	0.0000	0	0.0000	0	0.75000	0	0	0	0.0000	0
S_5 Chip removal system	0.0000	0	0.0000	0	0.25000	0	0	0	0.0000	0
S_6 Pneumatic system	0.13965	0	0.0000	0	0.0000	0	0	0	0.7500	0
S_7 Lubrication system	0.0000	0	0.31081	0	0.0000	0	0	0	0.0000	0
S_8 Numerical control system	0.0000	0	0.19580	0	0.0000	0	0	0	0.0000	0
S_9 Spindle system	0.0000	0	0.0000	0	0.0000	0	0	0	0.2500	0
S_{10} Guards	0.0000	0	0.0000	0	0.0000	0	0	0	0.0000	0

Table 3. Limited weighted supermatrix.

	S_1 Tool magazine system	S_2 Electrical system	S_3 Feed system	S_4 Cooling system	S_5 Chip removal system	S_6 Pneumatic system	S_7 Lubrication system	S_8 Numerical control system	S_9 Spindle system	S_{10} Guards
S_1 Tool magazine system	0.52784	0	0.00000	0	0.00000	0	0	0	0.0000	0
S_2 Electrical system	0.33252	0	0.00000	0	0.00000	0	0	0	0.0000	0
S_3 Feed system	0.00000	0	0.49339	0	0.00000	0	0	0	0.0000	0
S_4 Cooling system	0.0000	0	0.0000	0	0.75000	0	0	0	0.0000	0
S_5 Chip removal system	0.0000	0	0.0000	0	0.25000	0	0	0	0.0000	0
S_6 Pneumatic system	0.13965	0	0.0000	0	0.0000	0	0	0	0.7500	0
S_7 Lubrication system	0.0000	0	0.31081	0	0.0000	0	0	0	0.0000	0
S_8 Numerical control system	0.0000	0	0.19580	0	0.0000	0	0	0	0.0000	0
S_9 Spindle system	0.0000	0	0.0000	0	0.0000	0	0	0	0.2500	0
S_{10} Guards	0.0000	0	0.0000	0	0.0000	0	0	0	0.0000	0

Table 4. Weight of subsystem influence degree.

subsystem	**Impact weight**	**sort**	**subsystem**	**Impact weight**	**sort**
S_1 Tool magazine system	0.131959	3	S_6 Pneumatic system	0.222412	1
S_2 Electrical system	0.083129	5	S_7 Lubrication system	0.077703	6
S_3 Feed system	0.123346	4	S_8 Numerical control system	0.048950	8
S_4 Cooling system	0.187500	2	S_9 Spindle system	0.062500	7
S_5 Chip removal system	0.062500	7	S_{10} Guards	0.00000	9

3.2. A Posteriori information analysis of fault occurrence frequency based on DEMATEL/ISM/Bayes

① Construction of Bayesian Networks

In view of the fact that the fault association model constructed by DEMATEL-ISM is highly consistent with the Bayesian network in terms of system structure description, the factors in DEMATEL-ISM can be mapped as BN nodes, and the causal relationship between factors can be mapped as directed edges of BN, as shown in Fig. 3.

According to the above mapping rules, the fault correlation model is directly transformed into the initial Bayesian network. The prior probability for the root node is determined based on the occurrence rate of failure events. Conditional probability tables are used to characterize causal dependencies between nodes in the Bayesian networks. Based on the direct influence relation matrix and reliability database, the conditional probability table of Bayesian network is obtained.

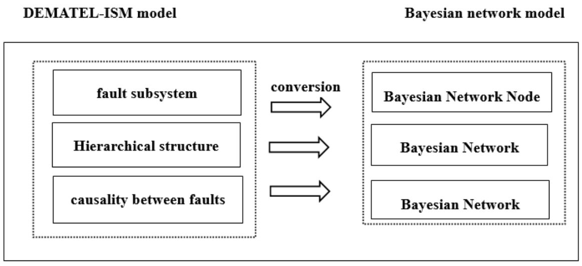

Figure 3. Transformation rules from DEMATEL-ISM to Bayesian networks,

A directed acyclic graph consists of N nodes: nodes correspond to risk events, and directed edges represent causal associations between them. A preliminary risk BN structure was constructed with GeNIe software, as shown in Fig. 4.

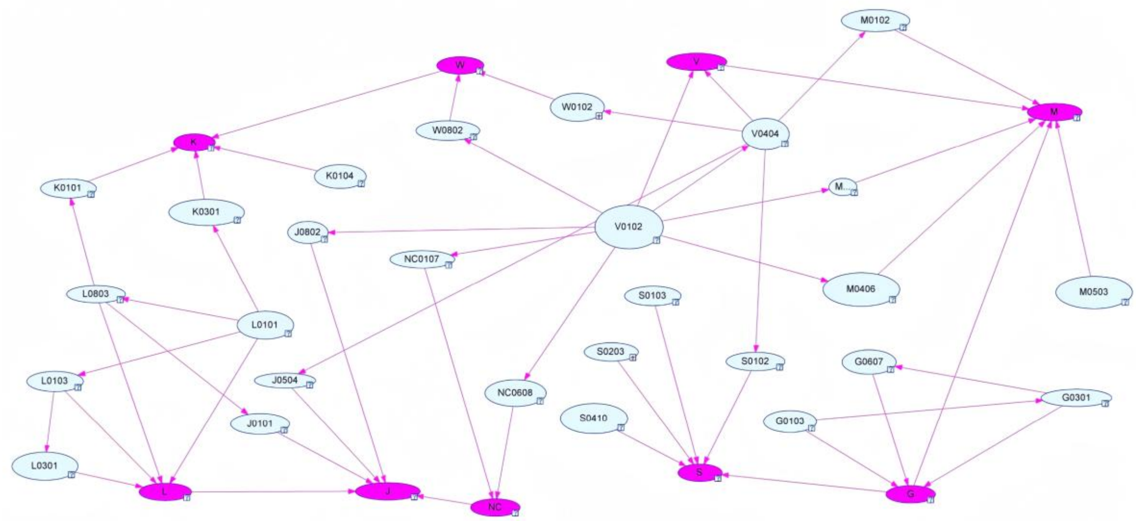

Figure 4. Preliminary structure of Bayesian network.

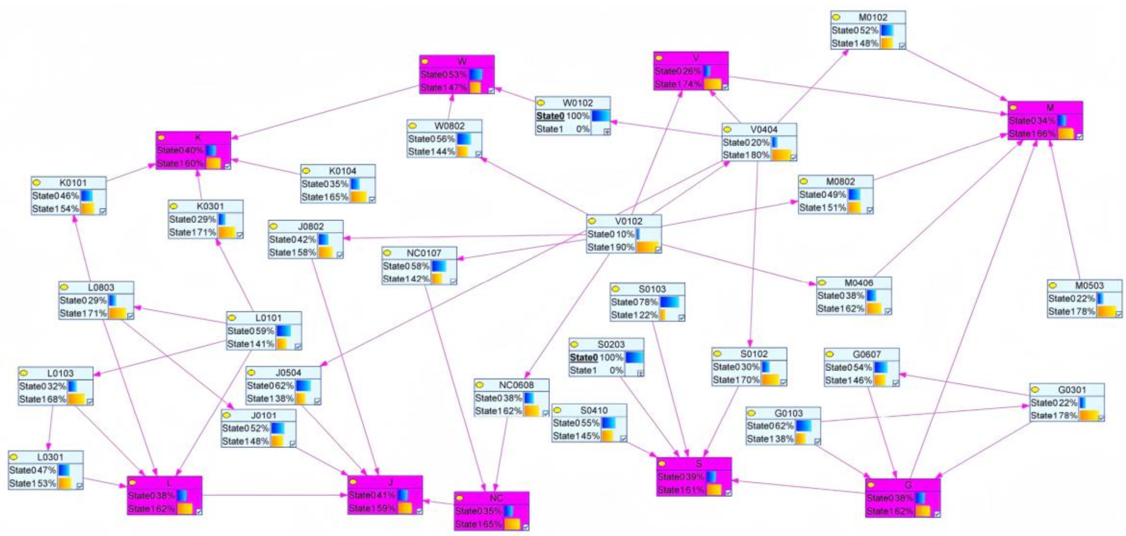

Figure 5. Bayesian network causal inference.

② A Posteriori Information Analysis of Fault Frequency Based on Bayesian Network

1) Determination of BN posterior probability and causal inference

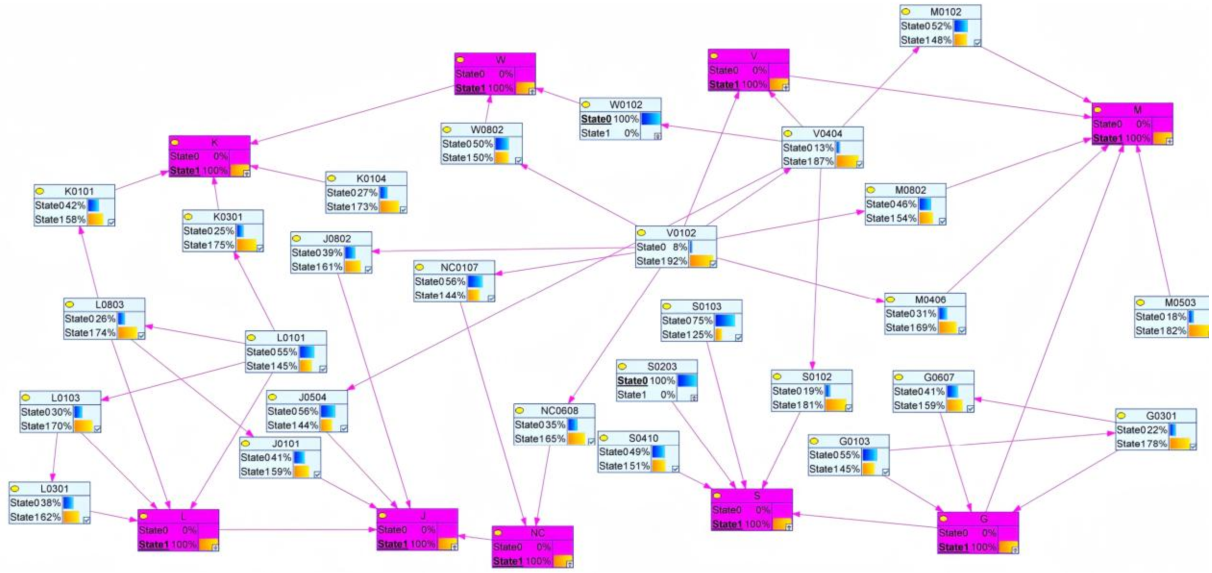

Figure 6. Bayesian network diagnostic reasoning results.

Table 5. BN analysis results.

Subsystem	Failure mode serial	number	Relative probability of the whole machine	Proportion of relative subsystems
(S)spindle (0.59)	S0102-component damage (0.69)	①	0.4071	0.4035
	S0103-Damage of liquid, gas and oil components and components (0.22)	②	0.1298	0.1287
	S0203-loose preload mechanism (0.35)	③	0.2065	0.2047
	S0410-Spindle misalignment (0.45)	⑤	0.2655	0.2632
(M) tool magazine system (0.66)	M0102-component damage (0.51)	㉒	0.3366	0.2114
	M0406-Motor Overload (0.62)	⑦	0.4092	0.2570
	M0503-transposition, displacement not in place (0.78)	⑩	0.5148	0.3233
	M0802-Not operating properly (0.51)	⑪	0.3366	0.2082
(J) feed system (0.59)	J0101-parts damaged (0.48)	⑫	0.2832	0.3333
	J0504-transposition, shift override (0.38)	⑬	0.2242	0.2639
	J0802-Not operating properly (0.58)	⑯	0.3422	0.4028
(NC) numerical control system (0.65)	NC0107-Short circuit of lines and cables (0.42)	⑰	0.273	0.2710
	NC0608-Unstable performance (0.62)	㉔	0.403	0.4000
	NC0802-Not operating properly (0.51)	㉙	0.3315	0.3290
(V) electrical system (0.71)	V0102-component damage (0.90)	㉞	0.639	1.0000
(G) pneumatic system (0.62)	G0103-Damage of liquid, gas and oil components and components (0.38)	㉟	0.2356	0.2346
	G0301-Liquid, Gas and Oil Leakage (0.78)	㉛	0.4836	0.4815
	G0607-Loss of Component Function (0.46)	㉕	0.2852	0.2840
(L) lubrication system (0.62)	L0101-parts damaged (0.41)	㊱	0.4216	0.2615
	L0103-Damage of liquid, gas and oil parts and components (0.68)	㉜	0.4216	0.2615
	L0301-Liquid, Gas and Oil Leakage (0.53)	㉖	0.3286	0.2038
	L0803-poor lubrication (0.71)	㉝	0.4402	0.2731
(W) cooling system (0.61)	W0102-component damage (0.46)	㉗	0.2806	0.5111
	W0802-Not operating properly (0.44)	⑱	0.2684	0.4889
(K) chip removal system (0.61)	K0101-parts damaged (0.54)	㉘	0.3294	0.2842
	K0104-Motor Damage (0.65)	⑲	0.3965	0.3421
	K0301-Liquid, Gas and Oil Leakage (0.71)	⑳	0.4331	0.3737

Fault frequency is the key factor to determine the prior probability of the root node. When determining other nodes, there are usually two situations. One is that for complete data, it can be obtained directly by querying the statistical data and related records of the database; Second, for missing data, it is necessary to obtain it with the help of professionals or software. In this study, the reasonable probability of each node is obtained by scoring experts. On the basis of determining the prior probability and conditional probability of each factor, the data are imported into GeNIe software ("state0" means that the event does not occur, and "state1" means that the event occurs), and a complete BN model is constructed. As shown in Fig. 5.

Through the analysis of the results, it can be seen that the top three subsystem fault probability rankings are V electrical system (0.71), M tool magazine system (0.66), and NC numerical control system (0.65).

2) Diagnostic reasoning based on BN model

Analyze the BN model that has been built by GeNIe software (that is, set the state of each subsystem node to "state1 = 100%"), and the inference graph can be obtained, as shown in Fig.6.

Table 5 shows the BN analysis results, such as the posterior probability of failure for each system and relative probability of failure of each failure mode for each subsystem. The electrical system has the largest failure probability (0.71), which comes from component damage (V0102) with relative probability of 1.0000 in the electrical system. Tool magazine system ranked second (0.66), which is mainly due to transposition/displacement not in place (M0503) with relative probability of 0.3233 in the tool magazine system. Numerical control system ranked third (0.65), with unstable performance (NC0608) being the most harmful mode with 0.4000 relative probability.It indicates that maintenance plans should be prioritized for the electrical system, tool magazine system, and CNC system.

3.3. Calculation of comprehensive failure rate of machining center subsystem based on fault correlation

In this study, Copula function [30–33] is introduced, combined with the fault correlation model and relevant fault data obtained by the DEMATEL/ISM method, the correlation relationship function between subsystems with relevant faults is established, so as to solve the correlation coefficient between subsystems and calculate the comprehensive failure rate of subsystems. Refer specifically to the calculation of the comprehensive failure rate in the literature [34]. The results are shown in Table 6.

Table 6 shows all the comprehensive failure rates of all subsystems calculated with the Copula function using fault correlations. The subsystems with the highest overall failure rates are the feed system, the tool magazine system and the spindle system. The comprehensive failure rates are also different from the order of failure rates with fault frequencies only (Table 5), so fault correlations have impacts on the overall failure risk.

Table 6. Calculation of the average comprehensive failure rate of subsystems.

Part and code	λ_i	sort	Part and code	λ_i	sort
Tool magazine system M	0.001751675	2	Pneumatic system G	0.000458470	9
Spindle system S	0.001124435	3	Lubrication system L	0.000502001	8
Feed system J	0.001921738	1	Cooling system W	0.000521772	7
Numerical control (NC)	0.000788108	6	Chip removal system K	0.001007195	4
Electrical system V	0.000426637	10	Guard Q	0.000987127	5

3.4. Determine the maintenance time of the fault subsystem

Through statistical analysis, the maintenance time of the machining center subsystem is obtained, as shown in Table 7.

Table 7. Machining center maintenance time.

Part and code	maintenance time	sort	Part and code	maintenance time	sort
Tool magazine system (M)	54.6	5	Pneumatic system (G)	54.7	4
Electrical system (V)	52.7	10	Lubrication system (L)	54.5	6
Feed system(J)	55.1	3	Numerical control (NC)	59.1	1
Cooling system (W)	53.8	8	Spindle system (S)	54.2	7
Chip removal system (K)	56.0	2	Guard (Q)	53.5	9

Table 7 presents the average maintenance time of every subsystem. The NC system needs the longest maintenance time, followed by the chip removal system, and feed system. The electrical system has the lowest maintenance time. The maintenance time for NC system and feed system is longer because of the structure’s complexity and difficulty for fault diagnosis, which increases downtime and maintenance costs.

3.5. Determination of qualitative indicators based on cloud models

There are many quantitative methods for qualitative indicators, such as expert scoring, fuzzy evaluation and analytic hierarchy process. However, a single index assignment is easy to introduce deviations, and fuzzy evaluation relies on membership functions, which is significantly affected by subjectivity, so it is difficult to ensure the scientificity and rationality of decision-making. In view of this, this study uses a cloud model to describe the evaluation information given by decision makers, so as to take into account fuzziness and randomness, thereby effectively deal with the quantification of qualitative indicators in the market competition matrix.

Cloud model [35] is a mathematical tool to describe the uncertainty between qualitative concepts and quantitative data. This model realizes the qualitative and quantitative transformation by combining fuzziness and randomness. Its digital characteristics are represented by the expected value E_x, entropy E_n and super entropy H_e. The three digital features of the cloud model perform their own duties, and together describe the complete distribution shape of qualitative concepts in the quantitative domain. The expected value corresponds to the geometric center in the universe space, is the point with the highest membership degree, and can best represent the typical value of the concept, so it can be regarded as the "prototype" of the concept; Entropy measures the fuzzy degree of the extension boundary of the concept. The larger the boundary is, the wider the acceptable value range of the concept is, the more fuzzy the boundary is, the smaller the boundary is, the sharper and more precise the concept is; Super entropy describes the dispersion of cloud droplets, reflecting the disturbance intensity of randomness to fuzziness. The larger the cloud droplets are, the wider the dispersion of cloud droplets is, and the more significant the random fluctuation is. When it approaches 0, the cloud droplets almost concentrate on the expected curve, and the influence of randomness is weakened. Through the golden section method, the comments are uniformly divided into five levels of "good, good, general, poor, and poor", and the corresponding cloud model is constructed accordingly. Suppose the middle cloud is $C_0(E_{xo}, E_{n0}, H_{eo})$, and the adjacent clouds to the left and right of the middle cloud are:

$H_{\varepsilon 0} = 0.005[0,1](0, 0.104, 0.013)(0.309, 0.064, 0.008)$
of which,

$$(0.5, 0.039, 0.005) \tag{9}$$

$$(0.691, 0.064, 0.008) \tag{10}$$

$$(1, 0.104, 0.013) \tag{11}$$

Referring to the common settings in relevant cloud model research,the effective domain is $[0, 1]$, this study takes $H_{\varepsilon 0} = 0.005$, corresponding to an overlapping area of approximately 5% between adjacent evaluation cloud models. through the above formula, the corresponding domains of different levels of cloud models can be calculated, and the results can be obtained from poor to good, and the values of the domains are (0, 0.104, 0.013) , (0.309, 0.064, 0.008) , (0.5, 0.039, 0.005) , (0.691, 0.064, 0.008),(1, 0.104, 0.013), as shown in Fig.7.

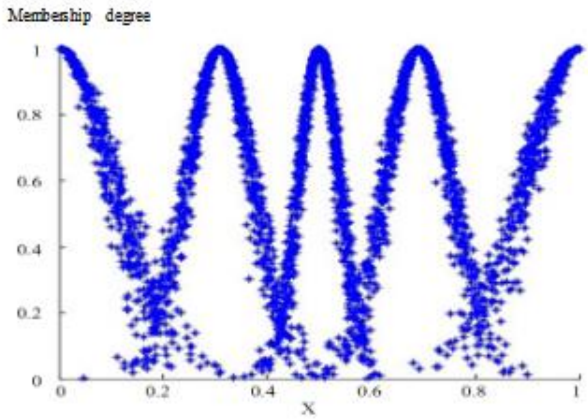

Figure 7. Cloud model for five evaluation levels.

Using the qualitative language evaluation of h experts, each language evaluation value corresponds to a cloud model, so the h language evaluation values can finally be integrated into a unified comprehensive cloud model [36].

$$E_x = \frac{E_{x1}E_{n1} + E_{x2}E_{n2} + \cdots E_{xh}E_{nh}}{E_{n1} + E_{n2} + \cdots + E_{nh}} \tag{12}$$

$$E_n = E_{n1} + E_{n2} + \cdots E_{nh} \tag{13}$$

Combined with the availability characteristics of machining centers, this study determines the scoring criteria, as shown in Table 8.

Table 8 gives the scoring index of the qualitative indicators (maintenance difficulty, maintenance ergonomics requirements and maintenance cost) for cloud model with the five decision levels (good, better, general, bad, worst). Table 9 shows the initial decision matrix of aggregated evaluation experts by cloud model. As illustrated in Table 9, the score of cooling system (W), the chip removal system (K) and guards (Q) is the highest for the maintenance difficulty, that means cooling system (W), the chip removal system (K) and guards (Q) are most difficult to repair, while electrical system (V) and spindle system (S) score the lowest , that means they are the easiest to repair. For maintenance ergonomics, the score of cooling system (W), the chip removal system (K) and guards (Q) is the greatest, which have the best compliancy with human factors engineering.

Table 8. Scoring checklist.

Availability Requirement Metrics	Good (1, 0.104, 0.013)	Better (0.691, 0.064, 0.008)	General (0.5, 0.039, 0.005)	Poor (0.309, 0.064, 0.008)	Bad (0, 0.104, 0.013)
Easy to repair degree	Quickly complete repairs without tools.	It requires the use of universal tools and can be completed by a single person.	More than two people are required to collaborate and use common tools.	Professional tools must be used and can be operated by a single person.	More than two people are required to use professional tools for maintenance.
Human-machine-environment engineering compliance	Maintenance position, posture and tool use are comfortable.	Maintenance is slightly inconvenient, but it does not cause fatigue.	Maintenance is prone to fatigue, but will not cause damage.	Part of the operation is easy to cause fatigue damage.	During maintenance, it is often necessary to adopt a vulnerable posture.

Table 9. Initial decision matrix.

Part and code	Maintenance difficulty	sort	Meet maintenance ergonomics	sort	maintenance cost	sort
Tool Magazine System(M)	0.568	3	0.500	4	0.500	3
Electrical System (V)	0.309	1	0.118	1	0.118	1
Feed System(J)	0.619	4	0.118	1	0.619	4
Cooling system (W)	0.691	5	0.691	6	0.691	5
Chip removal system (K)	0.691	5	0.691	6	0.691	5
Pneumatic System (G)	0.309	1	0.381	3	0.309	2
Lubrication System (L)	0.500	2	0.619	5	0.118	1
Numerical Control (NC)	0.568	3	0.309	2	0.500	3
Spindle System (S)	0.309	1	0.118	1	0.118	1
Guard (Q)	0.691	5	0.691	6	0.691	5

3.6. Fault risk assessment of NC equipment based on DEA

Data Envelopment Analysis (DEA) is introduced to integrate multi-dimensional information. First of all, the ranking of each subsystem under each index is converted into a score value: 10 points for the first place, 1 point for the last place.Subsequently, the product of the seven key influencing parameters is taken as the output variable of the DEA. The advantage of DEA is that it can automatically calculate the hidden weight of each index based on the ranking score, without artificial setting, so as to objectively evaluate the relative effectiveness of each subsystem. Finally, according to the DEA score, the high and low ranking of subsystem fault risk can be obtained, which provides a quantitative basis for designers to determine the priority. In the framework of data envelopment analysis, the evaluation boundary is set with "fault risk". The higher the super-efficiency value, the higher priority the subsystem needs to be improved. The fault risk value of each subsystem is regarded as an independent decision-making unit (DMU), and its corresponding input and output data are shown in Table 10.

DEA is used to assess the failure risk of the machining center subsystem, and the results are shown in Table 11.

Table 10. Input/output data of DMU of each fault subsystem.

DMU	Failure Impact Degree X1	Failure Frequency X2	Comprehensive Failure Rate X3	Maintenance Time X4	Maintenance Difficulty X5	Maintenance Ergonomics Requirements X6	Maintenance Cost X7	Ranking Results of Seven Indicators Y1
Tool Magazine System(M)	8	9	9	6	8	7	8	1741824
Electrical System (V)	6	10	1	1	10	10	10	60000
Feed System (J)	7	5	10	8	7	10	7	1372000
Cooling system (W)	9	6	4	3	6	5	6	116640
Chip removal system (K)	4	6	7	9	6	5	6	272160
Pneumatic System (G)	10	7	2	7	10	8	9	705600
Lubrication System (L)	5	7	3	5	9	6	10	283500
Numerical Control (NC)	3	8	5	10	8	9	8	691200
Spindle System (S)	4	5	8	4	10	10	10	640000
Guard (Q)	2	4	6	2	6	5	6	17280

Table 11. Fault risk assessment results based on DEA.

DMU	efficiency value
Tool Magazine System (M)	1
Electrical System (V)	0.283
Feed System (J)	1
Cooling System (W)	0.147
Chip removal System (K)	0.309
Pneumatic System (G)	1
Lubrication System (L)	0.423
Numerical Control (NC)	1
Spindle System (S)	0.731
Guard (Q)	0.039

The higher the super-efficiency value, the higher the risk. As can be seen from Table 11, for this type of machining center, the risky systems are tool magazine system, feed system, pneumatic system, numerical control system, and spindle system. Among them, the tool magazine system, feed system, CNC system, and spindle system are the key components of the machining center. The reliability of these systems has a direct impact on the machining quality of the machining center. The pneumatic system covers most components of the machining center. Once the pneumatic system If there is a problem, the machining center will stop and affect the operation of the equipment. When choosing the data envelopment method to analyze the fault risk of subsystems, the risk increases with the increase of the super-efficiency value, and at the same time, it can complete the objective ranking of subsystems, which is also consistent with the concept that people think that it is necessary to improve the fault risk. Applying the data envelopment method to synthesize more effective information from the perspective of weighting makes the evaluation results more comprehensive and objective.

4. Conclusion and implications

4.1. Conclusions

(1) Considering fault correlation, this study constructs a multi-indicator risk assessment system including fault impact degree, fault frequency, comprehensive failure rate, maintenance time, maintenance difficulty, maintenance ergonomics, and maintenance cost. By integrating DEMATEL/ISM/ANP, Bayesian inference, Copula function, cloud model, and DEA, the subjectivity in assessment is effectively reduced, and the evaluation accuracy is significantly improved.

(2) This study establishes a fault correlation model through DEMATEL-ISM and converts it into ANP network structure and Bayesian network respectively. It not only considers the severity of the fault mode itself, but also considers the relationship between the fault modes, which lays the foundation for the accurate assessment of the fault risk of CNC equipment.

(3) This paper uses DEA to rank the failure risks. It can detect high-risk subsystems objectively without subjective weight presetting, providing a direct quantitative basis to decide the prioritization of maintenance reliability design.

4.2. Implications

This fault risk assessment method of the study has explicit engineering significance for the reliability management of CNC equipment.

(1) The fault correlation model enables enterprises to identify high-risk subsystems and their major failure modes, providing a quantitative basis for reliability design optimization and preventive maintenance planning.

(2) The quantified impact degree of the fault and the posterior failure frequency are key inputs for DEA evaluation. Enterprises can choose these indexes when making decisions on maintenance plan and reduce the risks by optimal design and improved condition monitoring.

(3) Copula-based comprehensive failure rate indicates the influence of fault correlation on system risk. The DEA result can provide objective ranking of risk of subsystems and enterprises can locate the weak links and make targeted reliability improvements accordingly.

Acknowledgment

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References

1. Gupta G, Mishra PR.Comparative analysis of traditional and fuzzy FMECA approach for criticality analysis of conventional lathe machine. *International Journal of System Assurance Engineering and Management* 2020; 11(Suppl 2): 379-386. https://doi.org/10.1007/s13198-019-00938-y.
2. Zhang HR, Hong RJ, Chen,FX,Zhang YB.Reliability analysis method of CNC machine tools on FMECA and fuzzy evaluation.

Manufacturing Technology & Machine Tool 2020; 11: 125-129. (in Chinese).

3. Sezer SI, Ceylan BO, Akyuz E, Arslan O.D-S evidence based FMECA approach to assess potential risks in ballast water system (BWS) on-board tanker ship. *Journal of Ocean Engineering and Science* 2025; 10(4): 509-520. https://doi.org/10.1016/j.joes.2022.06.040.
4. Tian HL, Sun YZ, Chen CH, Zhang ZY, Liu TY, Zhang TY, He JL, Yu LJ. A novel FMECA method for CNC machine tools based on D-GRA and data envelopment analysis. *Scientific Reports* 2024; 14: 26596. https://doi.org/10.1038/s41598-024-77920-7.
5. Chen HX, Chen WH, Li HY, Zhang JT, Niu B. FMECA-Based Reliability Analysis of Heavy-Duty CNC Machine Tools. *Quality and Reliability Engineering International* 2025; 41(5): 1804-1814. https://doi.org/10.1002/qre.3777.
6. Sun YZ, Tian HL, He JL, Chen CH, Liu ZF. Dynamic failure modes and effects analysis method considering synergistic standards of failure correlation and expert evaluation. *Expert Systems with Applications* 2025; 279: 127461. https://doi.org/10.1016/j.eswa.2025.127461.
7. Bowles JB.An assessment of RPN prioritization in a failure modes effects and criticality analysis. *Journal of the Institute of Environmental Sciences and Technology* 2004; 47(1): 51-56. https://doi.org/10.17764/jiet.47.1.y576m26127157313.
8. Chen HX, Ren J, Zhang JF, Wang F, Xie SX. FMECA Analysis of Heavy-duty CNC Machine Tools Based on Comprehensive Maintenance Information. *Machine Tool & Hydraulics* 2025; 53(06): 9-15.(in Chinese).
9. Sun SG, Zhou WJ, Zhang M, Liu XY, Mou XW. Fault analysis of CNC equipment based on DEMATEL/ISM/ANP. *Journal of Mechanical Science and Technology* 2020; 34(8): 3181-3188. https://doi.org/10.1007/s12206-020-0709-z.
10. Li H, Deng ZM, Golilarz NA, Guedes Soares C. Reliability analysis of the main drive system of a CNC machine tool including early failures. *Reliability Engineering & System Safety* 2021; 215: 107846. https://doi.org/10.1016/j.ress.2021.107846.
11. Yu LJ, Zhang TY, Tian HL, Yang ZJ, Liu A. FMECA of CNC machine tool design stage based on CBWM and DEA. *Quality and Reliability Engineering International* 2024; 40(1): 154-169. https://doi.org/10.1002/qre.3312.
12. Nguyen TS, Likitlersuang S, Tanapalungkorn W, Phan TN, Keawsawasvong S. Influence of copula approaches on reliability analysis of slope stability using random adaptive finite element limit analysis. *International Journal for Numerical and Analytical Methods in Geomechanics* 2022; 46(12): 2211-2232. https://doi.org/10.1002/nag.3385.
13. Zhao ZY. Fault risk assessment of CNC lathe components based on grey clustering. [dissertation].Changchun: Jilin University; 2017. (in Chinese).
14. Datta S, Balodi KC, Jakhar SK.Assessing Critical Success Factors for Industry 4.0-Enabled Circular Startups: A Fuzzy AHP-DEMATEL Approach. *Business Strategy and the Environment* 2025; 34(6): 7591-7621. https://doi.org/10.1002/bse.4344.
15. Agarwal A, Ojha R. Prioritisation of barriers in the journey of regenerative tourism - a DEMATEL perspective. *Journal of Advances in Management Research* 2026; 23(1): 1-18. https://doi.org/10.1108/JAMR-08-2024-0308.
16. Sen MK, Dutta S, Kabir G.Evaluation of interaction between housing infrastructure resilience factors against flood hazard based on rough DEMATEL approach. *International Journal of Disaster Resilience in the Built Environment* 2021; 12(5): 555-575. https://doi.org/10.1108/IJDRBE-08-2020-0089.
17. Demirci SME, Cicek K.Innovative strategy development approach for enhancing the effective implementation of the International Safety Management (ISM) Code. *Transportation Research Record* 2023; 2677(1): 25-48. https://doi.org/10.1177/03611981221098394.
18. Kumar R, Goel P.Exploring the Domain of Interpretive Structural Modelling (ISM) for Sustainable Future Panorama: A Bibliometric and Content Analysis. *Archives of Computational Methods in Engineering* 2022; 29(5): 2781-2810. https://doi.org/10.1007/s11831-021-09675-7.
19. Liu H, Li RC.Risk research on military family members based on ANP and fuzzy clustering. *Operations Research and Management* 2021; 30(3): 7-14.(in Chinese).
20. Wang JG, Yu YP.Research on the classification and evaluation model of water conservancy engineering professional and technical talents based on ANP-FCE. *Science and Technology Management Research* 2022; 42(13): 34-42. (in Chinese).
21. Karuppiah K, Sankaranarayanan B, Ali SM. A fuzzy ANP–DEMATEL model on faulty behavior risks: implications for improving safety in the workplace. *International Journal of Occupational Safety and Ergonomics* 2022; 28(2): 923-940. https://doi.org/10.1080/10803548.2020.1847486.
22. Guo BT, Wang SB, Wang JN, He YM. Research on the co-construction performance evaluation system of new R&D institutions based on

network analytic hierarchy process. *Science and Technology Management Research* 2020; 40(10): 72-79. (in Chinese).
23. Chen HX, Song R, Yuan Y.Research on the index system of incubator innovation management: based on triple helix theory and ANP method. *Technical Economics* 2020; 39(4): 86-94. (in Chinese).
24. Dun S, Mao JQ. Research on innovation and decision-making of trust guarantee model of sharing economy enterprises: comparative analysis of multiple cases based on ANP model. *Journal of Shanghai Administration College* 2024; 25(3): 80-100. (in Chinese).
25. Salmani Y, Partovi FY.The validity study of a channel-based demand estimation ANP model. *Journal of Multi-Criteria Decision Analysis* 2023; 30(5-6): 190-202. https://doi.org/10.1002/mcda.1817.
26. Wang QA, Chen J, Ni YQ, Xiao YF, Liu NB, Liu SK, Feng WS.Application of Bayesian networks in reliability assessment: A systematic literature review. *Structures* 2025; 71: 108098. https://doi.org/10.1016/J.ISTRUC.2024.108098.
27. Li YL, Hou XY. Risk diagnosis and prediction of major engineering slag yard based on fault tree and Bayesian network integration. *Journal of System Management* 2022; 31(5): 861-874. (in Chinese).
28. Li JL, Tan T.Measurement of scientific and technological innovation efficiency of research and development institutions and countermeasures for improvement: based on data envelopment analysis and Malmquist index method. *Science and Technology Management Research* 2023; 43(4): 94-99. (in Chinese).
29. Ma YL, Wei SG.Under the background of high-quality development, the scientific research efficiency of universities in western my country and its influencing factors-based on the super-efficiency DEA window-Malmquist-Tobit model. *Science and Technology Management Research* 2023; 21: 11-19. (in Chinese).
30. Song H, Lu N, Jiang B, Shi W, Meng LH, Wang YJ, Lyu JH. Multivariate degradation modeling with long-term dependency for operational reliability assessment. *Reliability Engineering & System Safety* 2026; 272 (part 1): 112496. https://doi.org/10.1016/j.ress.2026.112496.
31. Shi Y, Yan Z, Peng X. Statistical analysis of the k/n (G) system with dependent competing failure components influenced by Gumbel-Hougarrd Copula and progressively hybrid censored data. *Heliyon* 2025; 11(2). https://doi.org/10.1016/j.heliyon.2025.e41784.
32. Andrade ABB, do Nascimento AR, Rathie PN.Parametric and nonparametric inference for the reliability of copula-based stress-strength models. *Quality and Reliability Engineering International* 2020; 36(7): 2249-2267. https://doi.org/10.1002/qre.2694.
33. Gu DW, Zhong YH, Xu Z, Chen BK, Wang ZQ.An importance measure of a CNC lathe considering failure correlations. *Quality and Reliability Engineering International* 2022; 38(3): 1367-1379. https://doi.org/10.1002/qre.2963.
34. Zhao XZ. Machining center maintainability assignment based on failure dependence. [dissertation]. Changchun: Jilin University; 2018.(in Chinese).
35. Wang P, Xu XH, Huang S, Cai CG.A Linguistic Large Group Decision Making Method Based on the Cloud Model. *IEEE Transactions on Fuzzy Systems* 2018; 26(6): 3314-3326. https://doi.org/10.1109/TFUZZ.2018.2822242.
36. Liao LC, Fan LJ, Wang P. An organizational performance evaluation method based on cloud theory. *Systems Engineering* 2010; 28(1): 99-104. (in Chinese).