IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received June 26, 2019, accepted July 2, 2019, date of publication July 5, 2019, date of current version July 25, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2927008

Cascading Fault Analysis and Control Strategy for Computer Numerical Control Machine Tools Based on Meta Action

GUANGQUAN HUANG[1,2], BINGKUI CHEN[1,2], LIMING XIAO[1,2], YAN RAN[1,2], AND GENBAO ZHANG[1,2,3]

[1]State Key Laboratory of Mechanical Transmission, Chongqing University, Chongqing 400044, China
[2]College of Mechanical Engineering, Chongqing University, Chongqing 400044, China
[3]School of Mechanical and Electrical Engineering, Chongqing University of Arts and Science, Chongqing 402160, China

Corresponding author: Yan Ran (ranyan@cqu.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 51705048 and Grant 51575070, and in part by the National Major Scientific and Technological Special Project for High-grade CNC and Basic Manufacturing Equipment of China under Grant 2016ZX04004-005 and Grant 2018ZX04032-001.

ABSTRACT Cascading faults of computer numerical control machine tools will lead to frequent machine faults, but an effective fault analysis and control strategy can significantly reduce the frequency of such cascading faults. The numerous studies have focused on faulty parts using established fault diagnosis models centered on faulty parts and developed measures for controlling machine tool reliability from the parts' perspective. However, the internal parts of machine tools are strongly coupled, and when one part or assembly begins operating abnormally, it can easily initiate the abnormal operation of other parts or the entire assembly, which can lead to failures. Thus, a fault diagnosis method that considers only individual faulty parts ignores the problem of fault propagation between parts, which may lead to failure to locate the root cause. To address this problem, this paper proposes a cascading fault analysis and control strategy based on meta action. First, the functional components are decomposed into meta actions using the "function-motion-action" principle. Second, the directed edges and hierarchical digraph of meta action fault propagation are obtained. Third, the PageRank algorithm is used to calculate the fault propagation impact degree of each directed edge, and the key paths of meta action fault propagation are extracted based on the hierarchical digraph and the impact degree. Finally, the fault tree analysis method is applied to analyze the meta action on key paths, and feasible machine control measures are developed. The feasibility and effectiveness of the method are demonstrated using an example machining center.

INDEX TERMS Machine tools, fault diagnosis, reliability engineering, fault location, machine control, quality management, data analysis, risk analysis, cause effect analysis.

I. INTRODUCTION

A computer numerical control (CNC) machine tool can be considered a complex system consisting of multiple subsystems. Across these subsystems, faults propagate due to the integration and embeddedness of the units and subsystems. Faults often start from one unit in a subsystem and propagate along multiple paths to other units, causing a series of subsystem faults that results in a cascading equipment fault and abnormal production [1], [2]. A cascading fault occurs when a certain functional component fault causes other functional components to become faulty, which can result in complete machine breakdown [3]. A cascading fault of machine tools will cause machine shutdown, reduce the quality of product processing, and affect normal processing, and it can even cause human injuries. Such faults can cause enormous economic losses and increase production costs [4]. Therefore, it is necessary to analyze and control cascading faults in CNC machine tools to improve their reliability.

To reduce the fault propagation frequency, it is necessary to locate the key paths and key nodes of CNC machine tool fault propagation through risk analysis and then develop the

The associate editor coordinating the review of this manuscript and approving it for publication was Gerard-Andre Capolino.

safeguard measures necessary to improve machine reliability. Therefore, fault analysis is an important step in CNC machine tool quality management. At present, many methods exist for analyzing cascading faults. The most common method of qualitative analysis is the display model method, which includes the event tree, causal table, and fault tree [5], [6]. Quantitative methods refer primarily to parameter models such as sensitivity analysis, decision tree, and the basic parameter model [7], [8]. These methods are good approaches for studying cascading faults based on fault monitoring and prediction that are made possible by the industrial Internet of Things (IoT) [9], [10]. Product defects can be detected using the fault location method and a mechanistic prediction model. This approach can effectively identify the fault root cause and has achieved good effects in the fault analysis field [11], [12]. Fault diagnosis methods based on data and virtual technology can also analyze and control faults. A global approach consisting of programming, modeling, measuring, monitoring and quality control is constructed to achieve parameter optimization and thus adequately constrain the operational status of the product to the process specifications [13]. Diagnosing product faults by establishing cyber-physical systems (CPSs) in Industrial 4.0 projects is another good approach. CPSs are equipped with technologies such as sensors, microprocessors, telematics or complete embedded systems and characterized by their ability to collect data concerning themselves and their environment and then process and evaluate these data, connect and communicate with other systems, and initiate actions [14].

Many researchers have applied complex system theory to study the cascading faults of CNC machine tools using model-driven methods and data-driven methods. The classical model-driven methods include directed causality graph, Bayesian network, Petri net, neural network model, model simulation, and topological network model [15]–[20]. Many researchers have also applied model-driven methods to study cascading faults. Geng *et al.* [21] proposed a fault prediction method in which a fault prediction algorithm based on rough set and back propagation (BP) neural network is divided into three parts: a data acquisition module, a data prediction module and a fault prediction module. The fault prediction module takes both normal and fault data as input, outputs the fault type, and trains the BP neural network to achieve fault prediction. Yau *et al.* [22] proposed an extension theory for predicting product life through different fractional order chaotic systems. In this approach, the boundaries of the product states are fed into the extension model, and a relational function is calculated to identify the product state.

Data-driven methods based on cascading fault analysis mainly include signal processing and machine learning. Zhang *et al.* [23] analyzed the impact of uncertain faults on product performance by using a Monte Carlo simulation to simulate and quantify the uncertain fault propagation caused by different control input values and to analyze the fault propagation process. Coro *et al.* [24] proposed a novel approach for product inspection scheduling based on reliability calculations and maintenance. They developed an improved first-order reliability method to analyze faults and achieved an effective control method for products.

The above studies are highly meaningful for machine tools. These studies generally focus on faulty parts, such as worm gears, shafts and gears. They establish a fault diagnosis model centered on the faulty parts and then develop measures to control the reliability of the functional component from a parts control perspective. However, because of the strong coupling and intersection among parts, when a part fails, it can easily cause faults in other parts of a functional component. Then, the functional component can fail due to fault propagation from part to part. A fault diagnosis method considers only individual faulty parts and ignores the fault propagation process among parts, which may lead to a fault diagnosis that fails to reflect the root cause. Besides, it is important to note that a functional component contains hundreds of parts. If fault diagnosis is implemented from the parts perspective, the modeling process will be extremely complicated and the workload will be excessive.

In view of above shortcomings, an integrated method based meta action (MA) and cascading fault analysis and control strategy (CFACS) is proposed for studying the fault propagation mechanism between MAs of CNC machine tools. First, because the number of MAs decomposed from a functional component fewer than that of parts. MA is used to simplify the modeling process and to reduce workload. Second, considering fault propagation process instead of ignoring the fault propagation in functional component, the hierarchical and impact degree of MAs fault propagation can be obtained and the fault propagation mechanism between MAs can be found to determine the fault root causes, which addressing the weakness that fault diagnosis considers only individual faulty parts. Besides, from an action perspective, MAs achieve functions in machine, the functions reliabilities depend on the MAs'. Therefore, using MA to study the cascading fault in functional component is reasonable. Based on above analysis, MA is developed to study the cascading faults and the fault propagation mechanisms of functional components for obtaining the fault root causes; then, reliability control measures are developed to ensure the reliability of the MA and improve the reliability of the functional components.

The implemented idea of this paper is as follows: Based on the digraph model of fault propagation and hierarchical decomposition technology, a structured and hierarchical model of fault propagation among the MAs is constructed using a decision-making trial and evaluation laboratory (DEMATEL) and an interpretative structural model (ISM). This structured and hierarchical model can describe the propagation steps and the diffusion behavior of CNC machine tool faults. Then, considering the fault propagation probability and the structure of the cascading fault propagation model, the key nodes and the key paths of fault propagation are identified, and the root cause and the internal propagation mechanisms of fault occurrences are studied. Fault tree analysis (FTA) is applied to analyze the key nodes on the key paths,

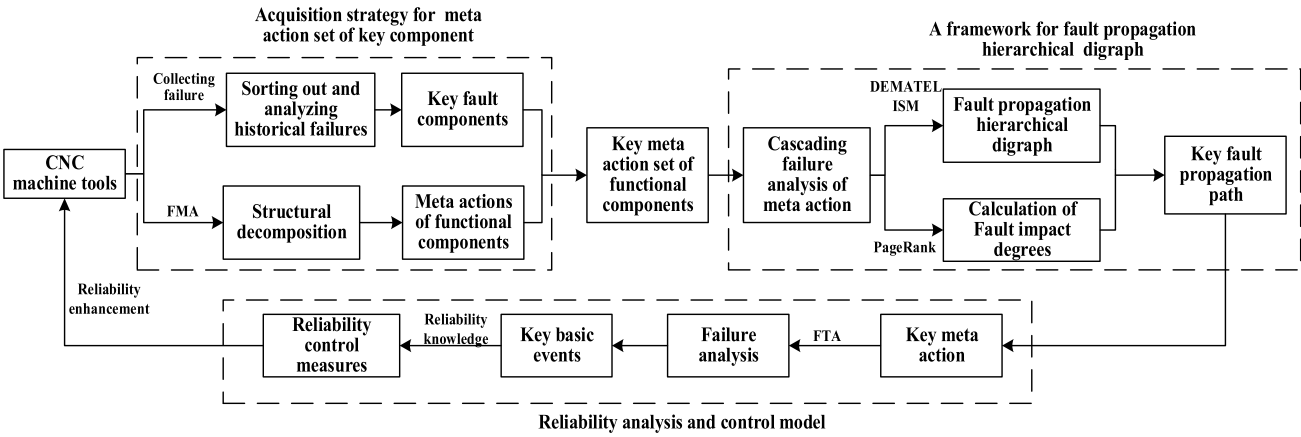

FIGURE 1. Cascading fault analysis and reliability control flow for CNC machine tool based on MA.

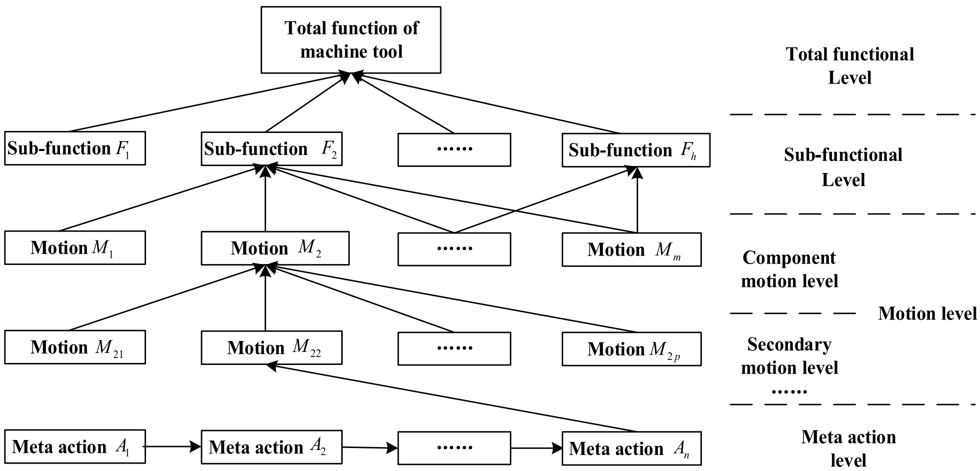

FIGURE 2. Structural decomposition model for CNC machine tool based on MA decomposition.

and reliability control measures for the key fault MA are implemented to ensure the reliability of the MA and the functional components of the machine tool. Cascading fault analysis and a control strategy provide the basis for improving fault diagnosis and system reliability, and they help ensure safe CNC machine tool operation.

II. IDENTIFICATION AND CONTROL OF FAULT PROPAGATION PATH FOR KEY MA

To improve the reliability of CNC machine tools, feasible reliability control measures should be taken. The common approach is to analyze the existing product faults, define the quality control points and formulate specific measures. Therefore, it is important to analyze the fault data and extract the reliability control points. Reliability control flow based on a cascading MA fault is shown in Fig. 1.

First, the key MA set of the functional components is obtained based on the historic fault information and the structural decomposition results of the MAs. Then, based on the data analysis results of the key MAs, the fault propagation path and the impact degree of the fault propagation are found to determine the root cause of the fault. Finally, the root cause is analyzed to determine the key basic events, and targeted reliability control measures are proposed to improve the reliability of the CNC machine tools.

A. STRUCTURAL DECOMPOSITION MODEL BASED ON MA

The decomposition process of CNC machine tools can be modeled from the motion perspective, considering the process by which the machine tools realize their function through minimum action. That is, the structural decomposition of CNC machine tools is conducted through the basic decomposition principle of "function – motion – action" (FMA), as shown in Fig. 2.

To achieve the overall machine function, the machine must achieve a set of corresponding subfunctions, the realization of these subfunctions depends on the motion of corresponding components and secondary motion, and the realization of motion depends on the corresponding MAs. An MA is the most basic form of motion for transmitting motion and power in machine tools. The force and motion relationship between all relevant parts is established by the MA. In this paper, a unit that is relatively independent in structure and achieves certain action goals that are controllable and need not (cannot) be subdivided is called an MA [25]. If a machine center is to achieve various part processing procedures, the B-axis worktable must be able to lift and rotate positively. To realize the rotary motion of the B-axis worktable, the servo motor, worm gear, worm and rotary cylinder should be able to operate normally. The last actions layer of the machine center is an MA (such as the rotation of the worm and worm wheel). The B-axis rotation generated by the action of the servo motor, worm gear, worm and rotary cylinder is a secondary motion.

Based on the above analysis, the reliability of the MA obtained by FMA affects the reliability of the machine. The historical fault data of a machine is collated and analyzed; when the machine contains e functional components, its set of functional components is defined as $F = (f_1, f_2, \cdots, f_p, \cdots, f_e)$. The fault set of component f_p is defined as $G = (g_{p1}, g_{p2}, \cdots, g_{pk}, \cdots, g_{pt})$, and g_{pk} is the k-th fault of the functional component p. The number of occurrences of a fault is defined as $Y = (y_{p1}, y_{p2}, \cdots, y_{pk}, \cdots, y_{pt})$, and y_{pk} is the number of times the k-th fault occurred. The fault frequency of component f_p is defined as follows:

$$Q_p = \sum_{k\geq 0}^{t} g_{pk}y_{pk} \div \sum_{p\geq 0}^{e}\sum_{k\geq 0}^{t} g_{pk}y_{pk} \tag{1}$$

After sorting the faults based on the magnitude of their fault occurrence rates, functional components with higher fault rates are selected as the key fault components (e.g., B-axis rotary table) by the 80/20 rule, and the set of MAs for the key components is defined as the key MA set. The key fault components with high fault rates are the main factors that affect machine tool performance.

B. HIERARCHICAL DIGRAPH OF MA FAULT PROPAGATION BASED ON DEMATEL-ISM

The MA of functional components has strong coupling with the structure design, assembly and running sequence. If an MA operates abnormally or fails, it can easily cause other MAs to fail, resulting in fault propagation among MAs. Therefore, it is necessary to clarify the transmission mechanism of the cascading fault in the key MA set. One method for analyzing and making decisions about complex systems is DEMATEL, which was proposed by the American professors A. Gabus and E. Fontatela in 1971 [26]. DEMATEL can effectively analyze the interactions among various influencing factors to extract the key impact factors. In recent years, DEMATEL has been widely applied to different fields by scholars from Japan, the United States, and South Korea [27]. ISM is a structured modeling method developed by J. Warfield in the United States for analyzing complex socioeconomic system structures [28], [29]. ISM mainly uses digraph and matrix theory to describe the structural relationships among the elements (or subsystems) of complex systems. Thus, the complex and ambiguous relations among the elements in the system can be arranged hierarchically and organized.

In this paper, DEMATEL is used to analyze the fault propagation process among the MAs of functional components and determine the relationship of fault propagation within the MAs. Then, ISM is used to determine the primary and secondary relationships of fault propagation among the MAs, and the hierarchical relationship of cascading fault propagation among MAs is obtained. The DEMATEL-ISM process is implemented as follows. First, the DEMATEL method is used to derive the comprehensive impact matrix and the overall impact matrix for various factors. Then, the overall impact matrix is transformed into a reachability matrix. Finally, based on the reachability matrix and ISM method, the hierarchical structural model of system factors is obtained. A hierarchical decomposition flow chart of the integrated DEMATEL-ISM method is shown in Fig. 3.

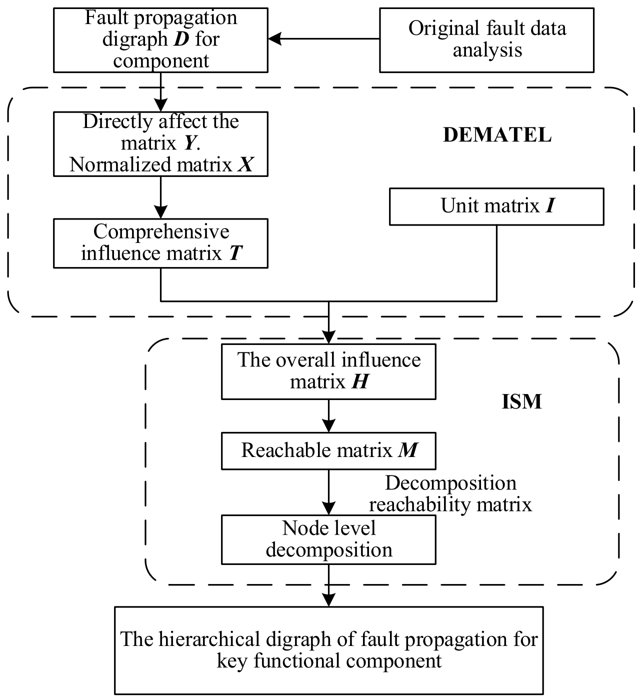

FIGURE 3. A hierarchical decomposition flow chart of the integrated DEMATEL-ISM method for obtaining hierarchical digraph.

The calculation process is as follows:

(1) Each MA of functional components is defined as a node set $A = (A_1, A_2, \cdots, A_i, \cdots, A_n)$. Fault propagation among MAs is represented by a set of directed edges $E = \{e_{ij}\}$ $(1 \leq i, j \leq n)$. Based on cause effect analysis of fault modes and the causes among MAs, a digraph $D = (A, E)$ of MA fault propagation can be constructed.

(2) According to the fault impact relation of the cascading fault of MAs, the digraph of fault propagation can be transformed into a direct impact relation matrix $\boldsymbol{Y} = (y_{ij})_{n\times m}$, and y_{ij} is calculated as follows:

$$y_{ij} = \begin{cases} 0, & i = j \\ u, & i = j \end{cases} \tag{2}$$

where u is the number of times the MA A_i affects the MA A_j.

(3) The direct impact relation matrix $\boldsymbol{Y}$ needs to be normalized. The equation for normalizing the direct impact relation matrix $\boldsymbol{Y}$ is as follows:

$$\boldsymbol{X} = \frac{\boldsymbol{Y}}{\max\limits_{1<j<n} \sum\limits_{j=1}^{n} y_{ij}} \tag{3}$$

(4) The comprehensive action matrix $\boldsymbol{T}$ for MA faults that are directly and indirectly related to the underlying fault is obtained as follows:

$$\boldsymbol{T} = \lim_{k\to\infty} (\boldsymbol{X}+\boldsymbol{X}^2+\cdots+\boldsymbol{X}^K) = \boldsymbol{X}(\boldsymbol{I}-\boldsymbol{X})^{-1} = (t_{ij})_{n\times n} \tag{4}$$

where t_{ij} indicates whether the MA A_i has an effect on the MA A_j; $t_{ij} = 1$ when the MA A_i does affect MA A_j; otherwise, $t_{ij} = 0$. $\boldsymbol{I}$ represents the unit matrix.

(5) Calculation of overall impact matrix of the system, $\boldsymbol{H}$. The comprehensive impact matrix $\boldsymbol{T}$ reflects only the relationships among and correlation degrees of the fault propagations of different MAs. However, the impact of the MA fault is not considered. Therefore, the overall impact matrix of the system, $\boldsymbol{H}$, is obtained as follows:

$$\boldsymbol{H} = \boldsymbol{T} + \boldsymbol{I} = \left[h_{ij}\right]_{n\times n} \tag{5}$$

where h_{ij} represents the direct and indirect impacts of factor i on factor j.

(6) The reachability matrix $\boldsymbol{M}$ is defined as $\boldsymbol{M} = [m_{ij}]_{n\times n}$, and the element m_{ij} is calculated as follows:

$$m_{ij} = \begin{cases} 1, & h_{ij} > \lambda \\ 0, & h_{ij} \le \lambda \end{cases} \tag{6}$$

where m_{ij} represents whether the MA A_i has an effect on the MA A_j at a given threshold. For a system with few MAs, λ can equal 0.

(7) Domain decomposition. The reachable set, the antecedent set, the common set, the initial set and the termination set of MA fault propagation are defined below.

The reachable set $R(A_i)$ of the system element A_i represents a collection of all elements that A_i can reach in a reachability matrix $\boldsymbol{M}$:

$$R(A_i) = \left\{A_i | A_i \in A, m_{ij} = 1, i = 1, 2, \cdots, n, j = 1, 2, \cdots, n\right\} \tag{7}$$

The antecedent set $R(A_i)$ of system element A_i represents a collection of all the elements from which A_i can be reached in a reachability matrix $\boldsymbol{M}$.

$$A(A_i) = \left\{A_j | A_j \in A, m_{ji} = 1, i = 1, 2, \cdots, n, j = 1, 2, \cdots, n\right\} \tag{8}$$

The common set $C(A_i)$ of system element A_i represents the common part of the reachable set $R(A_i)$ and the antecedent set $A(A_i)$.

$$C(A_i) = \left\{A_j | A_j \in A, m_{ij} = 1, m_{ji} = 1, i, j = 1, 2, \cdots, n\right\} \tag{9}$$

The initial set $B(A)$ of the system MA A_i represents the set of MAs that affect other MAs but not the other MAs. The MAs in the initial set $B(A)$ are the input MAs of the system, and its digraph consists only of outflowing arrows with no inflowing arrows. When the opposite is the case, the set of MAs is defined as the termination set $E(A)$:

$$B(A) = \left\{A_j | A_j \in A, C(A_i) = A(A_i), i = 1, 2, \cdots, n\right\} \tag{10}$$

$$E(A) = \left\{A_j | A_j \in A, C(A_i) = R(A_i), i = 1, 2, \cdots, n\right\} \tag{11}$$

(8) Division of levels. For the same area, the MAs satisfying Eq. (12) are sequentially acquired, and the sets of all levels are found and defined.

$$C(A_i) = R(A_i) \cap A(A_i) = R(A_i) \tag{12}$$

(9) Establishment of a hierarchical digraph model for MA fault propagation.

C. CALCULATING THE IMPACT DEGREES OF MA FAULTS USING THE PAGERANK ALGORITHM

The hierarchical digraph model of MA fault propagation performs only a qualitative analysis of all the main root causes and fault propagation paths; it cannot accurately describe the magnitude of fault propagation among MA mathematically. The PageRank algorithm was proposed by Google founders Brin and Page in 1998 [30], and it effectively calculates the correlations between and relative importance of different web pages [31]. Therefore, the PageRank algorithm is used to measure the fault impact degrees of an MA on its outwardly linked MAs and to quantitatively analyze the MA fault impact degree.

The PageRank process is implemented as follows: if a fault in MA A_i causes a fault in MA A_j, MA A_i can be considered to pass an important degree value, PR, to MA A_j. The magnitude of the PR value is related to the importance $PR(A_i)$ of MA A_i and the number of outgoing links. There is a mutual connection relationship among MAs, and the relationship will iterate all the time. Therefore, the value $PR(A_i)$ based on the iteration of MA A_i is taken as the impact degree of MA A_i.

If the faulty nodes that link in to MA A_i are MAs A_1, A_2, $\cdots$, A_j ($0 \le j \le n$), then the importance $PR(A_i)$ of MA A_i can be calculated as follows:

$$PR(A_i) = \frac{1-d}{n} + d \sum_{A_j \in I(A)} \frac{PR\left(A_j\right)}{O(A_i)} \tag{13}$$

where n represents the number of MAs, d represents the damping factor, $PR(A_i)$ represents the probability that the fault will continue to move down at the directed edge after reaching a certain mate action. $I(A_j)$ represents the linked MA set of MA A_j, $O(A_j)$ represents the outgoing MAs set of MA A_j, and $PR(A_j)/O(A_j)$ represents the fact that MA A_j assigns its PR value evenly across its own outgoing MAs set.

When the number of nodes in the digraph is small, the PR values of the nodes can be calculated by Eq. (13). However, when the number of nodes is large, the solution obtained using Eq. (13) will be quite complicated. The PageRank algorithm assumes that fault propagation conforms to a Markov process. For a digraph $D = (A, E)$ consisting of nMAs and the corresponding linked relationships, the number of element 1 in the adjacency matrix $\boldsymbol{Q}$ is the number of links in the digraph. Each row element of matrix $\boldsymbol{Q}$ is divided by the sum of the row elements to obtain a normalized matrix $\boldsymbol{Q}'$, where $\boldsymbol{Q}'$ is the Markov state transition matrix. Then, matrix $\boldsymbol{Q}'$ is transposed to obtain the transposed matrix $[\boldsymbol{Q}']^T$.

The PR value can be calculated by the probability of the transposed matrix as follows:

$$\boldsymbol{PR}^{x+1} = \frac{1-d}{d}\boldsymbol{e} + d[\boldsymbol{Q}']^T \boldsymbol{PR}^x \tag{14}$$

where $\boldsymbol{PR}^{x+1}$ represents the $(n \times 1)$-order matrix of the impact degrees of the nodes, and the impact degrees are obtained by the $(x+1)$-th iteration, $\boldsymbol{e} = (1, 1, \cdots, 1)^T$.

The equation can be expanded as follows:

$$\begin{bmatrix} PR(1) \\ PR(2) \\ \cdots \\ PR(n) \end{bmatrix}^{x+1} = \begin{bmatrix} (1-d)/n \\ (1-d)/n \\ \cdots \\ (1-d)/n \end{bmatrix} + d \begin{bmatrix} l(p_1, p_1) & l(p_1, p_2) & \cdots & l(p_1, p_n) \\ l(p_2, p_1) & l(p_2, p_2) & \cdots & l(p_2, p_n) \\ \vdots & \vdots & l(p_i, p_j) & \vdots \\ l(p_n, p_1) & l(p_n, p_2) & \cdots & l(p_n, p_n) \end{bmatrix} \begin{bmatrix} PR(1) \\ PR(2) \\ \cdots \\ PR(n) \end{bmatrix}^{x} \tag{15}$$

In the above equation, when a fault link exists in which MA A_i is connected to MA A_i, then $l(p_i, p_j) = 1$; otherwise, $l(p_i, p_j) = 0$. The initial values of an MA generally do not affect the convergence of the equation or the final iteration effect. Generally, $\boldsymbol{PR}^{(1)} = [1, 1, \cdots, 1]^T$ can be set.

Assuming that ε is a specified iteration stationary convergence threshold, each MA is given an initial PR value. When $\max\limits_{1 \le i \le n} \left| \boldsymbol{PR}^{x+1} - \boldsymbol{PR}^x \right| < \varepsilon$ is satisfied, the iteration ends and the fault impact degrees of MAs are obtained.

Combined with the hierarchical digraph model of MA fault propagation, the impact degrees of MAs faults can be regarded as the directed edge values of the digraph. Then, the impact degree hierarchical digraph model of MA fault propagation can be obtained.

By defining the n-dimensional vector $\boldsymbol{C}_I = (C_1, C_2, \cdots, C_n)^T$, the elements in $\boldsymbol{C}_I$ represent the fault impact degrees of each MA in the digraph. During fault propagation, the fault impact degree refers to the ability of an MA to cause faults in other MAs, and its magnitude is positively correlated with MA faults and the number of outgoing links. Each element value represents the probability that an MA will influence faults in other MAs. Therefore, the PageRank algorithm can be used to calculate the fault impact degree $\boldsymbol{C}_I$ of an MA fault. The system consists of n elements; the elements in $\boldsymbol{C}_I$ represent the fault impact values of MA, and the elements of $C_I^{(x+1)}$ represent the $(n \times 1)$-order matrix of the fault impact value of MA obtained by the $(x+1)$-th iteration. The iterative matrix calculation equation for a value is defined as follows:

$$\boldsymbol{C}_I^{(x+1)} = \frac{(1-d)}{n} \cdot \boldsymbol{e} + d \cdot [[\boldsymbol{C}^T]']^T \cdot \boldsymbol{C}_I^{(x)} \tag{16}$$

where $[\boldsymbol{C}^T]'$ is a normalized matrix obtained from the transposed matrix $\boldsymbol{C}^T$ of the adjacency matrix $\boldsymbol{C}$.

By considering the calculated fault impact degrees of MA, combined with the hierarchical digraph model of MA fault propagation, the impact degree hierarchical digraph of MA fault propagation can be obtained. Then, the hierarchical digraph model and the fault impact degree value of the directed edge are comprehensively analyzed to determine the key paths of MA fault propagation.

D. ANALYSIS AND RELIABILITY CONTROL OF KEY FAULT MA

The MAs on the key path of fault propagation have a strong impact on the functional components and on the machine. Therefore, they should be closely controlled. Fault tree analysis (FTA) is an effective method for performing fault analysis. All the possible causes and the key factors can be identified using FTA. In addition, FTA also makes it possible to perform both qualitative and quantitative fault analyses [32], [33]. Therefore, FTA is used to analyze the MAs on the key path and determine the key basic events that underlie the faulty MAs. Then, corresponding reliability control measures are developed to control the key basic events to improve the reliability of the MA and reduce the frequency of fault propagation during system operation. As a result, the goal of improving machine reliability can be achieved. The flow analysis of a key fault MA based on FTA is shown in Fig. 4.

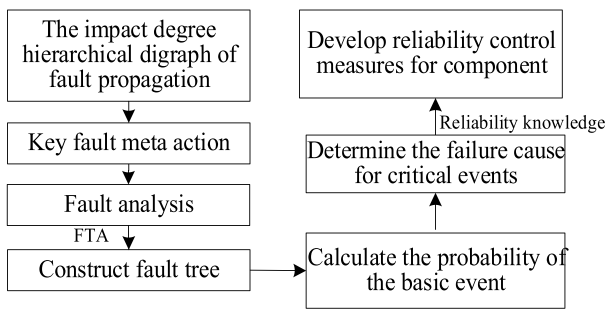

FIGURE 4. The fault analysis and control flow for a key fault MA.

III. APPLICATION EXAMPLE

Based on the fault information provided by the after-sales service department and a fault analysis of a CNC machining center from 2013 to 2018, the fault rate of each functional component can be obtained, as shown in Table 1. It can be found that the automatic pallet changer (APC) has the highest fault rate. Therefore, the APC was selected as the analysis and control object for this example. To realize the function of machining parts for a machine center, the APC must complete corresponding motions, such as "lifting motion of pallet changer" and "rotation motion of pallet changer". To realize

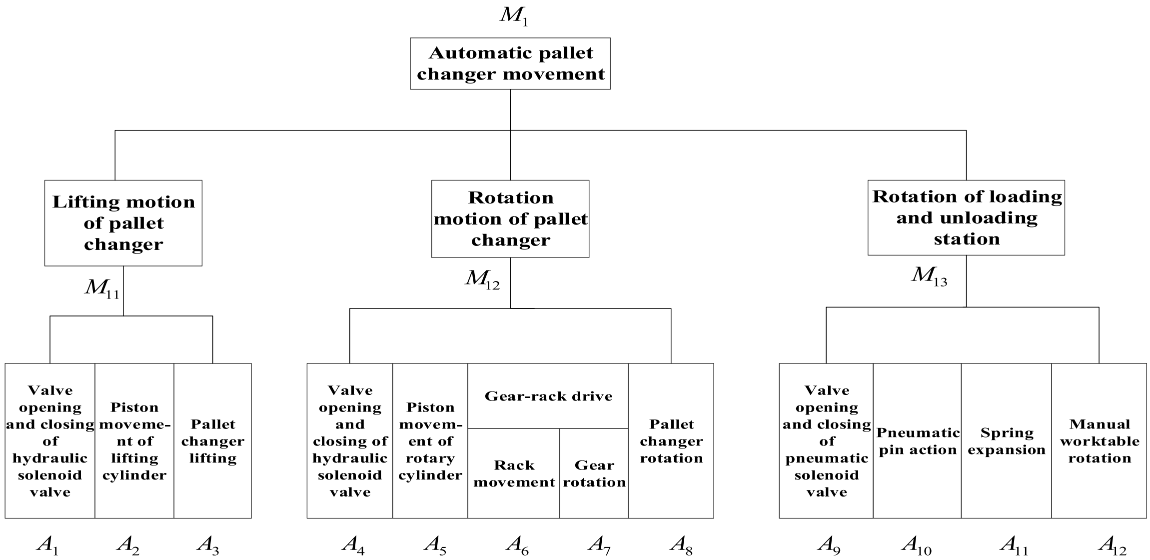

FIGURE 5. The structural decomposition of the APC based on MA.

TABLE 1. The original fault data and fault rate of a CNC machining center.

Functional components	Fault occurrences	Fault rate	Functional components	Fault occurrences	Fault rate
APC	142	16.82%	Electric	79	9.36%
Spindle	113	13.39%	Hydraulics	74	8.77%
Turntable	102	12.09%	Cooling system	70	8.29%
Auto tool changer	89	10.55%	Others	175	20.73%
	Total			844	

rotation motion of pallet changer, the pallet is driven by the piston movement, and then the rearward portion rotates. The gear and the pallet changer are connected by screws and nuts. After the gear rotates, the pallet changer of the APC is driven to rotate and then achieves the pallet changer rotation.

A. MA ACQUISITION

According to the above decomposition process and the FMA decomposition model shown in Fig. 2, the APC is structurally decomposed. The result of the FMA structural decomposition for the APC is shown in Fig. 5, and A_i ($i = 1, 2, \cdots, 12$) represents MA i.

B. OBTAINED HIERARCHICAL DIGRAPH OF MA FAULT PROPAGATION

The original historical fault data of the APC were analysis point by point. It can be observed that 45 of these faults were related, that is, the total number of cascading faults of the APC was 45. Considering the effective relations between the cascading fault data, the digraph of MA fault propagation for the APC is constructed, as shown in Fig. 6.

Based on Fig. 6 and Eq. (2), the direct impact relation matrix $\boldsymbol{Y}$ between the MAs of the APC can be obtained. Then, the reachability matrix $\boldsymbol{M}$ is obtained using Eq. (6). Based on Eqs. (8) – (12), the reachable set $R(A_i)$, antecedent set $A(A_i)$, common set $C(A_i)$, initial set $B(A)$ and termination set $E(A)$ are obtained, respectively, as shown in Table 2. Based on Eq. (14), the level division of all MAs can be obtained as shown in Table 3.

TABLE 2. The reachable set, antecedent set, common set, initial set and termination set of MAs for the APC.

A_i	Reachable set $R(A_i)$	Antecedent set $A(A_i)$	Common set $C(A_i)$	Initial set $B(A)$	Termination set $E(A)$
1	1,3,12	1,2,5	1		
2	1,2,3,4,5,7,8	2	2	2	
3	3	1,2,3	3		3
4	4,7,8,9	2,4	4		
5	1,5,8,11	2,5	5		
6	6,7,8	6	6	6	
7	7,8,12	2,4,6,7	7		
8	8	2,4,5,6,7,8,9,11	8		8
9	8,9,12	4,9,10	9		
10	9,10,11	10	10	10	
11	8,11,12	5,10,11	11		
12	12	1,7,9,11,12	12		12

TABLE 3. Level division table of MAs for the APC.

Element set	A_i	$R(A_i)$	$A(A_i)$	$C(A_i)$	$E(S)$	Level division set
$P_1 - L_0$	1	1,3,12	1,2,5	1		$L_1 = \{A_3, A_8, A_{12}\}$
	2	1,2,3,4,5,7,8	2	2		
	3	3	1,2,3	3	3	
	4	4,7,8,9	2,4	4		
	5	1,5,8,11	2,5	5		
	6	6,7,8	6	6		
	7	7,8,12	2,4,6,7	7		
	8	8	2,4,5,6,7,8,9,11	8	8	
	9	8,9,12	4,9,10	9		
	10	9,10,11	10	10		
	11	8,11,12	5,10,11	11		
	12	12	1,7,9,11,12	12	12	
$P_1 - L_0 - L_1$	1	1,	1,2,5	1	1	$L_2 = \{A_1, A_7, A_9, A_{11}\}$
	2	1,2,4,5,7	2	2		
	4	4,7,9	2,4	4		
	5	1,5,11	2,5	5		
	6	6,7	6	6		
	7	7	2,4,6,7	7	7	
	9	9	4,9,10	9	9	
	10	9,10,11	10	10		
	11	11	5,10,11	11	11	
$P_1 - L_0 - L_1$ $-L_2$	2	2,4,5	2	2		$L_3 = \{A_4, A_5, A_6, A_{10}\}$
	4	4,	2,4	4	4	
	5	5	2,5	5	5	
	6	6	6	6	6	
	10	10	10	10	10	
$P_1 - L_0 - L_1$ $-L_2 - L_3$	2	2	2	2	2	$L_4 = \{A_2\}$

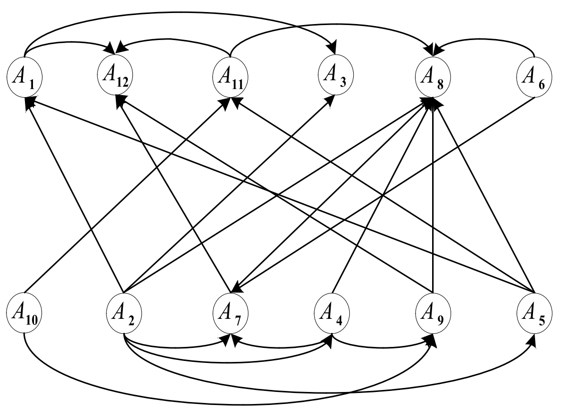

FIGURE 6. The fault propagation digraph of the APC based on MA.

Based on Table 2 and Table 3, the hierarchical digraph of MA fault propagation for the APC is constructed, as shown in Fig. 7.

C. CALCULATION OF FAULT IMPACT DEGREE

Before calculating the fault impact degree, matrix $\boldsymbol{C}^T$ and matrix $[\boldsymbol{C}^T]'$ need to be obtained. $\boldsymbol{C}^T$ is the transposed matrix of the adjacency matrix $\boldsymbol{C}$, and it can be obtained based on the adjacency matrix $\boldsymbol{C}$ described in Section B and mathematical knowledge. $[\boldsymbol{C}^T]'$ is a normalized version of the transposed matrix $\boldsymbol{C}^T$ obtained by dividing each row element of the

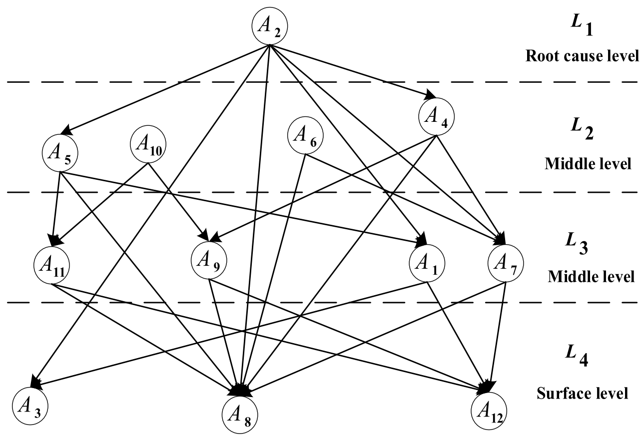

FIGURE 7. The hierarchical digraph of MA fault propagation for the APC.

transposed matrix $\boldsymbol{C}^T$ by the sum of the rows.

$$
\boldsymbol{Y} = \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \\ A_6 \\ A_7 \\ A_8 \\ A_9 \\ A_{10} \\ A_{11} \\ A_{12} \end{array}
\begin{bmatrix}
0 & 0 & 2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
1 & 0 & 2 & 5 & 4 & 0 & 1 & 2 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 2 & 3 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 3 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 2 & 2 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 2 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 2 & 0 & 3 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 2 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
$$

$$\boldsymbol{M} = \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \\ A_6 \\ A_7 \\ A_8 \\ A_9 \\ A_{10} \\ A_{11} \\ A_{12} \end{array} \begin{bmatrix} 1&0&1&0&0&0&0&0&0&0&0&1 \\ 1&1&1&1&1&0&1&1&0&0&0&0 \\ 0&0&1&0&0&0&0&0&0&0&0&0 \\ 0&0&0&1&0&0&1&1&1&0&0&0 \\ 1&0&0&0&1&0&0&1&0&0&1&0 \\ 0&0&0&0&0&1&1&1&0&0&0&0 \\ 0&0&0&0&0&0&1&1&0&0&0&1 \\ 0&0&0&0&0&0&0&1&0&0&0&0 \\ 0&0&0&0&0&0&0&1&1&0&0&1 \\ 0&0&0&0&0&0&0&0&1&1&1&0 \\ 0&0&0&0&0&0&0&1&0&0&1&1 \\ 0&0&0&0&0&0&0&0&0&0&0&1 \end{bmatrix}$$

$$\boldsymbol{C}^T = \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \\ A_6 \\ A_7 \\ A_8 \\ A_9 \\ A_{10} \\ A_{11} \\ A_{12} \end{array} \begin{bmatrix} 0&1&0&0&1&0&0&0&0&0&0&0 \\ 1&0&0&0&0&0&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&1&0&1&0&1&0&0&0&0&0&0 \\ 0&1&0&1&1&1&1&0&1&0&1&0 \\ 0&0&0&1&0&0&0&0&0&1&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&1&0&0&0&0&1&0&0 \\ 1&0&0&0&0&0&1&0&1&0&1&0 \end{bmatrix}$$

$$\left[\boldsymbol{C}^T\right]' = \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \\ A_6 \\ A_7 \\ A_8 \\ A_9 \\ A_{10} \\ A_{11} \\ A_{12} \end{array} \begin{bmatrix} 0&0.5&0&0&0.5&0&0&0&0&0&0&0 \\ 1&0&0&0&0&0&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0.33&0&0.33&0&0.33&0&0&0&0&0&0 \\ 0&0.143&0&0.143&0.143&0.143&0.143&0&0.143&0&0.143&0 \\ 0&0&0&0.5&0&0&0&0&0&0.5&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0.5&0&0&0&0&0.5&0&0 \\ 0.25&0&0&0&0&0&0.25&0&0.25&0&0.25&0 \end{bmatrix}$$

The number of nodes in the digraph composed of the MA fault propagation of the APC is 12, and the total number of cascading faults of MAs inside the APC is 45. In this paper, the damping factor is defined as the ratio of the total number of cascading faults to the total number of faults. Therefore, $d = 45/142 = 0.3191$, where 142 is the total number of APC faults. Here, based on experience, the convergence threshold is $\varepsilon = 0.0001$. According to Eq. (16), the MA fault impact degree is calculated, as shown in Table 4.

TABLE 4. The fault impact of the directed edge for the APC.

Directed edge	The impact degree	Directed edge	The impact degree
$A_{2\to5}$	0.2379	$A_{4\to8}$	0.1861
$A_{5\to11}$	0.1873	$A_{4\to7}$	0.2454
$A_{11\to8}$	0.2201	$A_{7\to8}$	0.2892
$A_{11\to12}$	0.1894	$A_{7\to12}$	0.1937
$A_{5\to8}$	0.2682	$A_{10\to11}$	0.2883
$A_{5\to1}$	0.2138	$A_{10\to9}$	0.2451
$A_{1\to3}$	0.2314	$A_{6\to8}$	0.1903
$A_{1\to12}$	0.1493	$A_{6\to7}$	0.1871
$A_{2\to4}$	0.2731	$A_{2\to3}$	0.1652
$A_{4\to9}$	0.2155	$A_{2\to8}$	0.1584
$A_{9\to8}$	0.1527	$A_{2\to1}$	0.0982
$A_{9\to12}$	0.1842	$A_{2\to7}$	0.1028

After calculating the MA fault impact degree, the impact degree hierarchical digraph of MA fault propagation of the APC can be obtained as shown in Fig. 8. The digraph intuitively shows the level of fault propagation, the directed edge of MA fault propagation and the MA fault impact degree of the APC.

As Fig. 8 shows, the fault gradually propagates downward from the root cause level L_1, and MA A_2 is the root fault of the APC and has 6 fault propagation paths to other MAs. Based on Fig. 8, $PR(e_{2\to4}) = 0.2731 > PR(e_{2\to5}) = 0.2379 > PR(e_{2\to3}) = 0.1652 > PR(e_{2\to8}) = 0.1584 > PR(e_{2\to7}) = 0.1208 > PR(e_{2\to12}) = 0.0982$. Therefore, path $A_2 \to A_4$ of the MA cascading fault is the highest priority selection for propagating faults. By repeating this step, it can be determined that the key MA nodes are A_2, A_4, A_7, and A_8. The path connected by these g nodes can be regarded as the key fault propagation path of the APC, i.e., $A_2 \to A_4 \to A_7 \to A_8$, and their corresponding MAs are the piston movement of the lifting cylinder → valve opening and closing of the hydraulic solenoid valve → gear rotation → pallet changer rotation, respectively. The piston movement of the lifting cylinder MA is the power mechanism of the APC, and it is the root cause of fault propagation. The MAs on the end of the fault propagation path are gear rotation MA and the pallet changer rotation MA, both of which are the actuator and exhibit many faults, which is consistent with the numerous faults in the historical fault data of the APC.

Implementing effective reliability control measures for the MA on the key fault propagation path can effectively reduce the number of fault occurrences and the number of fault propagations along this path. Consequently, the reliability of APC is improved.

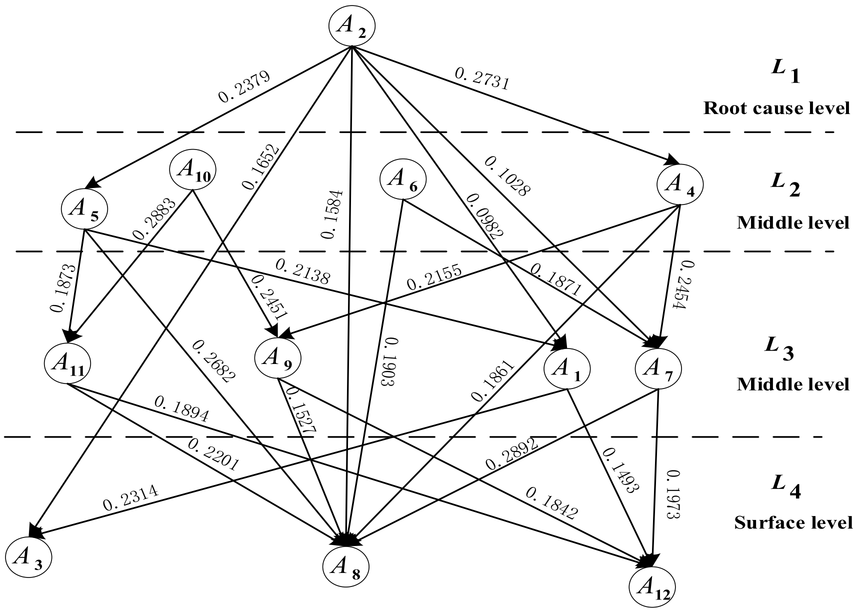

FIGURE 8. The impact degree hierarchical digraph of MA fault propagation for the APC.

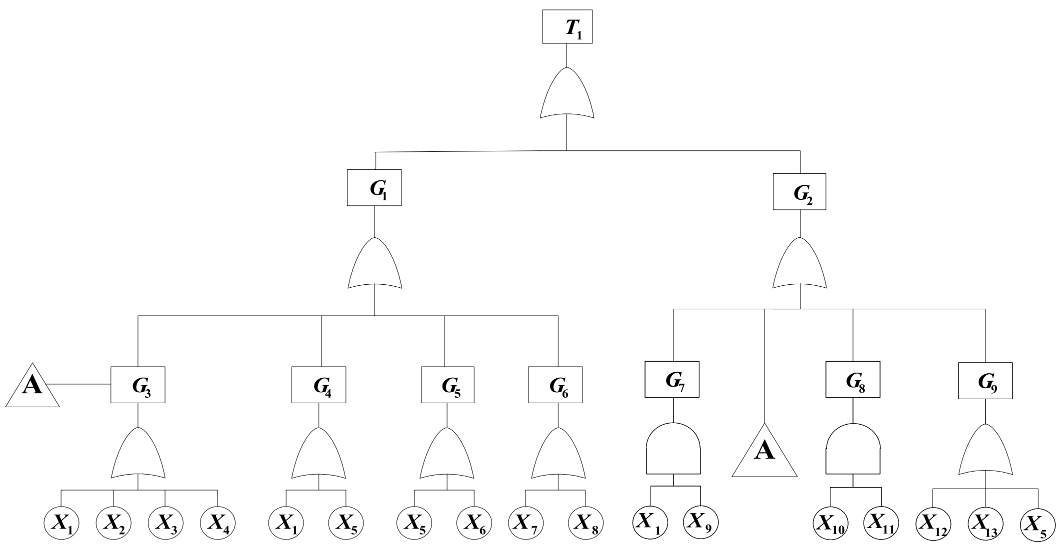

FIGURE 9. The fault tree for lifting cylinder piston failure of the APC.

D. MA FAULT ANALYSIS AND RELIABILITY CONTROL ON THE KEY FAULT PROPAGATION PATH

According to the analysis results of Fig. 8, MAs A_2, A_4, A_7, and A_8 should be effectively analyzed and controlled. Here, taking MA A_2 as an example, FTA is used to analyze and control this MA fault.

Considering the historical fault data, ''lifting cylinder piston failure'' is used as the top event when establishing an MA fault tree, as shown in Fig. 9. The meanings of the relevant symbols in the figure are shown in Table 5, where A is a transfer event.

After constructing the fault tree, it is necessary to calculate the importance of each basic event and select the basic events that strongly impact the top event, i.e., ''lifting cylinder piston fault'', as the reliability control point. According to the relevant fault data of the basic events of the APC, the minimum cut sets of the fault tree can be used to calculate the importance of the probability and the relative probability of these basic events, as shown in Table 6.

Based on the calculated results, the most important basic events are X_6, X_9, X_8, and X_5. These basic events strongly impact the reliability of the lifting cylinder piston and are defined as the reliability control points. Then, all the fault sources are analyzed, and the corresponding relationships between the key basic events and the fault source are obtained. Finally, corresponding reliability control measures

TABLE 5. The symbols of the fault tree for lifting cylinder piston failure.

	Symbol	Meaning
Top event	T_1	Lifting cylinder piston failure
Event or gate	G_1	Insufficient hydraulic pressure
	G_2	Insufficient flow
	G_3	leakage
	G_4	The relief valve is wrong or worn.
	G_5	Insufficient oil in tank
	G_6	Pump fault
	G_7	Filter clogging
	G_8	Valve or pipe blockage
	G_9	fault of flow adjustment valve or reversing valve
Basic events	X_1	Hydraulic oil is not clean with solid particles.
	X_2	Hydraulic oil temperature is too high.
	X_3	Hydraulic oil corrodes metal wall
	X_4	Excessive pressure damage the sealing ring.
	X_5	Human error
	X_6	Pipeline oil leakage
	X_7	Electrical wiring error
	X_8	Pump fatigue damage
	X_9	Filter will not change for a long time.
	X_{10}	Hydraulic oil flow rate too low
	X_{11}	There are impurities in hydraulic fluid.
	X_{12}	Electrical system fault
	X_{13}	Rust or solid particles stuck.

TABLE 6. The probability importance and relative probability importance of the basic events of the fault tree for lifting cylinder piston failure.

Basic events	Probability importance	Relative probability importance
X_1	0.09352	4.4587×10^{-3}
X_2	0.05472	4.1773×10^{-3}
X_3	0.02759	3.8438×10^{-3}
X_4	0.35862	4.6319×10^{-3}
X_5	0.49731	5.9582×10^{-3}
X_6	0.63714	7.6392×10^{-3}
X_7	0.46901	5.5316×10^{-3}
X_8	0.54584	6.8938×10^{-3}
X_9	0.59293	7.1322×10^{-3}
X_{10}	0.1381	3.3726×10^{-3}
X_{11}	0.2537	4.2316×10^{-3}
X_{12}	0.2151	3.1524×10^{-3}
X_{13}	0.09714	2.937×10^{-3}

are developed to improve the reliability of the APC. Based on reliability knowledge, the corresponding control measures shown in Table 7 (partial) are developed to improve APC reliability.

IV. ANALYSIS AND DISCUSSION

The traditional methods for fault analysis of CNC machine tools mainly include empirical methods that consider individual faulty parts and often result in repairing or replacing the faulty parts. However, this approach may not reveal the root cause of the fault, leading to fault recurrence and an increase in the production costs of manufacturing enterprises. In contrast, by considering the faulty parts, the CFACS can effectively detect whether other MAs are faulty along the fault propagation path where the fault MA is located and can determine the abnormal states of MAs that cause the fault. Two illustrative examples are presented below.

A. CASE 1

The abnormal position accuracy fault occurred frequently in the pallet exchanger of the APC described in Section III. Based on APC fault statistics, it can be found that the abnormal position accuracy of the pallet exchanger occurred 4 times in 7 months, resulting in 4 machining center shutdowns. After the first three faults, technicians diagnosed and controlled the faults using the traditional (empirical) method. Pallet exchanger disassembly revealed that some parts were worn and deformed. Because the pallet exchanger contains many parts, they could not all be analyzed individually. Instead, the technicians inspected only the faulty parts and their surrounding parts. The fault was controlled by replacing the damaged parts and reassembling the pallet exchanger.

In comparison, the CFACS is used to analyze and control the fault after the fourth abnormal position accuracy occurrence in the pallet exchanger. The APC was divided into MAs, and the abnormal positioning fault was analyzed from an MA perspective. Fig. 8 shows that the fault occurs on A_8 and is located on the key fault propagation path $A_2 \rightarrow A_4 \rightarrow A_7 \rightarrow A_8$. When the pallet exchanger rotation MA A_8 was repaired, the technicians inspected the other MAs along the key fault path and found abnormal states (assembly position and displacement error) in the parts for MAs A_2, A_4 and A_7, that is, cascading faults were occurring for MA A_8. Consequently, A_2, A_4 and A_7 were adjusted to run normally. After this maintenance was complete, MA A_8 was tracked for 5 months, during which abnormal position accuracy of the pallet exchanger did not reoccur. A comparison between the traditional method and the CFACS is shown in Table 8. It should be noted that the average frequency per month in Table 8 represents only the average number of faults per month for MA A_8 during the specified tracking durations (5 or 7 months). The data change over time.

In the original case, the technicians analyzed faulty MA A_8 using traditional methods but neglected to consider fault propagation between MAs. As a result, the fault root cause (errors in assembly position and displacement of A_2, A_4 and A_7) was not found. After the fault was repaired by replacing parts, the pallet exchanger again worked normally. However, the same fault occurred 4 times in 7 months, a frequency that exceeded the normal range. The CFACS can analyze other MAs along the fault propagation path $A_2 \rightarrow A_4 \rightarrow A_7 \rightarrow A_8$ and determine the root cause. After analyzing and controlling the cascading fault, the fault frequency of MA A_8 was significantly reduced, which demonstrates the effectiveness of the proposed method.

TABLE 7. Reliability control measures for the APC.

Serial number	Main cause of fault	Reliability control measures
1	Component damage	① Improve the switch fixed mode to facilitate the adjustment of the switch position. ② Establish inspection requirements for switch installation position and sensing distance, and strictly control them. The process stipulates that "rotation 180°", the sensing distance is controlled by a parallelism of "0.1-0.2 mm". ③ Improve the quality of purchased parts.④ Strengthening user training.
2	Bolt loosening	① Refine the process documentation to clarify the preload force and achieve quantitative assembly. ② Assembly with a pretightening wrench. ③ Dash and mark the contact between the bolt and the hole after assembly.
3	blocking	① Deburring in pipeline, chamfering at interface. ② Cleaning before installation. ③ Regular replacement of hydraulic fluid. ④ Regularly clean all oil holes, air holes and liquid holes.
4	Link loosening	① Refine the process documentation to clarify the preload force and achieve quantitative assembly. ② When connecting the pipeline, lock the throat hoop and tighten the connector. ③ Users regularly check whether the interface is loose. ④ Keep account records during assembly.
5	Bearing fault	① Cleaning parts before installation. ② Refine the process documentation to clarify the preload force and achieve quantitative assembly. ③ Adjust the lubrication parameters during assembly. ④ Improve the quality of purchased parts. ⑤ Keep account records during assembly. ⑥ Improve the quality of lubricating oil.
6	Pump fatigue and wear	① Improve oil quality. ② Control temperature rise. ③ Improve the quality of purchased parts.
7	abrasion	① Making sure that all lubrication points are normal during assembly. ② Adjust lubrication parameters during assembly. ③ Clean the lubrication area regularly.
8	Long-term nonreplacement of filter.	① Strengthen user training and replace filters regularly. ② The factory documentation clearly identifies the filter replacement time. ③ Tips for the corresponding parts of the product.

TABLE 8. A comparison between the traditional method and the CFACS.

Fault diagnosis and control method	Fault tracking duration (months)	Failure occurrences	Average frequency per month
Traditional Method (Empirical Method)	7	4	0.571
CFACS	5	0	0

B. CASE 2

After assembly, the spindle of a certain type of CNC machine tool must run continuously for 120 hours without abnormal operation During 44 hours of operation, abnormal heating of the spindle resulted in damage to the spindle, while the vice-spindle, which has the same structure as the spindle, ran normally. Based on experience, the technicians believed that the fault was caused by poor assembly; thus, they replaced the damaged parts. After reassembly, the spindle again ran normally for 53 hours, but then was damaged again. All the relevant parts were analyzed using the CFACS, after which the technicians found that there was a machining error of 0.2 mm in the spindle sleeve after remeasuring the accuracy of all the parts in the spindle. After replacing the qualified spindle sleeve and cleaning all the parts, the spindle was reassembled and run, resulting in no abnormalities; the spindle met the factory requirements after 120 hours of operation. These two spindle damage occurrences caused direct economic losses of tens of thousands of yuan.

In this case, if technicians were to analyze the damage of the spindle using the fault propagation path idea to analyze why damage had occurred to the spindle and detect the relevant parts in a timely manner, the second fault would have been avoided. The root cause of spindle damage can be detected and controlled using the CFACS, thus demonstrating the feasibility and effectiveness of the proposed method when applied to different components in a machining center.

V. CONCLUSION

(1) Based on the FMA structural decomposition method, CNC machine tools can be decomposed into motions and MAs that describe the fault propagation behavior of the internal parts of the functional components. This approach effectively solves the difficult problem of describing the results of interactions between parts when there are too many parts in a functional component.

(2) Using DEMATEL to describe the complex relationships between MAs can clarify the vague interactions between MAs. By combining graph theory and matrix operations, the ISM is used to transform the complex influence relationships between MAs into a visual hierarchical digraph that reflects the MA fault propagation paths. Based on this digraph, all the fault propagation paths and fault sources between MAs can be obtained.

(3) The PageRank algorithm is used to quantify the fault intensity values of the directed edges of each fault propagation in the hierarchical MA fault propagation model. Then, the fault propagation impact degree of each directed edge is obtained. The PageRank algorithm can effectively improve the ISM method, which cannot accurately determine the strength of fault propagations between MAs. Integrating the PageRank algorithm with the DEMATEL-ISM method allows operators to obtain the impact degree hierarchical digraph of MA fault propagation. Based on this

digraph, the key MA fault root causes and the key fault propagation paths that highly influence functional component reliability can be identified.

(4) FTA is used to analyze the fault modes of the MAs along the key fault propagation paths that occur with high frequency, revealing the key basic events that cause MA faults. Then, corresponding reliability control measures can be developed to reduce the frequency of cascading faults in functional components and improve the reliability of CNC machine tools.

(5) It is difficult to find the root cause of a fault using the traditional method to replace or repair faulty parts; thus, maintenance quality cannot be guaranteed. However, using the CFACS, not only can the MA be maintained but the other MAs along the fault propagation path can be adjusted to a normal state, which can effectively reduce fault frequency, demonstrating the effectiveness of the CFACS. Fault analysis can be conducted based on this method; thus, the control of other functional components or machines can be modified to improve their reliability.

REFERENCES

[1] Y.-Z. Zhang, J.-T. Liu, Z. Long, S.-G. Sun, and G.-X. Shen, ''Reliability evaluation of machine center components based on cascading failure analysis,'' *Chin. J Mech. Eng.*, vol. 30, no. 4, pp. 933–942, Jul. 2017.

[2] R. Pi, Y. Cai, Y. Cao, and Y. Li, ''Machine learning based on Bayes networks to predict the cascading failure propagation,'' *IEEE Access*, vol. 6, pp. 44815–44823, 2018.

[3] Z. Shi and W. O'Brien, ''Development and implementation of automated fault detection and diagnostics for building systems: A review,'' *Automat. Construct.*, vol. 104, pp. 215–229, Aug. 2019.

[4] Q. Zhou, P. Yan, H. Liu, Y. Xin, and Y. Chen, ''Research on a configurable method for fault diagnosis knowledge of machine tools and its application,'' *Int. J. Adv. Manuf. Technol.*, vol. 95, nos. 1–4, pp. 937–960, Mar. 2018.

[5] E. Gascard and Z. Simeu-Abazi, ''Quantitative analysis of dynamic fault trees by means of Monte Carlo simulations: Event-driven simulation approach,'' *Rel. Eng. Syst. Saf.*, vol. 180, pp. 487–504, Dec. 2018.

[6] J. Tang and F. Zhu, ''Graphical modeling and analysis software for state space-based optimization of discrete event systems,'' *IEEE Access*, vol. 6, pp. 38385–38398, 2018.

[7] H. Zia, N. R. Harris, M. Rivers, and G. V. Merrett, ''A low-complexity machine learning nitrate loss predictive model–towards proactive farm management in a networked catchment,'' *IEEE Access*, vol. 7, pp. 26707–26720, 2019.

[8] J. Dong, Q. Wang, K. Peng, and M. Wang, ''Data-driven quality monitoring techniques for distributed parameter systems with application to hot-rolled strip laminar cooling process,'' *IEEE Access*, vol. 6, pp. 16646–16654, 2018.

[9] Z. Ge, Z. Song, S. X. Ding, and B. Huang, ''Data mining and analytics in the process industry: The role of machine learning,'' *IEEE Access*, vol. 5, pp. 20590–20616, 2017.

[10] L. Uriarte, S. Azcárate, L. N. L. de Lacalle, A. Lamikiz, and A. Herrero, ''Mechanistic modelling of the micro end milling operation,'' *Proc. Inst. Mech. Eng., B, J. Eng. Manuf.*, vol. 222, no. 1, pp. 23–33, Jan. 2008.

[11] B. Peña, G. Aramendi, L. N. L. Delacalle, and A. Rivero, ''Monitoring of drilling for burr detection using spindle torque,'' *Int. J. Mach. Tools Manuf.*, vol. 45, no. 14, pp. 1614–1621, Nov. 2005.

[12] S. Liu, L. Xu, X. Zhao, D. Li, and Q. Li, ''Fault diagnosis of water quality monitoring devices based on multiclass support vector machines and rule-based decision trees,'' *IEEE Access*, vol. 6, pp. 22184–22195, 2018.

[13] H. Gonzalez-Barrio, I. Cascon-Moran, and J. A. Ealo, ''A reliable machining process by means of intensive use of modelling and process monitoring: Approach 2025,'' *DYNA*, vol. 93, no. 6, pp. 689–696, Nov. 2018.

[14] N. Zhou, D. Li, S. Wang, C. Liu, and S. Li, ''Model-based development of knowledge-driven self-reconfigurable machine control systems,'' *IEEE Access*, vol. 5, pp. 19909–19919, 2017.

[15] P.-O. Amblard and O. J. J. Michel, ''On directed information theory and Granger causality graphs,'' *J. Comput. Neurosci.*, vol. 30, no. 1, pp. 7–16, Feb. 2011.

[16] D. N. Dongiovanni and T. Iesmantas, ''Failure rate modeling using fault tree analysis and Bayesian network: DEMO pulsed operation turbine study case,'' *Fusion Eng. Des.*, vols. 109–111, pp. 613–617, Nov. 2016.

[17] R. Han, S. Wang, T. Zhao, Z. Ye, and B. Liu, ''A novel model-based dynamic analysis method for state correlation with IMA fault recovery,'' *IEEE Access*, vol. 6, pp. 22094–22107, 2018.

[18] R. Huang, Y. Liao, W. Li, and S. Zhang, ''Deep decoupling convolutional neural network for intelligent compound fault diagnosis,'' *IEEE Access*, vol. 7, pp. 1848–1858, 2018.

[19] G. Urbikain and L. N. L. de Lacalle, ''Modelling of surface roughness in inclined milling operations with circle-segment end mills,'' *Simul. Model. Pract. Theory*, vol. 84, pp. 161–176, May 2018.

[20] Y. Chen, Y. Li, W. Li, X. Wu, Y. Cai, Y. Cao, and C. Rehtanz, ''Cascading failure analysis of cyber physical power system with multiple interdependency and control threshold,'' *IEEE Access*, vol. 6, pp. 39353–39362, 2018.

[21] R. Geng, X. Wang, N. Ye, and J. Liu, ''A fault prediction algorithm based on rough sets and back propagation neural network for vehicular networks,'' *IEEE Access*, vol. 6, pp. 74984–74992, 2018.

[22] H.-T. Yau, C.-C. Wang, J.-Y. Chang, and X.-Y. Su, ''A study on the application of synchronized chaotic systems of different fractional orders for cutting tool wear diagnosis and identification,'' *IEEE Access*, vol. 7, pp. 15903–15911, 2019.

[23] J. Zheng, J. Chang, D. Yu, and J. Ma, ''Performance uncertainty propagation analysis for control-oriented model of a turbine-based combined cycle engine,'' *Acta Astronautica*, vol. 153, pp. 39–49, Dec. 2018.

[24] A. Coro, M. Abasolo, L. N. L. de Lacalle, and J. Aguirrebeitia, ''Inspection scheduling based on reliability updating of gas turbine welded structures,'' *Adv. Mech. Eng.*, vol. 11, no. 1, pp. 1–20, Jan. 2019.

[25] H. Yu, G. Zhang, and Y. Ran, ''A more reasonable definition of failure mode for mechanical systems using meta-action,'' *IEEE Access*, vol. 7, pp. 4898–4904, 2018.

[26] P. Liu and D. Li, ''Some muirhead mean operators for intuitionistic fuzzy numbers and their applications to group decision making,'' *PLoS ONE*, vol. 12, no. 1, Jan. 2017, Art. no. e0168767.

[27] Y.-C. Lee, M.-L. Li, T.-H. Huang, and T.-M. Yen, ''Analysis of adopting an integrated decision making trial and evaluation laboratory on a technology acceptance model,'' *Expert Syst. Appl.*, vol. 37, no. 2, pp. 1745–1754, Mar. 2010.

[28] Y. Han, Z. Geng, Q. Zhu, and X. Gu, ''Energy efficiency analysis based on DEA integrated ISM: A case study for Chinese ethylene industries,'' *Eng. Appl. Artif. Intel.*, vol. 45, pp. 80–89, Oct. 2015.

[29] C. Zhang, L. Sun, and F. Wen, ''An interpretative structural modeling based network reconfiguration strategy for power systems,'' *Int. J. Elect. Power Energy Syst.*, vol. 65, pp. 83–93, Feb. 2015.

[30] X. Deng, Y. Dou, T. Lv, and Q. V. H. Nguyen, ''A novel centrality cascading based edge parameter evaluation method for robust influence maximization,'' *IEEE Access*, vol. 5, pp. 22119–22131, 2017.

[31] Z. Zhu, Q. Peng, Z. Li, X. Guan, and O. Muhammad, ''Fast PageRank computation based on network decomposition and DAG structure,'' *IEEE Access*, vol. 6, pp. 41760–41770, 2018.

[32] B. Javadi, D. Kondo, D. Epema, and A. Iosup, ''The failure trace archive: Enabling the comparison of failure measurements and models of distributed systems,'' *J. Parallel Distrib. Comput.*, vol. 73, no. 8, pp. 1208–1223, Aug. 2013.

[33] S. Li and D. Guo, ''Cache coherence scheme for HCS-based CMP and its system reliability analysis,'' *IEEE Access*, vol. 5, pp. 7205–7215, 2017.

GUANGQUAN HUANG received the M.S. degree in mechanical engineering from Chongqing University, Chongqing, China, in 2018, where he is currently pursuing the Ph.D. degree in mechanical engineering. His research interests include failure analysis of CNC machine tools, reliability assembly, and advanced manufacturing technology.

BINGKUI CHEN received the Ph.D. degree in mechanical engineering from Chongqing University, Chongqing, China, in 1995, where he is currently a Professor, the Director of the State Key Laboratory of Mechanical Transmission, and a Doctoral Supervisor for mechanical manufacturing. He has authored more than 200 academic papers and he holds 28 invented patents. His current research interests include gear drive, advanced manufacturing technology, and CNC machine tool reliability.

LIMING XIAO received the M.S. degree in mechanical engineering from Chongqing University, Chongqing, China, in 2018, where she is currently pursuing the Ph.D. degree in mechanical engineering. Her research interests include reliability allocation, failure analysis of CNC machine tools, and advanced manufacturing technology.

YAN RAN received the M.S. and Ph.D. degrees in mechanical engineering from Chongqing University, Chongqing, China, in 2012 and 2016, respectively, where she is currently a Lecturer and a Fixed Researcher with the State Key Laboratory of Mechanical Transmission. Her research interests include mechatronic product reliability technology and modern quality engineering. She is a member of the Chongqing Science and Technology Association and a member of the National Association of Basic Research on Interchangeability and Measurement Technology. She has presided over 20 projects, such as the National Natural Science Foundation, the Youth Foundation, the Natural Science Foundation Key Projects, the National 863 Projects, the National Major Projects, and the Transverse Projects of Enterprises. She has authored more than 40 academic papers, 11 invention patents, and two copyrights of computer software.

GENBAO ZHANG received the Ph.D. degree in mechanical engineering from the Swiss Federal Institute of Technology Lausanne (EPFL), Switzerland, in 1994.

From 1995 to 1997, he was a Postdoctoral Researcher with the Postdoctoral Research Station of Mechanical Engineering, Chongqing University, where he is currently a Professor with the College of Mechanical Engineering, the Director of the Institute of Advanced Manufacturing Technology, a Researcher with the State Key Laboratory of Mechanical Transmission, and a Doctoral Supervisor for mechanical manufacturing. From 1994 to 2018, he has published more than 400 academic papers and 11 monographs. His current research interests include advanced manufacturing technology, computer-integrated manufacturing systems, CNC machine tool reliability, modern quality engineering, and enterprise information. During the period, he has presided over 15 National Major Scientific and Technological Special Projects and the National Natural Science Fund projects. He enjoys a special government allowance from the State Council.