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Optimal Micro-Motion Unit Decomposition-Based Reliability Allocation for Computer Numerical Control Machine Using the Swarm Bat Algorithm

XIANLIN REN[1,2], (Member, IEEE), AND YI CHEN[3], (Senior Member, IEEE)

[1]School of Mechatronics Engineering, University of Electronic Science and Technology of China, Chengdu 611731, China
[2]Institute of Electronic and Information Engineering, University of Electronic Science and Technology of China, Dongguan 523808, China
[3]School of Engineering, Newcastle University, Newcastle upon Tyne NE1 7RU, U.K.

Corresponding authors: Xianlin Ren (renxianlin0@163.com) and Yi Chen (leo.chen@ieee.org)

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ABSTRACT In the reliability literature, reliability allocation is an important and widely studied topic. The existing reliability allocation methods, however, have limitations, including imprecise system decomposition, single-factor consideration, and poor practicability. To overcome those limitations, we propose an integrated fuzzy reliability allocation method based on micro-motion decomposition, cost function, and multi-factor analysis. The problems in the existing methods caused by equally weighted factors and influences of failures were overcome by correcting the traditional risk priority number method and evaluating the uncertainties and subjective factors during allocation using fuzzy language and triangular fuzzy number. A cost model was established based on the state of the art, subsystem intricacy, and environmental conditions, with which the issues of difficulty applying cost statistics and computational complexity in the current allocation methods were solved. The contribution of this paper is as follows. A fast approach of Pareto-optimal solution recommendation using the Pareto reliability index has been utilized to recommend a list of optimal ranking for decision-makers. Besides, the moving mean of the average precision and the moving mean standard deviation are utilized to demonstrate the trend of the evolutionary process. A multi-objective swarm bat algorithm has been developed to handle the multi-objective problems and its feasibility has been verified in a case study comparing the performance of the proposed method with that of the existing methods.

INDEX TERMS Micro-motion unit, reliability allocation, reliability cost function, swarm bat algorithm, uncertainty.

I. INTRODUCTION

The computer numerical control (CNC) machine is an important industrial equipment, and its reliability has been one of the most important symbols to measure the modernization of advanced manufacturing and it is critical in the aspects of reliability design improvement, fault monitoring and fault repair for the CNC machine. The CNC machine's assembly process is a significant part in its manufacturing process, and assembly operation is a major factor in determining the whole machine's quality, and assembly process quality analysis is necessary for CNC machines, in which, reliability allocation is an essential part of its reliability design.

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In the reliability engineering, the reliability allocation is a method to maximize the reliability of a system at minimal cost and is a process of assigning reliability requirements to individual components of a system to attain a pre-specified reliability. Over the past three decades, it has received plenty of attention. For a large system, the allocation process is often performed at different stages of system design. As the development of the system design evolves, more information about the components and their operating conditions is gained and more allocation methods can be applied. In the literature, the methods of reliability allocation are usually divided into the following two categories.

a) the optimal reliability allocation methods, which treat the reliability allocation problem as an optimization problem. The most applicable solutions can be sought by building an optimization model according to the system's configuration and physical constraints [6]–[8], redundancy allocation [20]–[22], minimization of system cost subject to reliability constraint [23], maximization of system reliability under cost constraint [24], [25], and system reliability optimization [24]–[27].

b) The weighting factors methods. Since reliability relates to many factors such as cost, maintenance costs, importance weight, and manufacturing technology, there are different reliability allocations methods corresponding to the different constraint goals, including: the equal reliability allocation method [29], [30], the integrated factors method (IFM) [31], the Aeronautical Radio Inc. (ARINC) method [9], the feasibility of objectives method [9], the Advisory Group on Reliability of Electronic Equipment (AGREE) method [10], Karmiol method [11], the integrated factors method [12], the comprehensive method [13], the maximal entropy ordered weighted averaging method [14], an approach based on the subsystem failure severity and its relative frequency [15], a modified criticality measure for subsystems reliability allocation [16], a fuzzy arithmetic based method [17], etc [18], [19]. The criticality or risk assessment in the Failure Mode and Effects Analysis (FMEA) [1]–[3] introduces the index of risk priority number (RPN) [1], [4], [5], [16], [28], which has been used to prioritize failures by considering three factors of severity (S), occurrence (O) and detection (D) have different weights is essential in risk assessments, different combinations of O, S, and D may computationally create the same values of RPN, in which, S: Indicates the gravity of the effects of a failure which affect the system or consumer that uses the component; O: Indicates the probability of a failure occurring; D: Measures a failure's visibility that is the attitude of a failure mode to be identified by controls or inspections.

The traditional allocation methods failed to consider the influence of failures on the system and are therefore inferior in the credibility of allocation outcomes. Focusing on either the failure effect or the manufacturing costs, all of the existing allocation methods are based on a single individual factor, which makes it difficult to achieve optimal allocation due to: 1) In terms of RPN-based allocation methods, allocation outcome deviates from reality due to factor weight inconsistency and arithmetic relations between different grades; 2) When it comes to cost-based allocation methods, it is difficult to make precise cost statistics, and the cost function is complex without much practicability; 3) It has lacked tool for optimal allocation design.

To fill this gap, this paper proposes a swarm bat algorithm with the variable population (BAVP) as the tool to construct and optimize the proposed approach - fuzzy function-motion-action (FMA) reliability allocation (fFMA), which will be embedded into the computational intelligence-assisted design (CIAD) framework [33], [34]. Integrated consideration of the influence of failures on a system and manufacturing costs requires a delicate decomposition of system structure, a precise decomposition method is proposed in this paper to improve the accuracy of reliability allocation. To this end, a Micro-motion Unit (MMU) decomposition-based allocation method that gave integrated consideration to failure effects and manufacturing costs was proposed in this study. By improving existing RPN methods, the index of an improved RPN value was used to characterize the failure effects of a system. The manufacturing cost of the system was described using the reliability and the maximum reliability of the current system based on the generalized cost function. The semi-quantitative cost function was built based on integrated consideration of SA, EC, and SI. Reliability allocation of the system was finally conducted by weighing and balancing the failures of various MMUs and the costs incurred by reliability improvement.

To perform the optimal design for the reliability allocation, this paper proposes a swarm bat algorithm with a variable population (BAVP), which is inspired by the echolocation behavior of bats. The first version of bat algorithm (BA) was firstly introduced by Yang [32] in 2010, which allocates computational resources by adjusting its population and accelerating the calculation speed. By using echolocation, a swarming bat can quickly respond to changes in the direction and speed of its neighbors during activities such as detecting prey, avoiding obstacles, and locating roosting crevices in dark surroundings. Useful behavioral information is passed among bats and guides them to move from one configuration to another as one unit. By borrowing this intelligence of social behavior, the proposed BAVP is parallel, independent of initial values, and able to achieve a global optimum.

The remainder of this paper is organized as follow: Section 2 describes the BAVP algorithm for the optimization; Section 3 discusses the modeling of the MMU Decomposition, which compares the reliability allocation models of traditional, RPN-based and cost-based approaches; Section 4 proposes the fFMA approach; Section 5 introduces the conceptual framework of CIAD and defines the fitness function for optimal design for the fFMA approach; Section 6 presents the empirical results and discussion on the optimal results; and Section 7 concludes the paper and briefs the future works.

II. SWARM BAT ALGORITHM WITH VARIABLE POPULATION

Inspired by the echolocation characteristics of bat swarms, the BAVP can be idealized as the four following assumptions:

1. As shown in Figure 1, all artificial bats (ABs) utilize the same echolocation mechanism to measure distance, and each AB individual Bi is able to detect the difference between prey (food) and obstacles.

2. Each individual B_i can generate ultrasounds to echolocate the prey and obstacles with a velocity of v_{ij} and a position of x_{ij} at time j, which are stated in Equations (1) and (2), respectively, where x_* is the current global best position.

$$v_{i,j+1} = v_{i,j} + \left(x_{i,j} - x_*\right) f_{i,j} \tag{1}$$

$$x_{i,j+1} = v_{i,j} + x_{i,j} \tag{2}$$

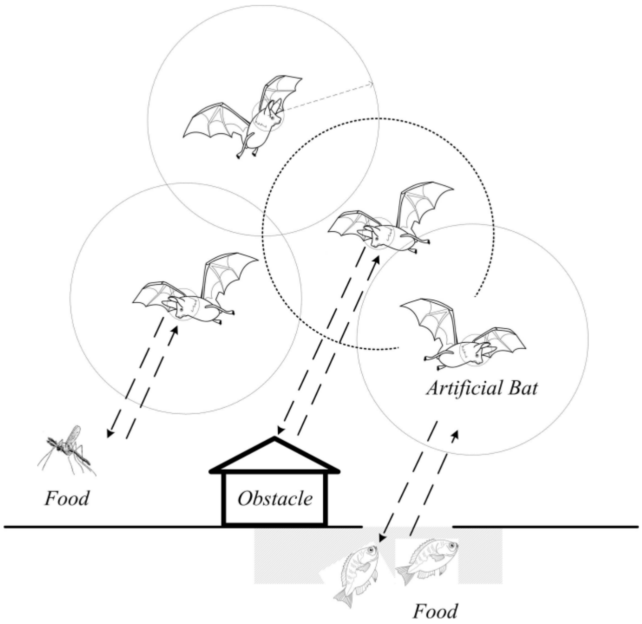

FIGURE 1. The bats' swarm behaviors.

3. Each individual B_i can adjust the frequency of the ultrasounds f_{ij} at time j within a range of [f_{min}, f_{max}], as given in Equation (3), where β is a random vector of uniform distribution in the range of [0,1]. corresponding to a wavelength λ in the range of [λ_{min}, λ_{max}] and a loudness A in the range of [A_{min}, A_{max}], as given in Equation (4), $A_{i,j}$ is the loudness of the bat B_i at time j, in which $\alpha \in [0,1]$ is a reduction factor.

$$f_{i,j} = f_{\min} + (f_{\max} - f_{\min})\,\beta \tag{3}$$

$$A_{i,j+1} = \alpha A_{i,j} \tag{4}$$

4. As shown in Equation (5), the population P_j of ABs varies from time j to another, which accelerates the optimization process, in which P_N is the non-replaceable population and P_{Rj} is the replaceable population at time j.

$$P_j = P_N + P_{R_j} \tag{5}$$

As shown in Figure 2, the following flowchart as the four steps are included in the BAVP pseudocode:
step 1, initialisation of parameters and variables, and moves into while loop;
step 2, global updating(), in which there are 3 sub-steps, namely:

step2.1, update of virtual bat movement with frequency fi, velocity vi and location xi;

step2.2, generates new local solution x_s and updates global solution x_{global} at current generation, and generates new local solutions x_0 using Equation (6), where $\varepsilon \in [-1, 1]$ is a random-walk factor.

$$x^0_{i,j+1} = x^0_{i,j} + \varepsilon A_{i,j}. \tag{6}$$

step 2.3, add flying randomness into x_{global};

```
Define fitness function Fitness(X)

Begin (1)

  /* Step 1 - Initialisation();*/
  t = 0 ;
  Initialise solutions:    locations X(0) = {x1,x2,...xi,xn};
                           velocities V(0)= {v1,v2,...vi,vn};
  Initialise parameters:   pulse frequency fi
                           pulse rate ri
                           loudness Ai

    While ( Not termination-condition) do

      Begin (2)

  {         t = t + 1;

        /* Step 2 - Global Updating();*/
        /* Step 2.1 - Movement of virtual bat generation;*/
         adjusting frequency fi,
         updating velocities vi;
         updating locations xi as xs;

        /* Step 2.2- check pulse rate ri ;*/
         if  (RAND > ri)
          (1) select a solution among xs randomly
          (2) generate a global solution xglobal within xs
         end if

        /* Step 2.3- generate flying solution ;*/
         generate a new solution xglobal by flying randomly;

       /* Step 3 - Local Updating();*/

        if  ( RAND < Ai  &&  Fitness(xi) < Fitness(xglobal) )
          (1) accept the new solutions xs
          (2) update ri and Ai - increase ri and reduce Ai
          (3) find the local best xlocal
        end if

    /* Step 4 - Generate final output: global result + local result */

         if  ( Fitness(xglobal) < Fitness(xlocal) )
                xi    =    xlocal ;
         else
                xi    =    xglobal;
         end if
  }
      End (2)

    End While

Begin (1)
```

FIGURE 2. The BAVP pseudo code.

step 3, update best local solutions by comparing the global solutions $x_{i,j}$ and local solutions $x^0_{i,j}$, as given in Equation(7).

$$x_{i,j} = \begin{cases} x_{i,j} & \left(if\ x_{i,j} \geq x^0_{i,j}\right) \\ x^0_{i,j} & \left(otherwise\ x_{i,j} < x^0_{i,j}\right) \end{cases} \tag{7}$$

step 4, fitness evaluation for each solution, and checking termination condition of convergence, continue running the calculation until the terminal conditions have been satisfied.

III. MMU DECOMPOSITION

An MMU is an independent indivisible action unit that performs the most basic action for the fulfillment of functions of the whole machine. The core components of the micro-motion and the assemblies that have assembly relations with the core components are known as an *MMU*, which can be used for not only MMU based product design, but also MMU based tests and manufacturing.

A CNC machine was selected to be decomposed to obtain its MMUs. Common decomposition methods of current machinery products, such as: the automated confluence prover (ACP), the frequency based substructuring (FBS) and the constraint satisfaction problem (CSP), are developed based on product structure (or component) system and are therefore oriented for use with static objects. However, the CNC machine is dynamic throughout its life cycle so the

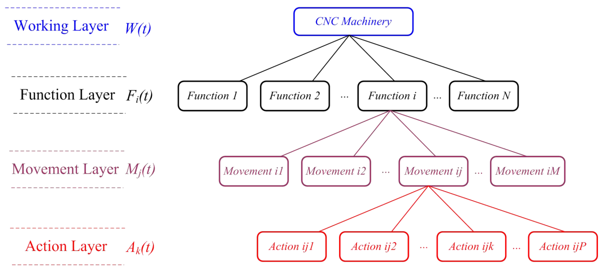

FIGURE 3. Diagram of FMA-based decomposition of a CNC machine.

loading and functional failures need to be taken into account during dynamic processes.

Thus, the structure of the selected CNC machine was decomposed by following a function-motion-action (**FMA**) principle. The core idea of the FMA decomposition was to divide the complex integrated motions of machining into a series of basic action units, as shown in Figure 3, in which, there are *four* layers, namely, the layers of Working W(t), Function F(t), Movement M(t) and Action A(t). Specifically,

- the selected CNC machine lies in the W(t) layer;
- the F(t) layer is to complete the function according to the user requirements to design. Usually a function is the combination of one or more pre-movement mechanism to achieve the desired motion;
- the M(t) layer consists of the various drive train mechanism, including: power, actuators, end-effectors and frame;
- the A(t) layer consists of moving and rotating components, such as the jaw moving, pulley rotating, stretching or compressing of spring.

Reliability allocation refers to the allocation of a system's overall reliability to various MMUs via measures in accordance with the requirements for system reliability and constraints. To allocate reliability, it was essential to find the solution to the following inequality:

$$\begin{cases} R_s(R_1, R_2, \cdots, R_i, \cdots, R_n) \geq R_s^* \\ \vec{g}_s(R_1, R_2, \cdots, R_i, \cdots, R_n) \leq \vec{g}_s^*. \end{cases} \tag{8}$$

where, $R_s(*)$ and $\vec{g}_s(*)$ are the functions of reliability and constraint, respectively, R_s^* denotes the system's reliability index, $\vec{g}_s^*$ is the constraint (such as cost, volume, weight), and R_i is the reliability index of the i^{th} MMU.

Suppose that a series system is composed of k MMUs, and $\lambda^*(t)$ is the failure rate of the system, and $\lambda_i^*(t)$ is the failure rate allocated to the i^{th} MMU, described in equation (9).

$$\lambda_i^*(t) = \omega_i \lambda^*(t), \quad t \geq 0,\ i = 1, 2, \ldots, k. \tag{9}$$

in which, ω_i denotes the weight allocated to the i^{th} MMU that could be obtained with the following formula as given in equation (10):

$$\omega_i = \frac{n_i}{\sum_{i=1}^{k} n_i}, \quad i = 1, 2, \ldots, k. \tag{10}$$

Here, n_i denotes the evaluated value of the i^{th} MMU, which could be the number of MMUs, failure rate, or something else [1,2]. As a result, it was n_i that resulted in different allocation methods.

A. TRADITIONAL RELIABILITY ALLOCATION METHODS

In traditional reliability allocation methods, subsystems are evaluated using objective or subjective information based on a single factor or multiple factors with the weight of each subsystem calculated by combination operations. These methods aim to provide the designs based on existing system reliability. In other words, the more reliable the current subsystem, the lower the failure rate allocated to the new corresponding subsystem. The requirement for reasonableness of system/unit reliability also depends on the granularity of the subsystem.

SA, SI, operating time (OT), and operating conditions (OC) of a system are closely associated with its current reliability, and are often taken as the factors of weight allocation in traditional allocation methods when reliability data is inadequate. Traditional allocation methods play a role in system reliability allocation, however, they do not consider the influence of failures on the system and system costs.

If system reliability is decomposed by the FMA method, the failures can directly correlate with the MMUs, which not only integrates the influence of failures on the system but also makes the requirements for reliability of various units more reasonable.

B. RPN-BASED RELIABILITY ALLOCATION

It is inevitable for a system to experience failures during operation. Different failures can result in varied effects on a system, and the same failure mode can lead to entirely different consequences in different systems. Whether major or minor, failures always accompany system loss. Therefore, potential failures and the corresponding consequences should be taken into account during system reliability allocation.

Over the past few years, RPN-based reliability allocation methods have been used in several studies [i,ii,iii,3]. RPN is a parameter to describe failure severity by measuring the severity (S), occurrence (O), and detectability (D) of various failure modes (scoring 1∼10) during system failure modes and effects analysis (FMEA). The RPN of the j^{th} failure mode in subsystem i is described in equation (11).

$$RPN_{ij} = S_{ij} \times O_{ij} \times D_{ij} \tag{11}$$

If the detectability of failure mode was taken into consideration when failure severity was measured [3,iv], Equation (11) could be transformed into equation (12).

$$RPN_{ij} = S_{ij} \times O_{ij} \tag{12}$$

Suppose that there were N failure modes in a certain system. According to a study by Itabashi-Campbell [3], based on the intentions of allocators, the allocation factor of subsystem i could be described as

$$n_i = B_i \tag{13}$$

or

$$n_i = 1 - \frac{B_i}{\sum_{i=1}^{k} B_i} \tag{14}$$

where

$$B_i = \frac{1}{N}\sum_{j=1}^{N} S_{ij} \times O_{ij} \tag{15}$$

In many studies (see [v,vi,vii,viii], for example), it has been reported that such RPN-based allocation methods were unreasonable since different risk factors were assigned with the same weights. For example, failure modes $S_1 = 2, O_1 = 8$ and $S_2 = 8, O_2 = 2$ shared the same risk priority number in the RPN-based allocation method although this did not hold true in the real world.

To overcome the drawbacks of RPN-based allocation methods, Kim *et al.* [15] developed a new allocation method by describing traditional severity using the exponential function. Suppose that S_{ij} was the severity of the j^{th} failure mode of the i^{th} subsystem; the new severity $\tilde{S}_{ij}$ could be denoted as given in equation (16).

$$\tilde{S}_{ij} = \exp(\alpha S_{ij}), \tag{16}$$

where α was the severity coefficient that was related to how the decision maker considered the failure mode; α grew larger when the decision maker took the failure mode more seriously, and vice versa.

Evaluation criterion of the i^{th} subsystem was given in equation (17).

$$n_i = \frac{1}{m_i \tilde{S}_i F_i} \tag{17}$$

where

$$\tilde{S}_i = \max(\tilde{S}_{i1}, \tilde{S}_{i2}, \ldots, \tilde{S}_{iN_i}) \tag{18}$$
$$j_i = \arg\max_j \tilde{S}_{ij}, \tag{19}$$

where m_i is the failure mode number that has the same severity with $\tilde{S}_i$ and F_i is the frequency ratio of failure mode j_i in subsystem i.

Although the equal weight problem was addressed, there was still unreasonableness in this method. Values that were used to evaluate various factors of failure modes were real numbers in the references, whereas, in practice, judgment of the failure severity was difficult due to subjectivity and uncertainty [36], [12]–[14]. Moreover, this RPN-based allocation method neglected the costs incurred by R&D and manufacturing of the system.

C. COST-BASED RELIABILITY ALLOCATION

Cost must be taken into account during the design and manufacturing of any system. Higher reliability is associated with higher manufacturing cost. Therefore, the manufacturing cost is an indispensable factor to be considered during reliability allocation.

Reliability allocation considering cost refers to the optimal planning of allocation. There are two methods of cost consideration: 1) the cost is considered a constant, which can be obtained by statistics; 2) the system cost is described as the growth function of reliability [ix,x].

In a study by Todinov [4], system cost and loss were considered as the cost factors during reliability allocation. Supposing that the cost of subsystem i was Q_i, and loss caused by failures of all subsystems was a constant L, then the total cost of subsystem i, denoted as C_i, was

$$C_i = Q_i + L \tag{20}$$

Wang *et al.* [35] measured manufacturing cost by means of cost sensitivity and described the relationship between cost and reliability of each subsystem using the numerical values of 0–1 based on expert experience,

$$C_i = \frac{\Delta C_i}{\Delta R_i} \tag{21}$$

where ΔC_i is the increased cost of subsystem i, and ΔR_i is the increased reliability of subsystem i.

In practice, however, system manufacturing cost often undulates drastically as technology and price level vary, making cost statistics rather difficult to utilize; in consideration of totally varied failure modes that had different influences, it was unreasonable to take the failure costs of various subsystems as a constant number.

In 1986, Dale [xi] developed the six basic properties of cost function and described system cost as the growth function of reliability. A cost function of the diesel engine system was established by Kuo et al. [xii] based on the basic properties developed by Dale:

$$c(R_i) = f_i \ln \frac{R_{i,\max} - R_{i,\min}}{R_{i,\max} - R_i} \tag{22}$$

where R_i was the reliability allocated to subsystem i; f_i was the cost coefficient of reliability enhancement of subsystem i, $0 < f_i < 1$, and a larger f_i indicated that the cost would be higher when the reliability of the subsystem was enhanced; $R_{i,\max}$ and $R_{i,\min}$ were the limits of reliability that subsystem i could reach with current technology and current reliability of subsystem i,respectively; $c(R_i)$ was the cost incurred as reliability of subsystem i was enhanced from $R_{i,\min}$ to R_i.

According to the three properties of cost function proposed in references [17], [18]: the cost function must be a positive definite function; it must be a non-decreasing function; and it must increase rapidly when reliability approaches 1. Charles [16] described the total system cost as

$$C_s = \sum_{i=1}^{s}\sum_{j=1}^{k_i} k_i \cdot h_i(\frac{\log(1-R_i)}{k_i}) \tag{23}$$

where k_i was the number of components of subsystem i, R_i was the reliability of subsystem i, s was the total number of subsystems, and $h_i(*)$ was the function that possessed the three properties mentioned above.

Although the cost function was able to describe the relationship between manufacturing cost and reliability of a subsystem to a certain extent, it was too complex to be used in practical engineering.

Recently, Yadav and Zhuang [16] took the effort of reliability enhancement into consideration and described effort of reliability enhancement as a failure rate-correlated function, and based on the allocation method developed by Kim, corrected the evaluation criterion of the i^{th} subsystem to

$$n_i = \frac{m_i \tilde{s}_i}{\delta_i e_i} \tag{24}$$

where δ_i denotes the coefficient of difficulty in reliability enhancement of the i^{th} subsystem, e_i denotes effort coefficient, and $e_i = \ln \lambda_i / \sum_{i=1}^{k} \ln \lambda_i$.

The influence of current reliability of the subsystem on reliability improvement was taken into account in the method developed by Yadav, yet it was the level of the most developed technology of each subsystem that exerted real effects on effort rather than failure rate. However, each subsystem was multiplied by a specific difficulty coefficient that was determined by the allocator's subjective awareness after severity and effort were corrected; specifically, the effort was corrected twice, which made the allocation more subjective and led to reduced credibility of allocation result.

The aforementioned deficiencies indicate the need for a new reliability allocation method that features integrated consideration and excellent practicability and credibility.

IV. THE FUZZY FMA RELIABILITY ALLOCATION APPROACH - *f*FMA

The fuzzy FMA reliability allocation approach (*f*FMA) – thesolution to the deficiencies of existing reliability allocation methods are proposed in this section. To begin with, the CNC system was divided into various MMUs based on FMA decomposition method, followed by the description of subjective information of uncertainties in reliability allocation using fuzzy language. The *f*FMA - a new practical reliability allocation method balancing failure effect and manufacturing cost was developed by giving integrated consideration to the influence of all system failure modes and the manufacturing cost of the system with certain reliability.

As shown in Figure 4, the *f*FMA method has 6 steps as described below:

Step 1 (Micro-Motion Subsystem Decomposition): A micro-motion is the smallest action unit of functions of a machine, and its status of reliability has a notable influence on the normal operation of the whole system. Importantly, the reliability of the whole system is built upon the reliability of each micro-motion (and joint of micro-motions). Motions of a part are made based on the combined action of multiple micro-motions; motions of the system are realized by one motion or interactions of multiple motions. Similarly, poor reliability of a micro-motion will lead to poor reliability of the motion, and even the function. System functions and reliability will not be secured unless the reliability of every micro-motion is enhanced.

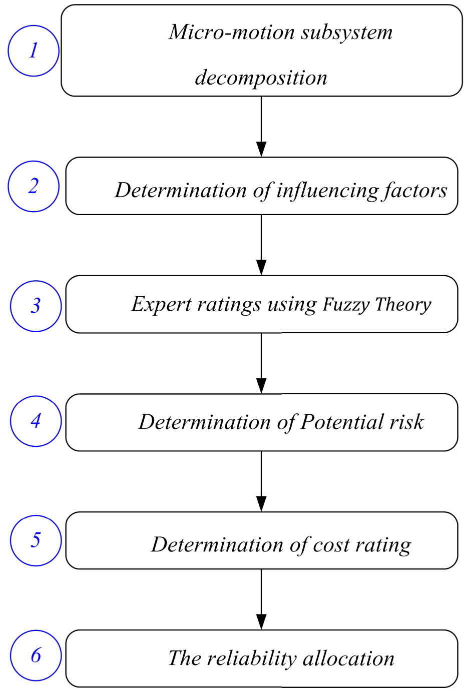

FIGURE 4. Flow-chart of *f*FMA.

Step 2 (Determination of Influencing Factors): The influence of failures of the MMUs on the whole system during operation is also known as the potential risk (PR). A system consists of several MMUs that have multiple potential failure modes. The potential risk of each micro-motion subsystem is determined by the severity (S) and occurrence (O) of all failure modes. As a result, S and O must be taken into account during reliability allocation, which is consistent with the cases of RPN-based methods. Secondly, it is inevitable that manufacturing cost rises along with reliability enhancement in any system. Restricted by manufacturing cost, it is impossible for every device to be as reliable as current technology would allow it to be. This means cost (C) that corresponds to a certain reliability is another factor to be considered during reliability allocation.

It is difficult to collect precise data of system manufacturing cost. Even collected with high precision, such data is not applicable. Cost function-based allocation methods that feature complex calculations are not feasible for practical engineering applications. Previous research suggests that the cost that is required for system reliability enhancement is subject to current system reliability and the maximum reliability that the system can reach with existing technology, and that there is a close relationship between system reliability and SA, SI, OT, and EC.

In this study, SA, SI, OT, and EC were taken as the factors to be considered, by which the cost of reliability enhancement was measured. As OT was basically the same at different

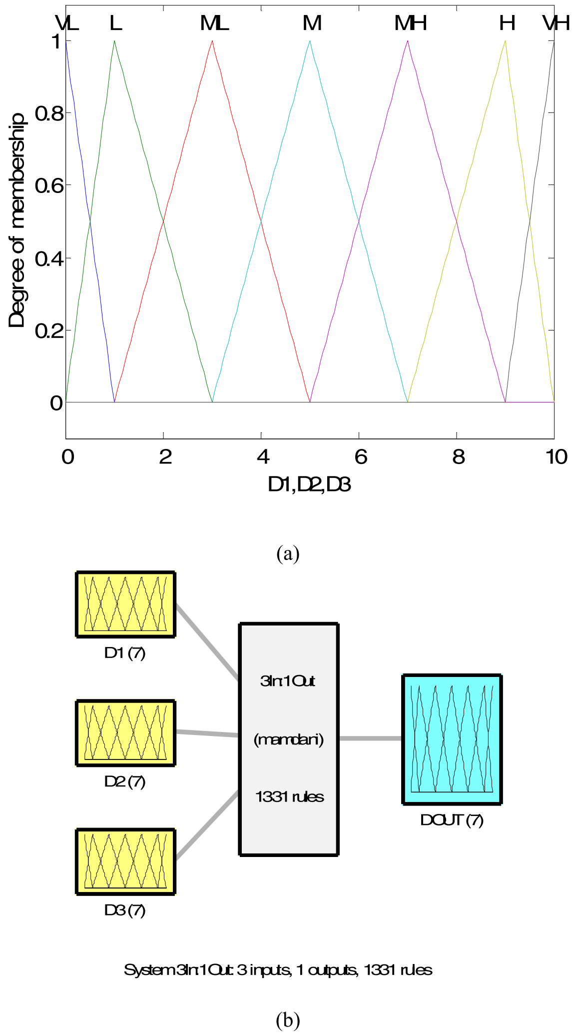

FIGURE 5. (a) Triangular membership function. (b) '3-inputs-1-output' fuzzy inference system.

levels within the same system, it was omitted for the sake of allocation simplification. Therefore, the influencing factor set K could be denoted as $K = \{PR, C\} = \{(O, S), (SA, SI, EC)\}$.

Step 3 (Expert Ratings Using Fuzzy Theory): Experts were invited to rate the influence factor set K based on existing objective information and their subjective judgment. Since data is incompletely or imprecisely collected in practice, and the opinions of decision-makers are essentially fuzzy, there is always error in judgment due to incomplete information if the description is made using a single numerical value. Therefore, the influencing factors were rated based on fuzzy language and triangular fuzzy number. Fuzzy language and its membership function relationship are shown in Table 1 and Figure 5, in which Figure 5 (a) is the triangular membership function, and (b) is the '3-inputs-1-output' fuzzy inference system.

Specifically, the ratings of failure modes were: a failure mode with a higher failure occurrence received a higher score, and that with a more severe influence also received a higher score. The ratings of MMUs were: suppose that a micro-motion subsystem with the highest SA, optimal EC, and the lowest SI currently possible was rated with a full score; therefore, a higher SA, better EC, and lower SI was given higher scores.

TABLE 1. Fuzzy rating range and membership function of linguistic terms.

Linguistic Variable	Triangular Fuzzy Number	Rating Range
Very low (VL)	[0,0,1]	[0,1]
Low (L)	[0,1,3]	[0,3]
Medium low (ML)	[1,3,5]	[1,5]
Medium (M)	[3,5,7]	[3,7]
Medium high (MH)	[5,7,9]	[5,9]
High (H)	[7,9,10]	[7,10]
Very high (VH)	[9,10,10]	[9,10]

The fuzzy rating result was defuzzified to calculate the numerical value of the decision. Methods that have been most commonly used for defuzzification are the mean of maxima (MOM), the center of area (COA), and α-cut [36]–[38]. Different methods exert different influence on the decision. For the sake of simplicity and practicability, the defuzzification number was calculated by substituting the rating result in Equation (25) using COA.

$$x(a) = a_1 + \frac{1}{3}[(a_3 - a_1) + (a_2 - a_1)], \tag{25}$$

where $x(a)$ is the value of defuzzification, and a_1, a_2, and a_3 are the upper limit, max probable value, and lower limit of triangular fuzzy number, respectively.

Step 4 (Determination of Potential Risk): Failure modes with varied severity levels had different influences on the system. Failure severity of the traditional RPN-based method was corrected in Equation (26) based on the method developed in Kuo *et al.* [39] in order to overcome the unreasonableness of weight allocation to various factors in the traditional RPN-based method. Not only did this method effectively make up for the deficiency of equal weight of various factors, but it also solved the problem of constant gradient that different severity levels shared in traditional RPN-based allocation methods.

$$S'_{ij} = a^{S_{ij}}, \quad a > 1, \tag{26}$$

where a is the risk coefficient, which is related to the product type. The more severe the influence of the failure, the larger the a.

The potential risk of a micro-motion subsystem PR_i was jointly determined by the number of failure modes, the severity of each failure mode, and failure occurrence. The single

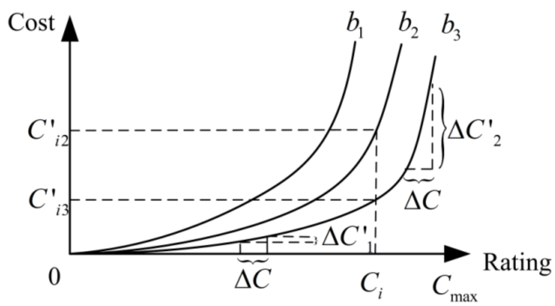

FIGURE 6. Conversion of cost ratings.

loss that was caused to the system by a failure was determined by the severity of a failure mode; frequency of loss within a period of time was determined by the number of failure modes and failure occurrence. As a result, the PR_i of each micro-motion subsystem could be characterized as

$$PR_i = \sum_{j=1}^{N_i} O_{ij} S'_{ij} \tag{27}$$

Step 5 (Determination of Cost Rating): A few research works have indicated that the relationship between system reliability enhancement and the cost required is not simply linear. The cost rises along with system reliability enhancement. When reliability approaches its limit, the cost can also be quite a large value. Therefore, the cost of system reliability enhancement was described based on this property using Equation (28):

$$C'_i = \log_b(1 - \frac{C_i}{C_{\max}}) \tag{28}$$

where, C'_i is the final score of cost of the i^{th} micro-motion subsystem; C_i is the score of cost of the i^{th} micro-motion subsystem after defuzzification as given in Equation (29), and the higher the C_i, the more reliable the i^{th} micro-motion subsystem and the lower potential for its reliability to be enhanced; $C_{\max}$ is the maximum level that i^{th} micro-motion subsystem currently could reach; b is the effort coefficient and $b \in (0, 1)$.

$$C_i = SA_i \times SI_i \times EC_i \tag{29}$$

As shown in Figure 6, the cost described in Equation (28) had the following features: (1)When the reliability was increased by ΔC, the more reliable the current system was, the higher the cost was, i.e. $\Delta C'_1 > \Delta C'_2$; (2) when current reliability remained the same, the cost of reliability enhancement of different types of products whose effort coefficients were not equal also varied, i.e. $C'_{i2} > C'_{i3}$.

To prevent one factor from being neglected during reliability allocation due to an excessive value of another factor, the PR and manufacturing cost of the micro-motion subsystem were kept within the same magnitude, i.e. $10^{-1} \leq F_i/C'_I \leq 10$. Then,

$$\frac{10\ln(1 - C_{i\min}/C_{\max})}{\exp(F_{\min})} \leq b \leq \frac{\ln(1 - C_{i\max}/C_{\max})}{10\exp(F_{\max})}. \tag{30}$$

Step 6 (The reliability Allocation): Integrated reliability of a system was based on the combination of the reliability of various MMUs since system reliability was finally allocated to each micro-motion subsystem. Reliability allocation was fundamentally aimed to minimize the potential loss of the system by means of reasonable allocation, which required a balance between PRs of various MMUs and manufacturing cost of the system with certain reliability. The greater the PR of the micro-motion subsystem, the greater the failure loss; the lower the manufacturing cost (C'), the greater the potential of reliability enhancement. To optimize the allocation results, a micro-motion subsystem with a greater PR and lower C' should be given a lower failure rate.

Thus, the following allocation method was proposed as given in Equation (31):

$$n_i = \varepsilon \left\| \sum_{i=1}^{k} PR_i - PR_i \right\| + (1-\varepsilon) \left\| C'_i \right\| \tag{31}$$

where, ε is a proportionality factor, included to balance the weight of the *Potential Risk*to that of the *Cost Rating.*Thus, the allocation weight in Equation (10) can be re-stated as Equation (32).

$$\omega_i = \frac{\varepsilon \left\| \sum_{i=1}^{k} PR_i - PR_i \right\| + (1-\varepsilon) \left\| C'_i \right\|}{\sum_{i=1}^{k} (\varepsilon \left\| \sum_{i=1}^{k} PR_i - PR_i \right\| + (1-\varepsilon) \left\| C'_i \right\|)}, \quad i = 1, 2, \ldots, k. \tag{32}$$

V. DEFINITION OF FITNESS FUNCTION

In this context, the *potential risk* and *manufacturing cost* are considered as the objectives of reliability allocation, which can perform the weighing and balancing the failures of various MMUs and the costs incurred by reliability improvement. As stated in Equations (33) and (34), two of the maximizing design objectives can be obtained from Equations (27) and (28), respectively.

$$f_1\left(\varepsilon, a, S_{ij}, O_{ij}\right) = \frac{1}{\varepsilon \sum_{i=1}^{k} \left(\left\| \sum_{i=1}^{k} PR_i - PR_i \right\| \right) + eps} \tag{33}$$

$$f_2\left(\varepsilon, b, SA_i, SI_i, EC_i\right) = \frac{1}{(1-\varepsilon) \sum_{i=1}^{k} \left\| C'_i \right\| + eps} \tag{34}$$

As shown in Figure 7, the optimal *fFMA* approach using CIAD framework can be summarized as the following 3 steps:

- Step 1: Pro-process. It defined fitness functions $[f_1, f_2, \ldots, f_N]$ on the basis of the reliability allocation model;
- Step 2: Optimal Design. Using the defined fitness functions to perform optimization, which includes 4 sub-steps. Specifically,

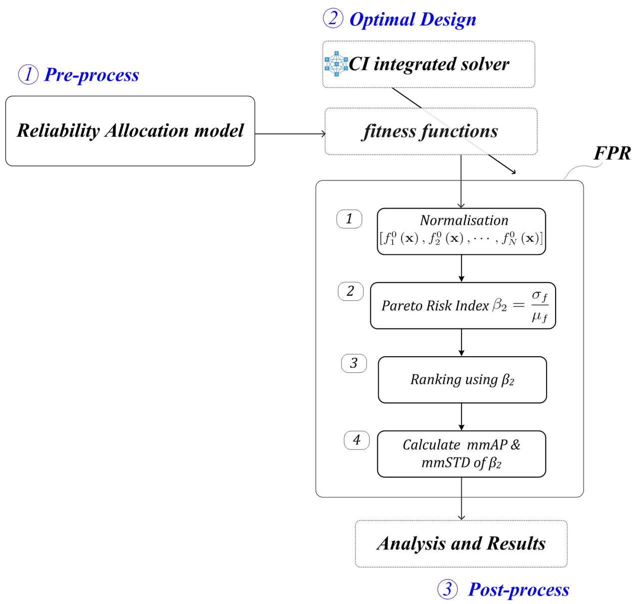

FIGURE 7. Optimal *fFMA* approach using CIAD framework.

Sub-step 1: normalization of the fitness function as $[f_1^0, f_2^0, \ldots, f_N^0]$;
Sub-step 2: calculate the Pareto Reliability Index β_2 *using* $[f_1^0, f_2^0, \ldots, f_N^0]$
Sub-step 3: rank using β_2*, as given in Equation (35);*

$$\beta_2(f) = \frac{\sigma_f}{\mu_f} \tag{35}$$

Sub-step 4: calculate the evolutionary trend indices as the fitness function as given in Equation (36), using mean average precision (mmAP) and mean standard deviation (mmSTD) for β_2. Based on the FPR approach [41], this multi-objective optimization fitness function can be expressed in Equation (36), by utilizing two design objectives, as defined in Equations (33) and (34) and the indices of the mean average precision (mmAP) and the mean standard deviation (mmSTD).

$$MAX : \{F = mmAP\,[\beta_2(f_1, f_2)]\} \tag{36}$$

The fitness function F is in a reciprocal form of the normalized 'potential risk and ' manufacturing cost' over-potential difference function, in which maximizing $\digamma$ is a way to minimize the normalized 'potential risk and ' manufacturing cost', and the goal of this function is to determine the optimal combination of eight parameters, $\varepsilon, a, S_{ij}, O_{ij}, b, SA_i, SI_i, EC_i$ that simultaneously minimizes the objective of f1 and f2. eps is the floating-point relative accuracy, which prevents singularity in the case where the denominator of f1 or f2 is approaching 0 and F is approaching *inf*.

- Step 3: Post-process. It is to perform the analysis and generate the results, then terminate the program.

VI. RESULTS AND DISCUSSION

In this section, an example of reliability allocation of a CNC machine's spindle system was used to illustrate the validity of the method proposed in this paper. The aim is to maximize the fitness function F that yields the minimum of potential risk and manufacturing cost, as defined in Equations (33) and (34), which is fulfilled by using the specially designed toolboxes SwarmBat [42], SECFLAB [43] and SGALAB [44], respectively. The computer facilities for the simulations are an Intel Core i7-5500U 2.4 GHz Intel dual-core processor, Windows 7 flagship x64 service pack 1, an 8.0 GB 1600 MHz dual-channel DDR3L SDRAM, MATLAB R2010a, and the simulation parameters are given in Tables 2 (as given in the appendix) and 3, respectively.

TABLE 2. Ratings of failure modes with respect to risk factors assessed by FMEA team members.

i Subsystem	SA_i			EC_i			SI_i			Failure mode	O_{ij}			S_{ij}		
	D1	D2	D3	D1	D2	D3	D1	D2	D3		D1	D2	D3	D1	D2	D3
1 Spindle body	MH	H	H	VH	H	MH	MH	VH	H	Inaccurate orientation (FM_{11})	H	MH	H	M	M	MH
										Precision out of tolerance (FM_{12})	ML	L	L	M	MH	M
										Abnormal noise (FM_{13})	VH	H	VH	ML	M	M
										Excessive Temperature rise (FM_{14})	ML	L	L	L	VL	L
2 Support bearings	VH	H	VH	H	M	MH	H	VH	H	Excessive clearance (FM_{21})	H	M	L	H	ML	M
										Ball dropdown (FM_{22})	VL	VL	VL	VH	VH	VH
3 Cooling system	H	H	H	VH	H	VH	VH	H	H	Refrigeration failure (FM_{31})	M	L	ML	MH	ML	ML
										Leakage (FM_{32})	VH	VH	H	L	L	ML
4 Broach mechanism	H	MH	MH	H	MH	MH	H	H	MH	Looseness (FM_{41})	MH	H	ML	M	L	MH
										Fracture (FM_{42})	L	VL	L	H	VH	VH
5 Rotation mechanism	MH	H	MH	H	H	H	H	H	MH	Seizure (FM_{51})	L	M	ML	MH	MH	H

As shown in Table 2, the spindle system of the CNC machine is composed of five MMUs: (1) the spindle body, (2) the support bearings, (3) the cooling system, (4) the broach mechanism, and (5) the rotating mechanism. Three experts, D1, D2 and D3, were invited to rate the MMUs and their failure modes using the fuzzy language in Table 1, with their fuzzy ratings shown in Table 3. According to the previous work and simulation experience, the simulation parameters defined in Section 2 are also initialized, as shown in Table 3. The fuzzy language was converted into a corresponding triangular fuzzy number, followed by the defuzzification of the mean value of ratings given by three experts, and the optimal rating result is shown in Table 4.

In Figure 8, the solid line represents the mmAP scores for the fitness function F as given in Equation (36), and

TABLE 3. Parameters for optimization.

Max generation	300
population	60
frequency range	[20000, 500000] Hz
test number	2
random step	0.1
reduction factor, α	0.9
proportionality factor, ε	[0,1]
risk coefficient, a	(1,5)
effort coefficient, b	(0,1)
S_{ij}	See Table 1 and Table 2
O_{ij}	See Table 1 and Table 2
SA	See Table 1 and Table 2
SI	See Table 1 and Table 2
EC	See Table 1 and Table 2

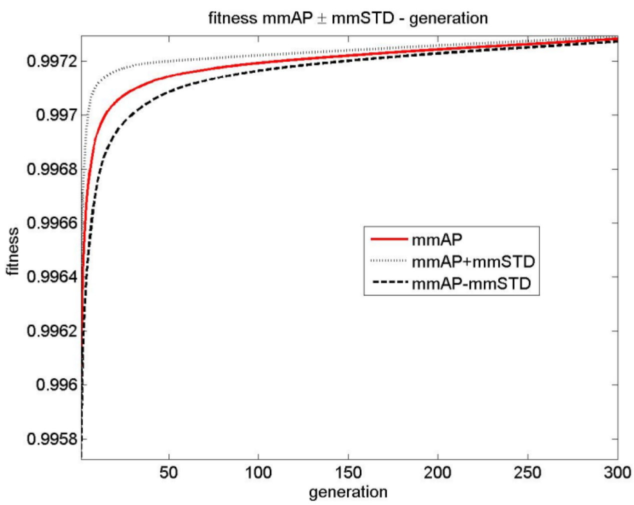

FIGURE 8. Optimization process.

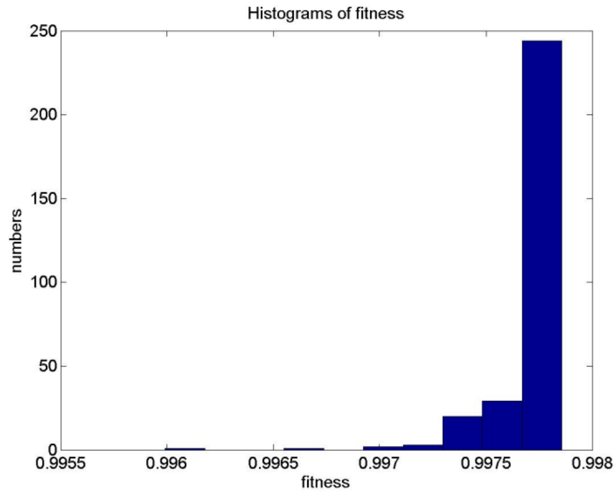

FIGURE 9. Optimization histogram.

TABLE 4. Optimal rating results.

i	SA_i	EC_i	SI_i	C_i	Failure mode	O_{ij}	S_{ij}	$\sum_{j=1}^{k} O_i S_i$
1	8.05	9. 01	8. 76	612.3008	FM_{11}	8.45	6.97	97.4327
					FM_{12}	1.69	6.12	
					FM_{13}	8.23	5.43	
					FM_{14}	2.12	1.08	
2	8.99	6.97	8.99	573.8183	FM_{21}	4.99	5.85	32.6873
					FM_{22}	1.14	8.69	
3	9.06	8.99	8.99	699.9854	FM_{31}	2.99	4.87	30.2079
					FM_{32}	8.67	2.01	
4	8.35	9.04	7.99	501.4229	FM_{41}	6.89	5.01	36.7268
					FM_{42}	1.29	8.99	
5	8.12	8. 98	9.21	611.4728	FM_{51}	2.99	8.08	23.43

TABLE 5. Comparison between different allocation methods.

i	PR_i	$\sum_{i=1}^{k} PR_i$ -PR_i	C'_i	w_i	λ^*_i		
					traditional	RPN	This research
1	261.7680775	506.8517183	401.1630529	0.186395699	0.000394743	0.000371581	0.000445863
2	119.9309261	601.5867726	300.4324361	0.214614657	0.000398981	0.000420729	0.000391218
3	83.49124652	659.3286921	412.9238462	0.249856864	0.000368286	0.000419981	0.000499861
4	162.1674620	571.3526173	219.1972321	0.187381734	0.000419986	0.000399184	0.000451149
5	141.5713619	591.8284347	260.9661439	0.161751046	0.000410874	0.000391121	0.000428197
Total	768.9290740	2930.948235	1594.682711	1	0.00199		

both the upper and lower boundaries of mmAP ±mmSTD are defined by the dashed lines for the optimization process (generation versus fitness F). Figure 8 illustrates the fitness mmAP curves, in which, the curves go down very quickly from generation 1 to reach a plateau point (within generation 200) and then remain steady from generation 200 to 300, the upper and lower range of mmAP ±mmSTD curves move closer and converge, indicating the high efficiency and accuracy of this optimization. Figure 9 shows the histogram over the optimization process.

As shown by Table 4 (as given in the appendix) and Figure 10, the failure rate allocated to each MMU varies among different methods. The failure rate of the cooling system was the highest according to the method developed in this study, which was consistent with the result of the RPN-based allocation method. As shown in Tables 4 and 5, C_i ratings of the cooling system were the highest among the five MMUs, indicating it was the most reliable. Thus, the

TABLE 6. Influence of cost coefficient *b* on allocation.

i	λ^*_i			
	b=0.9880	b=0.9920	b=0.9960	b=0.9990
1	0.000434361	0.000445062	0.000453863	0.000475213
2	0.000410132	0.000399703	0.000401287	0.000416426
3	0.000495481	0.000501152	0.000515287	0.000529422
4	0.000451451	0.000446428	0.000440642	0.000432348
5	0.000431093	0.000429178	0.000416287	0.000408613
Total	0.00199			

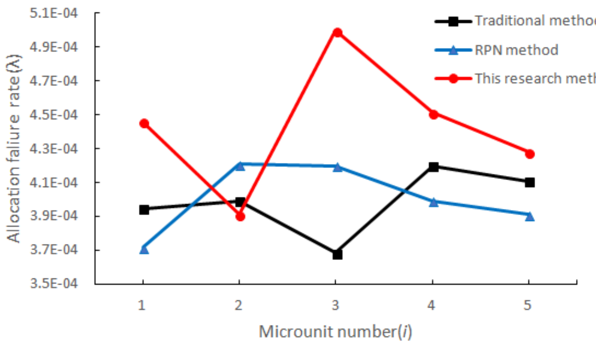

FIGURE 10. Comparison of allocation results between different allocation methods.

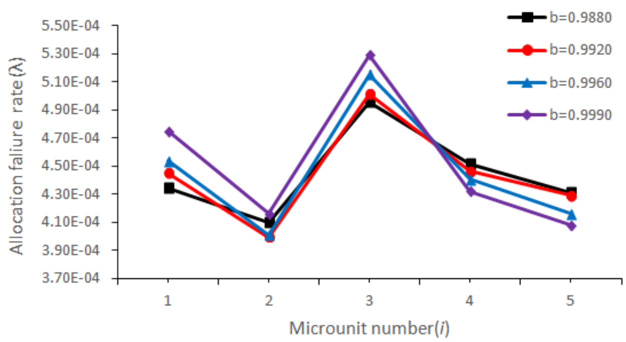

FIGURE 11. Influence of cost coefficient *b* on allocation.

reliability enhancement of the cooling system will inevitably incur a large amount of cost. On the other hand, its potential risk, PR_i, was the lowest, indicating that it had the least impact on the system. Thus, compared with the other four MMUs, the reliability enhancement of the cooling system was unnecessary, and the highest failure rate should therefore be allocated to it.

The lowest failure rate was allocated to the broach mechanism, according to the proposed method. In contrast, it was allocated to the cooling system by the traditional method and the spindle by the RPN-based method. This difference occurred because MMUs with higher reliability levels were allocated with lower failure rates in the traditional method that focused on the current system reliability, whereas MMUs that might cause severe consequences were allocated with lower failure rates in the RPN-based method that focused on the influence of failure of the micro-subsystem on the system in hope of reducing the influence of failure on the system. As demonstrated in Table 3 and Table 4, of all five MMUs, the C_i of the cooling system was the largest (reliability was the highest), and the mean value of the failure mode ratings of the spindle was the largest (the influence of potential failure on a system was the greatest). Therefore, the lowest failure rate was allocated to the cooling system and spindle with these two methods. However, instead of optimizing the allocation result, the allocation was made from a single aspect in both the traditional method and RPN-based method. Although the spindle system was the most potentially risky, it was more reliable. Thus, the reliability enhancement of the spindle system incurs a substantial cost. It was also unreasonable to allocate the lowest failure rate to the cooling system. The broach mechanism was not as reliable as the other four MMUs, so there was much room for its reliability to be enhanced. Furthermore, its potential risk was in the second place, so it deserved more attention from the designer. As a result, the lowest failure rate should be allocated to broach mechanism for the sake of optimal system allocation.

The allocation of various MMUs with varying cost coefficients b is shown in Table 6 (as given in the appendix) and Figure 11, respectively. The range of b satisfying the requirement that PR_i and C_i are of the same magnitude was calculated, i.e. $b \in [0.9867, 0.9998]$. As shown in Table 5 (as given in the appendix), failure rates allocated to various MMUs changed as cost coefficient b varied. When b approached its lower limit ($b = 0.9880$), the cooling system was assigned the highest failure rate while the spindle was assigned the lowest failure rate among the five MMUs. When b approached its upper limit ($b = 0.9990$), the broach mechanism was assigned the lowest failure rate while the failure rate of spindle was third. The reason was that the value of b in Equation (21) increased when the manufacturing cost of a product grew higher or the designer emphasized it more than others. The cost incurred by reliability enhancement was still small, compared with the failure effect, which played a dominant role during allocation when $b = 0.9880$. Therefore, the allocation (sorting) result of the method developed in this study was similar to that of the RPN-based method. The reason why the failure rates allocated to broach mechanism and rotation mechanism differed slightly was that the value taken in the RPN-based allocation in Equation (7) was a mean and the weight allocated to averaged broach mechanism increased. When $b = 0.9990$, however, it was the cost that dominated during allocation since the designer paid more attention to design cost.

Accordingly, the consequence of failure exerted little impact on allocation result; the allocation result was contrary to that of the traditional method. When b took a value beyond the given range, the factor with a far smaller weight than the other factor was neglected, and credibility of the allocation result was reduced.

VII. CONCLUSION AND FUTURE WORK

This paper presents a micro-motion subsystem decomposition-based fFMA (fuzzy FMA reliability allocation) reliability allocation method, in which the integration of failure effects, manufacturing cost, the potential risk, and reliability cost of the micro-motion subsystem were allocation factors. In this work, the potential risk of the micro-motion subsystem was characterized based on the corrected risk priority number, the cost function for system reliability was created using relative reliability, and the allocation model was built for the purpose of an optimal allocation result. Specifically, (1) adjustment of risk coefficient and cost coefficient was conducted in accordance with the allocator's intention with flexibility; (2) Uncertainties of allocation were described using the fuzzy method; (3) ranges of risk coefficient and cost coefficient were presented, ensuring the balance between various factors and improving the credibility of allocation result.

The contribution of this research lies the fact that this paper proposes a MMU decomposition-based fFMA reliability allocation method, which is weighing and balancing the failures of various MMUs and the Costs via the Improved RPN Value and the Semi-quantitative Cost Function using a CIAD framework embedded with a BAVP algorithm. The problems in current allocation methods, such as inadequate consideration of relevant factors and lack of practicability, were solved by the proposed method.

Our future research will focus on developing new types of CI algorithms, such as the heredity algorithm (HA), the artificial fish swarm algorithm, the artificial wolf pack algorithm, the firefly swarm algorithm, the swarm dolphin algorithm and their hybrid derivatives, to optimize further prediction decoupling of quality characteristics. To achieve a 'state-of-practice' design framework for the predictive control, further experimental research is needed to establish an advanced model for dynamical coupled behaviors and the CNC machines' reliability design and improvement [45]–[50].

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XIANLIN REN (M'11) received the B.Sc., M.Sc., and Ph.D. degrees in mechanical engineering from Chongqing University, in 1999, 2004, and 2010, respectively. He is currently an Assistant Professor of mechanical and electrical engineering with the University of Electronic Science and Technology of China, where he is also the Director of the Industrial Internet and Intelligent Manufacturing Institute. He has served as a PI or a Co-PI for over 20 research projects, including the National Natural Science Foundation Youth Foundation, the Natural Science Foundation General Projects and the Natural Science Foundation Key Projects, and the National 863 Projects, the National Major Projects, and the Transverse Projects of Enterprises. He has published over 60 journals and conference papers. He holds six authorized patents. His research interests include intelligent manufacturing systems, quality engineering, reliability modeling, reliability-based design optimization, and model validation. He is a member of the China Quality Association, the Sichuan Science and Technology Association, and the National Association of Basic Research on Interchangeability and Measurement Technology.

YI CHEN (M'10–SM'17) received the B.Sc., M.Sc., and Ph.D. degrees. He has been taking a leading role in the previous and current departments to maintain multi-disciplinary research links and develop external research collaborations both nationally and internationally. He has also been leading a few research grants in the areas of artificial intelligence, high-performance computing, robotics, and autonomous systems, and also studies in multidisciplinary contexts. He has a high-level output of research publications in leading international journals and presentations at international conferences, which related to the research area of robotics, digital manufacturing, and industry 4.0, which demonstrates significant research and grant potential in engineering and cross-disciplinary applications. He has been actively involved in both academic research and KTP projects as a PI and a Co-I funded by EPSRC (U.K.), Horizon2020 (EU), NSFC (China), the National Key Research and Development Program of China, and industrial funding bodies. He has published over 80 academic papers in both high-impact international academic journal and international conferences. He is a member of IET, AAAI, AIAA, and ASME, and a Fellow of HEA and IMechE. He is also a Chartered Engineer and an Editorial Board Member. He has been selected as a Publons' Top 1% of Reviewers in Computer Science and Engineering. One of the co-organizers of the WCCI 2016 Special Session on Computational Intelligence for Industry 4.0 and CEC 2019 Special Session on Evolutionary Computation for Creativity, Manufacture and Engineering Management in the Industry 4.0 Era. He has been a Guest Editor for five special issues.