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A Reliability Statistical Evaluation Method of CNC Machine Tools Considering the Mission and Load Profile

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ABSTRACT Reliability of the CNC machine tool (abbreviated as machine tool) relates to the product's reliability and has great influence on the manufacturing process. The traditional reliability statistical evaluation method of the machine tool neglects the influence of the mission profile and load profile (M&L), it causes that the evaluation result is not accurate enough to provide accurate references for the reliability-related works under specific M&Ls such as the preventive maintenance, product improvement, etc. To address these defects, this paper proposes an improved reliability statistical evaluation method considering the M&L. Firstly, the machine tool is decomposed by the meta-action decomposition method, and the mission profile of the machine tool is represented by the meta-action chain (MC). Secondly, load profile representation indicators of the machine tool are extracted based on the load composition and cutting force calculation. Then, the mapping model between the M&L and the machine tool's reliability is established using the radial basis function (RBF) neural network. Finally, the improved reliability statistical evaluation method is illustrated and validated by the engineering practical application. Comparing the evaluation results of the two statistical evaluation methods, it shows that the improved reliability statistical evaluation method is more accurate than the traditional reliability statistical evaluation method, under specific M&Ls, so that it can provide more accurate references for the reliability-related works.

INDEX TERMS CNC machine tool, reliability evaluation, mission and load profile, radial basis function neural network.

I. INTRODUCTION

The machine tool is closely related to the whole process of the product manufacturing, its reliability is important to the manufacturing enterprises.

From the enterprise investigation, the main production modes of the machine tool users are the multi-variety small-batch production mode and flow line production mode, shown as TABLE I.

Under these two kinds of production modes, the machine tool runs in the specific one or several kinds of M&Ls. As is known to all, the M&L has an important influence on the machine tool's reliability. Therefore, the accurate reliability evaluation of the machine tool under the specific one or more kinds of M&Ls can provide important references for the reliability-related work (such as the preventive maintenance, product improvement, etc.) of the machine tool under the multi-variety small-batch production mode or the flow line production mode.

The reliability evaluation method of the machine tool can be generally divided into the reliability test evaluation method and reliability statistical evaluation method (abbreviated as statistical method) according to the data source. The test evaluation method uses the fault data obtained from the reliability test to evaluate the machine tool's reliability, and the statistical method uses the fault data collected during the practical

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TABLE 1. Main production mode of the machine tool users.

Production mode	Machine tool users
Multi-variety small-batch production	CNC machine tool manufacturing enterprises, etc.
Flow line production	Automobile manufacturing enterprises, Electronic product manufacturing enterprises, etc.

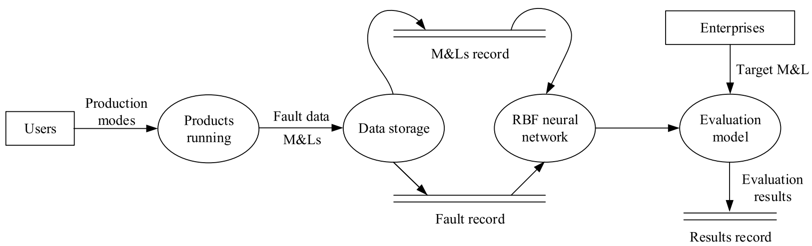

FIGURE 1. Data flow chart of the improved statistical method for the machine tool.

work process of the machine tool to conduct the reliability evaluation. Since the high time cost and material cost of the reliability test, enterprises prefer to use the statistical method to evaluate the machine tool's reliability.

However, the traditional statistical method uses a constant arithmetic mean of the machine tool's fault interval time collected during the practical work process to represent the reliability of the machine tool, neglects the fact that the machine tool's reliability is affected by the M&Ls. It causes that the traditional statistical method is not accurate enough to provide accurate references for the reliability-related works of the machine tool under the specific one or several kinds of M&Ls.

Therefore, to make the reliability evaluation method more accurate under the specific M&Ls, this paper proposes an improved reliability statistical evaluation method to evaluate the reliability of the machine tool considering the M&L. Firstly, the meta-action decomposition method [1] is introduced to decompose the machine tool and the mission profile is represented by the MC. Then, the load profiles are represented on the basis of the load composition and cutting force calculation. Finally, the mapping model between the M&L and the machine tool's reliability is established by using the RBF neural network to evaluate the machine tool's reliability under the specific M&Ls. Data flow chart of this paper is shown in FIGURE 1.

In this paper, Section 3 decomposes the machine tool by using the meta-action decomposition method and the mission profile is represented. In section 4, considering the load composition and cutting force calculation, the load profile of the machine tool is represented. Section 5 establishes the mapping model between the M&L and the machine tool's reliability by using the RBF neural network. And Section 6 illustrates and validates the feasibility and correctness of the improved reliability evaluation method through an engineering practical application.

II. LITERATURE REVIEW

We reviewed the current literature oriented on the research of the reliability evaluation from the mechanical system's reliability evaluation and other reliability evaluation.

For the research of the machine system's reliability evaluation, Agrawal *et al.* [2] used the Markov model to analyze the reliability of the earth pressure balance tunnel boring machine (EPBTBM). In Haiyang *et al.* [3], a piecewise-deterministic Markov process modelling framework is developed to evaluate the reliability of the man-machine system by incorporating the machine degradation and human errors. Zhang *et al.* [4] proposes a synthesis approach to analyze the milling machining accuracy reliability of the thin-walled components, and the machining experiment indicates the better predictive ability of the proposed method. In Lin *et al.* [5] and Gu *et al.* [6], reliability of the production system is evaluated, Lin *et al.* proposes a novel algorithm on the basis of depth-first search to derive the minimal machine vectors (MMVs) which presented for evaluating the system reliability. Gu *et al.* present a novel mission reliability modeling method of manufacturing systems integrating three indicators of task demands, machine processing capacity and the qualified rate of machine in manufacturing process respectively.

For other reliability evaluation method, present researches mainly include three aspects: structural reliability evaluation, network reliability evaluation and the multi-state reliability evaluation.

Regarding the structural reliability evaluation, Wang *et al.* [7] proposed a moment-based reliability evaluation method which depends on input variables' moment information rather than the probability distribution functions. In Xu *et al.* [8], a new approach is proposed to address the challenge of high-dimensional reliability analysis based on a small number of samples by using the maximum entropy method (MEM) with the low-order fractional moments as constraints.

About the network reliability evaluation, in Zhu *et al.* [9], a novel network reliability evaluation method is presented, the method evaluates the network reliability by identifying minimal path sets that may have edges in common and consist of only parallel and series structures when considered together. Chaturvedi *et al.* [10] developed the delay tolerant networks (DTNs) model based on the Time Aggregated Graph and presented the notion of the time-stamped-minimal path set between the given source-destination pair of nodes as well as its enumeration method.

For the multi-state reliability evaluation, in Wang *et al.* [11], a system reliability evaluation method based on the universal generating function (UGF) is presented to evaluate reliability of the multi-state system (MSS) with performance sharing, and its effectiveness were validated by the analytical and numerical examples. Song *et al.* [12] established the stochastic multi-valued (SMV) models, which avoid the large computational overhead of the universal generating function (UGF) and Monte Carlo simulation methods, to evaluate the reliability of the MSS with dependent multi-state components (MSCs). Larsen *et al.* [13] presented the multi-performance weighted multi-state components and two generalized multi-performance multi-state K-out-of-n system models to study the reliability evaluation of the multi-performance weighted multi-state K -out-of- n system.

In addition to the research of structural reliability evaluation, network reliability evaluation and the multi-state reliability evaluation, some other reliability evaluation researches are also conducted by the scholars. Wang *et al.* [14] presented three Bayesian inference models for establishing the relationship among pass/fail-type Bernoulli data, lifetime data and degradation data, and the data are integrated to solve relevant problems and improve the reliability prediction accuracy. Zhixue *et al.* [15] presented a specific trans-layer model learning (TLML) algorithm to conduct the general multi-component dynamic systems' real-time reliability analysis. In Wang *et al.* [16] an effective surrogate model for system reliability analysis of mechanisms which can deal with kinematic reliability problems of steering mechanisms, is developed based on the extreme-value kinematic error model and Kriging approximation.

In summary, among all the above researches, most of the researches on the reliability evaluation focus on the network reliability, multi-state reliability and structural reliability. There are a few researches on the reliability evaluation of the machine tool and few researches consider the M&L in the reliability evaluation of the machine tool. This paper improves the statistical method to evaluate the machine tool's reliability more accurate by considering the M&L.

III. REPRESENTATION OF MISSION PROFILE

Definition 1: Mission profile of the machine tool is the time series description for the machine tool's functions required during the completion of the mission.

Different functions of the machine tool are implemented by a variety of different complex motion combinations. It is difficult to represent the machine tool's motion combinations at the whole machine layer, so the machine tool must be decomposed first.

Traditional decomposition methods of component-suite-part (CSP), assembly unit-component-parts (ACP) [17] and function-behavior-structure (FBS) [18] decomposition decompose the machine tool according to its structure. The smallest unit obtained by decomposition is the part, it cannot implement and represent the motion combinations. Therefore, traditional decomposition methods are not suitable for the representation of the mission profile.

Meta-action decomposition method is a machine tool function decomposition method following the order of "function-motion-action" [19]. It decomposes the machine tool's functions into the smallest motions, i.e., meta-actions. Thus, the function can be represented by the meta-action combination, and the time series description of the meta-action combination can represent the mission profile of the machine tool easily. In conclusion, the meta-action decomposition method is suitable for the decomposition of the machine tool aiming at representing its mission profile.

This paper decomposes the machine tool by using the meta-action decomposition to simplify the representation of the mission profile.

A. META-ACTION DECOMPOSITION METHOD OF THE MACHINE TOOL

Meta-action decomposition method is a machine tool decomposition method considering its motions and functions, it decomposes the machine tool's functions into the smallest motions, i.e., meta-action, shown as FIGURE 2.

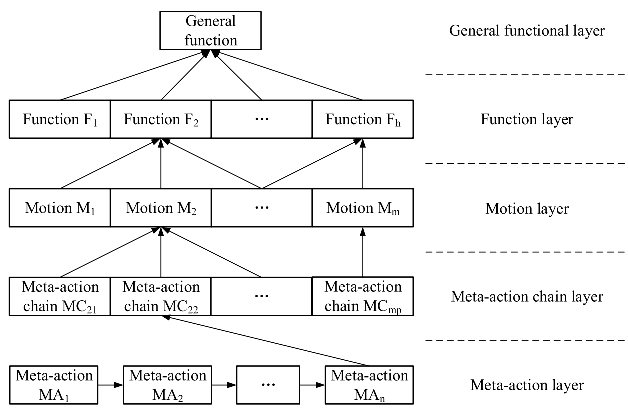

FIGURE 2. Meta-action decomposition of mechanical product.

Definition of the meta-action and MC are as follows [20].

Definition 2: Meta-action is the smallest motion in the machine tool.

Definition 3: The MC is a motion chain composed by the interrelated meta-actions based on the transmission relationship.

From the FIGURE 2, the function layer means the basic functions of the machine tool, e.g. the milling, turning, etc. The motion layer means the motions of the sub-systems for implementing the machine tool's function, such as the rotation of turntable sub-system, transmission of the X-axis feed sub-system, etc. The meta-action chain layer means the meta-action chains constituting the sub-system motion, e.g. the motion of the meta-action chain for loosing and clamping the turntable, the motion of the turntable rotating meta-action chain, etc. The meta-action layer means the meta-actions constituting the meta-action chain such as the rotation meta-action of the worm, transmission meta-action of the piton, etc.

The MC is obtained by composing the meta-actions based on the transmission relationship, composition of the MC is shown in FIGURE 3.

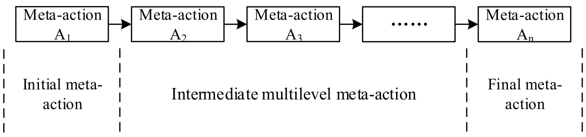

FIGURE 3. Composition of the MC.

B. REPRESENTATION OF THE MACHINE TOOL'S MISSION PROFILE

The mission profile composed by a large number of meta-actions, with which representing the mission profile will lead a very complicated representation form and calculation process. The MC, as an organic combination of the meta-actions, implements the only mission: realizing the final meta-action. Therefore, representing the mission profile with the MC is reasonable and can greatly simplify the representation form of the mission profile.

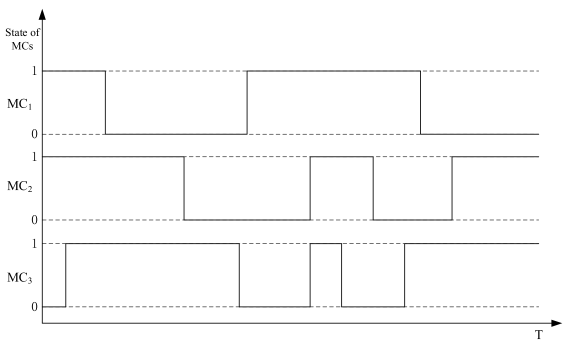

FIGURE 4. Mission profiles of the MCs.

As the form shown in FIGURE 4, the mission profile of the machine tool is implemented by the organic combination of MCs' running and stop in given time periods.

It is the total running time of each MC that affects the machine tool's reliability, not the running sequence of the MC. So representing the mission profile by the total running time of each MC is suitable.

Firstly, numbering the MC of the machine tool. MC_{ij} is used to represent the j^{th} MC in the i^{th} system of the machine tool.

Then, mission participation degree (Mpd) of the MC, which means the participation degree of the MC in one mission cycle of the machine tool, is introduced to represent its running time. The mission cycle is the machine tool's function combination to complete the production of a part, and it is the component of mission profile. Mpd of the MC is expressed by percentage of its own running time to the machine tool's total running time, shown as (1):

$$P_{ij} = \frac{T_{ij}}{T} \tag{1}$$

where, P_{ij} is the Mpd of MC_{ij}. T_{ij} is the total running time of MC_{ij} in one mission cycle. T is the total time of the corresponding mission cycle.

Referring to the universal generation function's form, combining the MC's name and Mpd, the machine tool's mission cycle can be synthetically characterized as (2):

$$\begin{aligned} M_{c,i} &= \sum_{j=1}^{n} P_{ij} MC_{ij} \\ M_c &= \sum_{i=1}^{m} M_{c,i} = \sum_{i=1}^{m} \sum_{j=1}^{n} P_{ij} MC_{ij} \end{aligned} \tag{2}$$

where, M_c is the mission cycle of the whole machine tool, $M_{c,i}$ is the mission cycle of the machine tool's i^{th} system. Similar to the universal generating function, Σ only represents the formal summation, not the numerical addition.

For the machine tool with multi-varieties small-batch production, there are several kinds of mission cycles, corresponding to the part variety, in the production process. Through the enterprise investigation, production plan in the enterprise is made according to the products' orders, it indicates that the mission cycle and its number in different periods are different. So using the actual mission cycle distribution to represent the machine tool's mission profile has not only poor operability, but also little referential significance for subsequent reliability evaluation. Furthermore, production in the enterprise is planned according to the part variety. A processing department is established to produce the same kind of parts. So, in the same machine tool, structure of the part is similar and the mission cycles are also consistent. It provides an important basis for the comprehensive representation of the mission profile.

Therefore, based on the above backgrounds, comprehensive representation of the mission profile only considers the type of mission cycle, but ignores the occurrence number of the same mission cycle, the arithmetic average of the Mpd is used to represent the mission profile as (3):

$$\begin{aligned} \overline{P_{ij}} &= \frac{\sum_{k=1}^{n_m} P_{ijk}}{n_m} \\ MP &= \sum_{i=1}^{m} MP_i = \sum_{i=1}^{m} \sum_{j=1}^{n} \overline{P_{ij}} MC_{ij} \end{aligned} \tag{3}$$

where, P_{ijk} represents the Mpd of the i^{th} system's j^{th} MC in the machine tool under the k^{th} mission cycle. n_m is the total number of the mission cycle. $\overline{P_{ij}}$ is the mean Mpd of MC_{ij} in all mission cycles. MP_i is the mission profile of the machine tool's i^{th} system. MP is the mission profile of the whole machine tool.

This paper attempts to establish the mapping relationship between the machine tool's reliability and the variable M&L. So more attention must be paid to the MC with higher Mpd fluctuation than the lower one. Screening out the MC with low fluctuation Mpd, the specific mission profile is expressed in the form of the vector, as (4):

$$MP = \left[\left(\overline{P_{1e}}\right), \cdots, \left(\overline{P_{if}}\right), \cdots, \left(\overline{P_{mg}}\right)\right] \tag{4}$$

where, e, f and g are the serial number of the MC with high fluctuation Mpd in the 1st, ith and mth system respectively.

IV. REPRESENTATION OF THE MACHINE TOOL'S LOAD PROFILE

In the running process of the machine tool, direct measurement of the load is difficult and will affect the enterprise's production. So indirect calculation of the loads is more appropriate.

According to the manufacturing knowledge, loads of the machine tool mainly come from three aspects: the machine tool's weight, the workpiece's weight and the cutting force.

The machine tool's weight is an inherent property, which will not change in different mission profiles. Practically, it is useless and unnecessary to consider the machine tool's weight into the load profile, so it should be screened out.

Workpiece's weight will only affect the loads, including the pressure and the internal friction, on the system related to the transportation and rotation of the workpiece, that is, the turntable and the z-axis feeding system. For the pressure, these two systems only run when the workpiece needs to be transported or rotated, it means the pressure belongs to the static load and has little effect on the two systems' reliability. For the friction, due to the existence of guide rails and bearings, increment of the internal friction is very small. Therefore, the workpiece's weight should also be excluded.

After eliminating the weight of the machine tool and the workpiece, the load profile is only represented by the cutting force. Based on the mechanical manufacturing knowledge [21], under different kinds of processing, there are different calculation formulas to calculate the machine tool's cutting force. Taking the turning processing as an example, the cutting force is calculated as (5):

$$F = \sqrt{F_c^2 + F_p^2 + F_f^2}, \quad \begin{cases} F_c = C_{F_c} a_p^{x_{F_c}} f^{y_{F_c}} v_c^{n_{F_c}} K_{F_c} \\ F_p = C_{F_p} a_p^{x_{F_p}} f^{y_{F_p}} v_c^{n_{F_p}} K_{F_p} \\ F_f = C_{F_f} a_p^{x_{F_f}} f^{y_{F_f}} v_c^{n_{F_f}} K_{F_f} \end{cases} \tag{5}$$

where, $C_{F_c}, C_{F_p}, C_{F_f}$ are the cutting force coefficients determined by the material and cutting condition. x_{F_c}, y_{F_c}, n_{F_c}, $x_{F_p}, y_{F_p}, n_{F_p}, x_{F_f}, y_{F_f}, n_{F_f}$ are the indices of the cutting depth a_p, the feeding rate f and the cutting velocity v_c in the three cutting force components. $K_{F_c}, K_{F_p}, K_{F_f}$ are correction coefficients of the three cutting force components when the actual processing conditions are not consistent with the standard conditions. All the above coefficients can be obtained from the mechanical processing handbook.

From the cutting force calculation formula, the cutting forces are a series of discrete constants during the processing process, shown as FIGURE 5. However, based on the background that the production plan is made according to orders, using these discrete constants to represent the load profiles will lead large data amount and variable data dimensions, so the cutting forces need to be further processed.

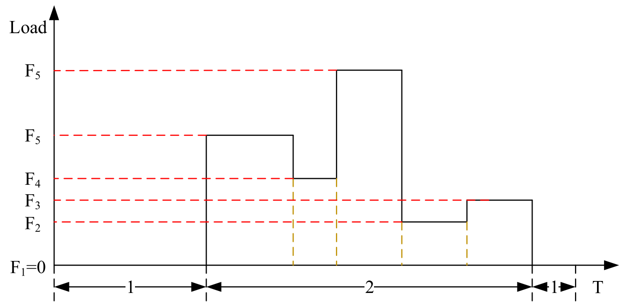

FIGURE 5. Load profile of the machine tool in a mission cycle.

Since the same parts correspond to the same cutting force curve during the processing process, and the types of the part are limited even in the multi-variety and small batch production mode, so the statistical parameters of the cutting forces are not difficult to obtain. This paper regards the discrete cutting forces as a series of discrete statistical data, and the maximum value, the minimum value, the mean value and the standard deviation of the cutting forces are used to represent the machine tool's load profile, shown as (6):

$$L = \left[F_{max}, F_{min}, \overline{F}, \sigma_F\right] \tag{6}$$

where, $F_{max}, F_{min}, \overline{F}$ and σ_F are the maximum value, the minimum value, the mean value and the standard deviation of the cutting forces, respectively.

V. RADIAL BASIS FUNCTION NEURAL NETWORK MODEL

The machine tool is the multi-variety small-batch product, its yield is limited as well as the fault data generated during its running process.

The RBF neural network, as a kind of neural network with a simple structure, low data size demand, fast convergence speed and the capability to approximate any non-linear function [22], is suitable for the reliability evaluation of the machine tool.

RBF neural network is a forward network composed of three layers: the first layer is the input layer, its node number equals to the input's dimension; the second layer is the hidden layer, its node number depends on the problem's complexity; the third layer is the output layer, its node number equals to the output's dimension. Structure of the RBF neural network is shown in FIGURE 6.

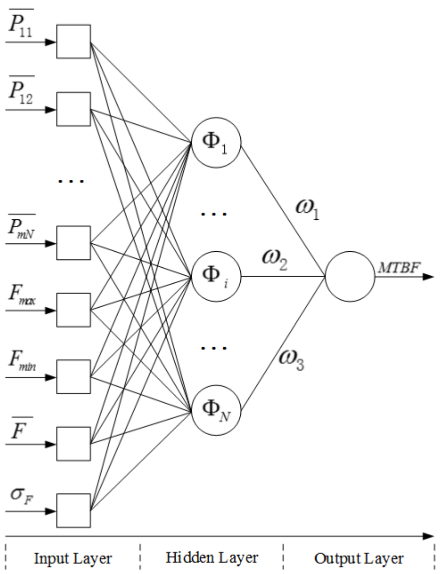

FIGURE 6. RBF neural network.

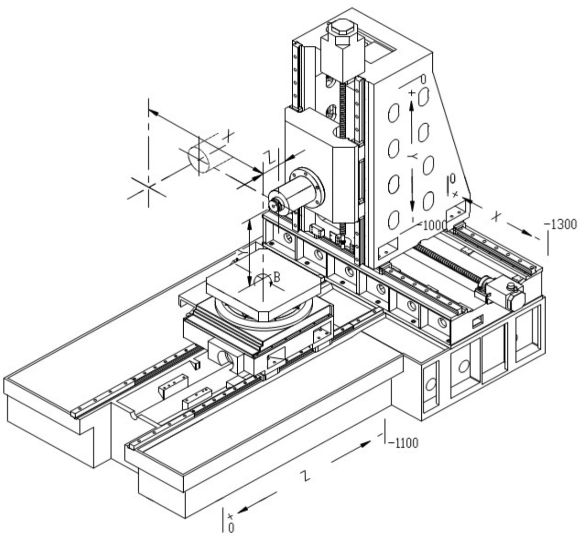

FIGURE 7. Overall structure sketch of THM6380 machining center.

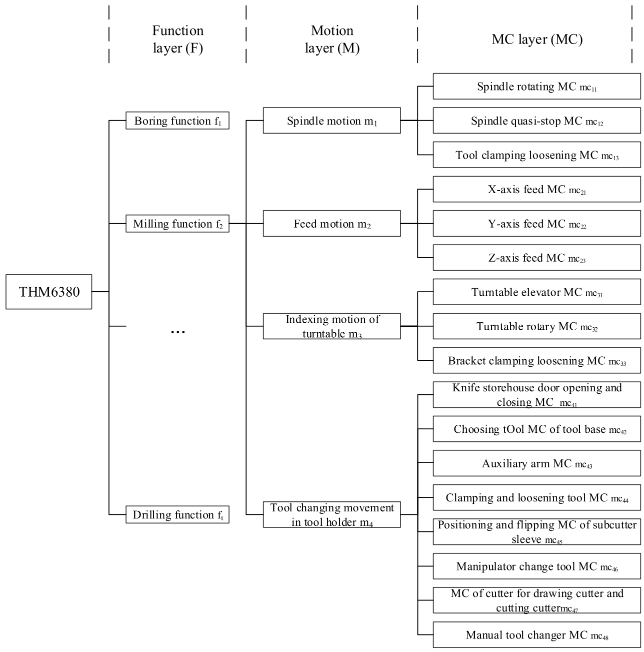

FIGURE 8. Meta-action decomposition model of THM6380 machining center.

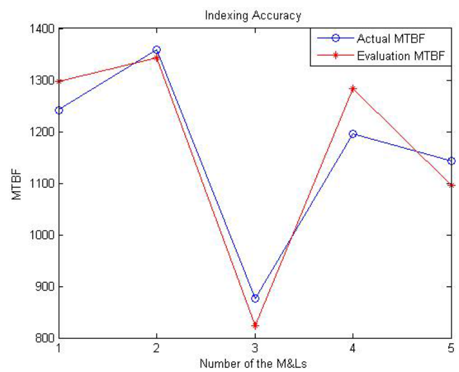

FIGURE 9. The comparison of the training results.

In this paper, the mapping relationship between the machine tool's reliability and the M&L is established by the RBF neural network. In MATLAB, there is an RBF neural network calculation toolbox and the mapping relationship between the data on both sides of the network can be obtained directly.

VI. PRACTICAL APPLICATION

A. ESTABLISHMENT OF THE EVALUATION MODEL

This paper validates the reliability evaluation method based on the fault data of THM6380 machining center (shown as FIGURE 7) under the specific M&Ls and the M&L information provided by users. The M&L information and the fault data are shown in TABLE 2 and TABLE 3, respectively.

Firstly, the machining center is decomposed into the MCs by the meta-action decomposition method, the result is shown in FIGURE 8. The pallet exchange system and the chip removal system are the accessories of the machining center, so the meta-action decomposition does not include these two systems.

Then, based on the decomposition result, the MC with low Mpd fluctuation should be screened out. During the running process of the machining center, the spindle quasi-stop element MC (mc12), the tool clamping relaxation MC (mc13), all MCs of turntable's indexing motion (mc31-mc33) and all MCs of tool library's tool changing motion (mc41-mc48) have short working time and low Mpd under all mission profiles. In addition, the spindle rotation MC runs in all executing process of the mission and its Mpd approaches to 1. Therefore, these MCs are screened out.

TABLE 2. The M&L information of the thm6380 machining center.

Sequence number	$\overline{P_{21}}$	$\overline{P_{22}}$	$\overline{P_{23}}$	F_{max}	F_{min}	$\overline{F}$	σ_F
1	0.617	0.748	0.241	5192.4	2889.7	3423.5	1093.5
2	0.552	0.526	0.708	5072.3	2798.4	3370.2	1113.7
3	0.75	0.337	0.624	7162.8	3158.8	4601.8	970.3
4	0.335	0.68	0.789	4558.4	3175.5	4639.6	1116.5
5	0.399	0.449	0.721	6436.3	2688.2	4307.1	1021.2
6	0.538	0.674	0.646	5910.3	3298.9	3420.8	1449.5
7	0.92	0.847	0.704	8179	2437.4	6473.2	1458.8
8	0.387	0.752	0.255	7362.6	5101.6	3540.6	1167.9
9	0.621	0.35	0.737	5495.6	2596.8	3521.7	1471.6
10	0.621	0.629	0.371	5371.3	3048.3	4610.2	1112.4
11	0.244	0.64	0.837	5244.5	2961.1	4645.8	1199.9
12	0.734	0.257	0.476	6119.7	3149.5	4284.6	958.3
13	0.662	0.634	0.569	5184.5	3460.1	3587.8	933.2
14	0.666	0.316	0.626	5236.9	3070.7	3507.7	1113.9
15	0.476	0.804	0.663	7192.5	3049.2	5325.3	1407.1
16	0.188	0.915	0.694	6762.9	2904.2	4417.7	1208.4
17	0.686	0.362	0.498	5663.5	2955.6	3569	1087.9
18	0.82	0.739	0.83	5076.6	3166.7	3599.6	965
19	0.689	0.421	0.734	7335.5	4253.9	5568.1	1125.1
20	0.355	0.449	0.419	5115.4	2733.1	3488.2	763.3
21	0.496	0.616	0.538	6524.2	3020.7	4462.1	1218.3
22	0.415	0.562	0.742	5422.4	3168.3	3404.7	1249.3
23	0.227	0.596	0.772	7644.2	2643.4	5438.2	1436.7
24	0.828	0.503	0.199	7903.5	2924.3	5784.4	1610.8
25	0.329	0.749	0.551	5649.6	3128.5	3474.1	937.2
26	0.539	0.643	0.644	6229.1	2765.7	3969	1108.8
27	0.359	0.63	0.871	5533.3	2872.8	4435.9	1251.3
28	0.764	0.487	0.633	7756.6	3024.4	4480.7	832.6
29	0.773	0.584	0.34	5171.7	3143.9	3575.1	974.8
30	0.383	0.717	0.635	5913.9	2723.3	4439.1	1563

TABLE 3. The reliability information of the thm6380 machining center.

Sequence number	1	2	3	4	5	6	7	8	9
MTBF	1107.7	1284.3	892.71	1055.3	1193.4	1125.6	610.4	1137	906.6
Sequence number	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
MTBF	1010	1120.6	1267.5	1232.1	982.5	1037.4	1018	1243.7	813.2
Sequence number	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**
MTBF	955.2	1470.5	1214.3	1170.4	1043.1	984.7	1269	1242.1	1358.9
Sequence number	**28**	**29**	**30**						
MTBF	875.7	1195.9	1143.2						

Finally, the previous 25 sets of fault and M&L data are used to establish the mapping relationship between the M&L and the machining center's reliability by RBF neural network, and the last 5 sets of data are used to validate the mapping relationship. The validation results are shown in FIGURE 9 and 10.

From FIGURE 9 and 10, the validation results show that the evaluation errors are within the allowable range, so this mapping model can accurately evaluate the THM6380 machining center's reliability under specific M&Ls.

B. COMPARING WITH THE TRADITIONAL METHOD

The traditional statistical method uses the mean value of the fault interval time to represent the machine tool's reliability. The approximate calculation of the THM6380 machining center is as (7).

$$MTBF \approx \frac{\sum_{i=1}^{30} MTBF_i}{30} = 1094.4h \tag{7}$$

Evaluation results of the two evaluation method are shown in TABLE 4 and FIGURE 11.

From TABLE 4 and FIGURE 11, traditional statistical method evaluates the machine tool's reliability by a constant value, regardless of the M&L, and it is obviously different from the actual MTBF. The improved statistical method evaluates the machine tool's reliability considering the M&L, its evaluation result is closer to the actual MTBF than that of the

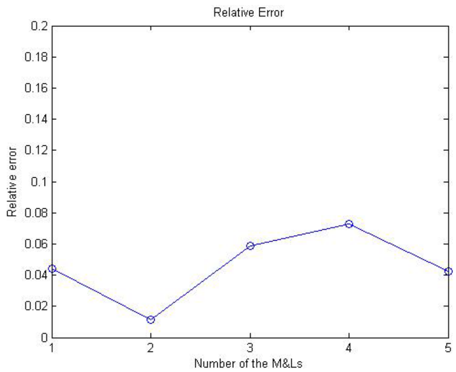

FIGURE 10. The Comparison of the training results.

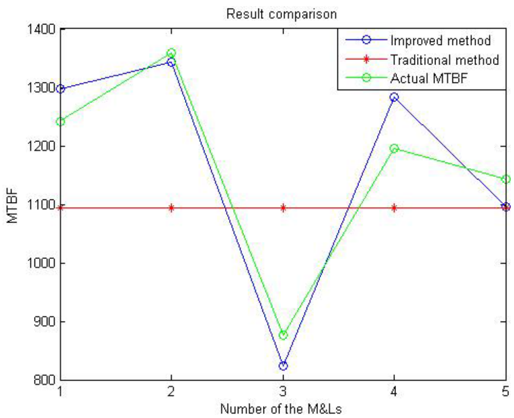

FIGURE 11. Comparison of the two evaluation methods.

TABLE 4. Evaluation results of the two evaluation methods.

Methods	M&L$_1$	M&L$_2$	M&L$_3$	M&L$_4$	M&L$_5$
Traditional method	1094.4	1094.4	1094.4	1094.4	1094.4
Improved method	1297.3	1343.2	824.5	1282.9	1094.9

traditional statistical method. Therefore, comparing with the traditional statistical method, the improved statistical method proposed in this paper is more accurate under the specific M&Ls.

VII. CONCLUSION

In this paper, to make the reliability evaluation method more accurate, an improved statistical method is proposed considering the M&L. The meta-action decomposition method is used to decompose the machine tool and the machine tool's mission profile is represented by the MC, the load profile is represented by combining the cutting force calculation and load composition. The main finding of this paper is the mapping model between the M&L and the machine tool's reliability which can evaluate the machine tool's reliability under specific M&Ls.

The engineering practical application shows that the improved statistical method is more accurate than the traditional statistical method, under specific M&Ls. Therefore, the improved statistical method is more suitable for providing accurate references for the reliability-related works under the specific one or several kinds of M&Ls such as preventive maintenance strategy development of the machine tool, etc.

Oriented on the improved machine tool's reliability evaluation method, there are several issues deserved to be further studied in the future:

- In this paper, representation of the M&L is simplified, but the representation is still somewhat complicated, so it is necessary to further simplify the representation of the M&L.
- In addition to the M&L, the machine tool's reliability is also affected by the environment profile, so the environmental profile needs to be considered into the machine tool's reliability evaluation in the further study.

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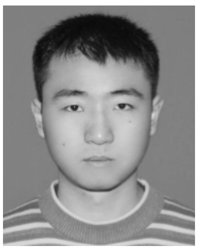

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