Research Article

Reliability Modelling of CNC Machine Tools Based on the Improved Maximum Likelihood Estimation Method

Zhaojun Yang, Dong Zhu, Chuanhai Chen , Hailong Tian, Jinyan Guo, and Shizheng Li

School of Mechanical Science and Engineering, Jilin University, Changchun, China

Correspondence should be addressed to Chuanhai Chen; cchchina@foxmail.com

Received 27 August 2017; Revised 15 March 2018; Accepted 29 March 2018; Published 10 May 2018

Academic Editor: Paolo Boscariol

Copyright © 2018 Zhaojun Yang et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The existing standard reliability models for computerized numerical control (CNC) machine tools are not satisfactory and they fall short of predicting failure rates or lifetime of key functional parts of CNC machine tools. This is attributed to two reasons: the small sample size of failure data and a large truncated ratio of the censored failure data. Improved correction method (ICM), maximum likelihood estimation (MLE), and empirical maximum likelihood estimation (EMLE) are presented and compared with each other in this study. In order to improve the shortage of reliability models developed by the traditional methods, an improved maximum likelihood estimation method (IMLE) is proposed through enlarging censored failure data. Moreover, the correction factors of mean ratio to extend censored time are designed, by which the censored failure data can be close to the true time between failures (TBF). Furthermore, a solution method of correction factors considering amount of calculation is proposed to meet the requirements of calculation precision. Finally, verification by the orthogonal experiment is simulated to verify the proposed model. The verifying test results show that the proposed method can be applied in reliability modelling for not only CNC machine tools but also the key functional parts of CNC machine tools.

1. Introduction

With the rapid development of automatic control and information technologies, computerized numerical control (CNC) machine tools, such as lathe (turning), milling, and boring machine tools, have become important manufacturing equipment in the manufacturing industry.

Key performance indicators on reliability and life-cycle modelling approaches are various for different purposes. Many scholars predicted remaining useful life (RUL) for cutting tools according to its wear-processing during the real cutting process [1–3]. Remaining useful life is described for nonrepairable products which are characterized by degradation failure, while machine tools are repairable and complicated system and their key components are all designed by the rigid method. So remaining useful life is seldom referred to as a performance indicator for machine tools. Machining precision is an important indicator for machine tools, such as positioning error [4], tool path error [5], and geometric accuracy [6]. However, it is difficult to measure those parameters of machining precision during short working time, and

if the machining precision is lower than the specific value, we would treat it as one type of failures. Productivity rate is employed for increasing economic efficiency by changing machining parameters or machining modes [7, 8], which ignores the influence of the failures which needs a long time to be repaired. As is known, reliability of CNC machine tools influences quality, productivity, and efficiency and furthers market competitiveness, so it has been one of the most important performance indicators for CNC machine tools. So, mean time between failures (MTBF) is employed as a main index of reliability evaluation for CNC machine tools [9–11]. And it is universally accepted by foreign scholars [12–14].

According to the characteristics of the failure data of CNC machine tools, the reliability model with the variable of time between failures (TBF) can be divided into two categories. One is the complete failure data model and the other is the incomplete failure data model. The reliability modelling method of CNC machine tools with the incomplete failure data can make full use of the test information and improve the accuracy of the reliability model, so it has been paid more and more attention [15–17]. Wang and

He [18] established five different reliability models by the survival ratio method, cumulative risk function method, correction method, improved correction method (ICM), and maximum likelihood estimation (MLE) method, respectively. With comparison of those models, they drew a conclusion that the ICM method is better than others when the censored data accounts for a large proportion. Chen and Li [19] conducted a large number of simulations with the case that the failure data is a small size sample following to Weibull distribution, and they came to a conclusion that the reliability model developed by the MLE method is better than those by the product limit estimation method and moment estimation method. In summary, the accuracy of the reliability model developed by the ICM or MLE method is higher than those of others. ICM and MLE method are regarded as traditional methods.

However, traditional methods cannot be well suitable to reliability modelling for CNC machine tools due to the small size sample failure data with lots of censored data. For this problem, researchers have proposed many reliability modelling methods based on Bayesian theory, such as Bayesian reliability inference method [20, 21], Bayesian modelling method (BMM) [22], and Bayesian networks [23–25]. All the methods mentioned above relative to Bayesian theory are subjectively influenced by experts' experience. Besides, the accuracy of those methods can also be partly affected by the accuracy of the MLE method. Therefore, we focus on the improvement of the MLE method when there is lots of censored failure data.

This paper is devoted to establish an improved maximum likelihood estimation (IMLE) method for reliability modelling of CNC machine tools with lots of censored failure data. The remainder of this paper is organized as follows: in Section 2, the traditional reliability modelling methods for CNC machine tools are presented, and goodness of modelling curves is proposed for comparing different modelling methods. In Section 3, a complex and rude method is proposed to solve the parameters of the IMLE method. In Section 4, the proposed method is applied to the key functional parts of CNC machine tools. Section 5 discusses the limitation of the new method. Section 6 concludes this paper.

2. Reliability Modelling of CNC Machine Tools

Failure of one system is the state of the system that does not perform the specified function. Failure of CNC machine tools mainly includes two meanings. One is that the machining task cannot be completed normally, and the other is that the processing precision cannot reach the predetermined requirements.

2.1. Classification of Failure Data. Due to the limitation of the test sample size and test time, there are three kinds of failure data. They are precensored failure data, complete failure data, and postcensored failure data. The precensored failure data is a set of time intervals from the beginning of the test to the first failure and the complete failure data refers to a set of time intervals between two continuous failures. The postcensored failure data is a set of time intervals from the last

failure to the end of the test. If the tested products do not fail during the trial, the postcensored failure data is the whole test time. The precensored failure data and postcensored failure data are both right censored data. The censored failure data mentioned in this paper belongs to the right censored data, which is also called type I censored data.

2.2. Assumption of Reliability Modelling. In order to simplify the reliability modelling process, it is assumed that the CNC machine tools tracked at the same time are from the same type and same batch of machine tools. Moreover, the CNC machine tools tracked in the field test are regarded as working under the same external conditions including temperature and humidity. Internal conditions, mainly working conditions, have a great impact on the reliability of CNC machine tools. As usual, the main working conditions are divided into heavy load, medium load, and light load groups. If the difference of working conditions of the tracked machine tools is large, we should divide them into two or more groups for making one group work in the similar working conditions. So the machine tools from the same group are regarded as working in the same working conditions. As CNC machine tools are typical mechatronic systems, it is always assumed that they can be repaired as new as the ones before they failed. So we mainly focus on the statistical reliability modelling method for CNC machine tools.

2.3. Modelling Process. The failure data of CNC machine tools collected from the field tracking test is the basis of reliability modelling. After preliminary processing, a set of incomplete failure data is obtained. Then, according to the relative frequency histogram of the failure data, Weibull distribution is selected as the distribution of TBF of CNC machine tools [26–28]. Then, different methods are used to estimate the parameters of the model according to the proportion of censored data. Finally, point estimation and interval estimation of MTBF are obtained. The specific process is shown in Figure 1.

2.4. Modelling Method. Because of the short test time and small batches of CNC machine tools, the failure data obtained in the field tracking test is usually small size sample. Therefore, two reliability models developed by the ICM and MLE methods have the disadvantage of instability. In order to improve the accuracy of the model, the precensored failure data is always treated as the complete failure data when applying the MLE method. This method is renamed as the empirical maximum likelihood estimation (EMLE) method. The three methods are introduced as follows.

2.4.1. Improved Correction Method. It is assumed that the field tracking test has been carried out under the same conditions for m machine tools which are of the same type and same batch. The number of the incomplete failure data is N with n complete failure data and $N - n$ censored failure data. Then the data is arranged from the smallest one to the largest one; that is, $t_1 \leq t_2 \leq t_3 \leq \dots \leq t_N$. It is assumed that t_i is regarded as the state of unrepairable product, where it works from the

beginning to t_i . The reliability function and relative functions established by the ICM method are shown as follows [29]:

$$\begin{aligned} R(t_i) &= \frac{Ns(t_i)}{N} \\ Ns(t_i) &= Ns'(t_i) + KP_k(t_i) [Ns(t_{i-1}) - Ns'(t_{i-1})] \\ P_k(t_i) &= \frac{[(t_i - t_{i-1}) Ns'(t_i) / N + t_{i-1}]}{t_i} \\ Ns'(t_i) &= N - i + 1 - d_i, \end{aligned} \quad (1)$$

where $R(t_i)$ is the reliability of CNC machine tools at t_i , $Ns(t_i)$ is the number of CNC machine tools that are still being tested at t_i and $Ns(t_0) = 0$, K is the correction factor (when N is 10, 25, 50, and 100, resp., K is 0.96, 0.96, 0.97, and 0.99, correspondingly), and $P_k(t_i)$ is the probability of the censored CNC machine tools samples from t_{i-1} to t_i . When a failure occurs at t_i , then d_i is 1; otherwise d_i is 0.

The failure data collected in the field tracking test can be used to calculate the reliability of discrete $R(t_i)$ sequence by (1). With the fitting curve of Weibull distribution, it is easy to obtain the scale parameter (η) and shape parameter (β). According to (2), MTBF of CNC machine tools can be obtained.

$$\text{MTBF} = \eta \Gamma \left(1 + \frac{1}{\beta} \right). \quad (2)$$

2.4.2. Maximum Likelihood Estimation. η and β can be calculated with (3) by the MLE method when $L(\theta)$ reaches the maximum value. Then, MTBF can be estimated by (2).

$$L(\theta) = \prod_{i=1}^n f(t_i, \theta) \prod_{j=n+1}^N R(t_j, \theta), \quad (3)$$

where t_i is the complete failure data, t_j is the censored failure data, θ is the parameter vector, $f(t_i, \theta)$ is the probability density function, and $R(t_j, \theta)$ is the reliability function.

2.4.3. Empirical Maximum Likelihood Estimation. In order to improve the accuracy of the model, the precensored failure data is always treated as the complete failure data when there is a large truncated ratio. Hence, the modelling method, namely, empirical maximum likelihood estimation method, can be described as

$$L(\theta) = \prod_{i=1}^{N-n_1-n_2} f(t_i, \theta) \prod_{j_1=1}^{n_1} f(t_{j_1}, \theta) \prod_{j_2=1}^{n_2} R(t_{j_2}, \theta), \quad (4)$$

where n_1 is the number of precensored failure data, n_2 is the number of postcensored failure data, t_{j_1} is the precensored failure data, and t_{j_2} is the postcensored failure data.

The solution of MTBF in the EMLE method is the same as that of the MLE method.

2.5. Simulation Contrast. Verification by the orthogonal experiment is simulated to verify the proposed model.

FIGURE 1: Reliability modelling procedure of CNC machine tools.

2.5.1. Goodness of Modelling Curve. In order to judge the accuracy of the modelling curves obtained by different modelling methods, goodness of the modelling curve is proposed and it can be computed by

$$S = \int_0^{+\infty} [R(t) - R^*(t)]^2 dt, \quad (5)$$

where $R(t)$ is the reliability function of the modelling curve, $R^*(t)$ is the reliability function of the true curve, and S is an indicator of $R(t)$ deviating from $R^*(t)$.

In order to compare the accuracy of modelling curves with different methods vividly, S is divided into three levels. For example, it is defined that when $S \leq 10$, modelling precision of $R(t)$ can be described as “Good”; when $10 < S \leq 50$, modelling precision can be described as “Normal”; when $S > 50$, modelling precision can be described as “Bad.” Here “Good,” “Normal,” and “Bad” are three precision levels for comparing different modelling methods. The three levels of S can be redefined for a better comparison according to rapid changes of $R(t)^*$ as shown in Figure 2.

In Figure 2, the two pictures are similar, while the time scale is different. And, from (5), it can be seen that S changes very much when $R^*(t)$ has a great change. Therefore, three levels of S also should be redefined for better comparison when $R^*(t)$ changes greatly.

2.5.2. Simulation Test. In order to compare the modelling methods mentioned above, simulation experiments are carried out with MATLAB under the conditions that 10 CNC machine tools are traced. The field test usually lasts two to three months, which is about 1800 hours, so the simulation test time is selected 1500 and 2000 h, respectively. The

FIGURE 2: Explanatory diagram for three levels of S .

TABLE 1: Test parameters for 8 simulation conditions.

Number	Test time T/h	Ideal parameters		MRCT
		β	η	
1	1500	0.8	1200	0.78
2		0.8	1600	0.83
3		1.2	1200	0.78
4		1.2	1600	0.86
5	2000	0.8	1200	0.70
6		0.8	1600	0.79
7		1.2	1200	0.69
8		1.2	1600	0.78

machine tools tracked in the field test are generally in the random failure period, which means β is near 1. Hence, β is set as 0.8 and 1.2. MTBF of CNC machine tools now reaches 1500 hours, so 1200 and 1600 are selected for η . Therefore, four kinds of Weibull distribution function (combined by $\beta = 0.8$ or 1.2, $\eta = 1200$ or 1600) are selected as the simulation conditions. Those four kinds of Weibull distribution functions are commonly described as the reliability functions of Chinese CNC machine tools. Hence, 8 simulation conditions are selected as shown in Table 1.

RCT calculated by (6) is the ratio of the censored data to the total data in the test. And RCT can be used to describe the constituent components of failure data. MRCT is the mean of RCT after 100 simulation times.

$$RCT = 1 - \frac{n}{N}. \quad (6)$$

Considering the calculation speed and simulation accuracy, reliability modelling process is simulated 100 times by ICM, MLE, and EMLE methods, respectively. Then S is obtained according to the simulation results. Based on the value of S , the best method of the mentioned methods is chosen. Thirdly, 100 values of S of the best method are sorted from small to large. Then, use two integers to divide them into three parts and the size of each part is close. Here the two integers are 10 and 50. Small changes of the two integers do not affect contrast effect for different modelling methods. Therefore, it is defined that when $S \leq 10$, modelling precision of $R(t)$ can be described as “Good”; when $10 < S \leq 50$, it

FIGURE 3: The procedure for modelling simulation in MATLAB.

can be described as “Normal.” The simulation procedure and simulation results are shown in Figures 3 and 4, respectively.

In the bottom of Figure 4, ICM (Good) refers to the proportion of the modelling curves whose S values are in “Good” level after 100 times of simulation modelling test by the ICM method. The number of 1 to 8 refers to different simulation conditions detailed in Table 1. Similar content can be explained in the same way for the similar pictures.

So, from Table 1 and Figure 4, it can be seen that the accuracy of the reliability model established by the EMLE method is higher than those established by the ICM and MLE methods when there is a large truncated ratio.

FIGURE 4: Comparison of the ICM, MLE, and EMLE methods.

3. Improved Method

3.1. Improved Maximum Likelihood Estimation (IMLE). The EMLE method is suitable for a large truncated ratio in a certain extent. But when the test time is short and there is a large truncated ratio ($MRCT > 0.8$), the reliability modelling of EMLE method has disadvantages of low accuracy and instability, especially in the condition of small size sample. By comparing the EMLE method with the MLE method, it can be seen that the larger the number of $R(t)$ factor is, the higher the accuracy of reliability model is. Therefore, the IMLE method is proposed where $f(t_j, \theta)$ replaces $R(t_j, \theta)$ of MLE and t_j is extended properly. The correction factors of mean ratio to extend censored time are denoted as a and b , respectively. The likelihood function of the IMLE method is shown in

$$L(\theta) = \prod_{i=1}^{N-n_1-n_2} f(t_i, \theta) \prod_{j_1=1}^{n_1} f(at_{j_1}, \theta) \prod_{j_2=1}^{n_2} f(bt_{j_2}, \theta). \quad (7)$$

t_{j_1} and t_{j_2} are censored failure data, so they are smaller than the true TBF. With the help of a and b , at_{j_1} and bt_{j_2} are close to the true TBF in order to make the model more accurate than the model obtained by the MLE method.

3.2. Solution of a and b . It is difficult to gain the best values of a and b by traditional methods. Hence, a complex and rude method is proposed. Firstly, we should determine the range of a , b according to the minimum error between the true TBF and at_{j_1} , bt_{j_2} . Then, according to discretization [30, 31], several values are selected orderly from the range in order to gain a better solution of a and b . Considering calculation precision and amount of calculation, a and b are orderly selected from 1.5, 2, and 2.5. The solution procedure is shown in Figure 5.

The incomplete failure data from 10 CNC machine tools simulated for 1500 hours is used to establish a reliability model, where a and b in (7) are orderly selected from 1.5, 2, and 2.5. In order to get the optimized parameters, the model got by the EMLE method is used as the reference. The simulation conditions are shown in Tables 2 and 3.

FIGURE 5: Flow chart of solutions of a and b in the IMLE method.

TABLE 2: Test simulation conditions.

Test time T/h	Ideal parameters		Number of CNC machine tools
	β	η	
1500	1.2	1600	10

It can be found from Figure 6 that the modelling accuracy by the IMLE method is higher than that by the EMLE method when the number is 2, 3, 5, 6, 8, and 9. In order to validate this conclusion, it is necessary to simulate it under different conditions. The simulation results are shown in Figure 7.

In the bottom of Figure 7, 0(G) refers to the proportion of the modelling curves whose S values are in "Good" level after 100 times of simulation modelling by EMLE method. Here 0 means EMLE method and other numbers (2, 3, 5, 6, 8, and 9)

TABLE 3: Values of a and b .

Number	Parameters	
	a	b
1	1.5	1.5
2		2
3		2.5
4	2	1.5
5		2
6		2.5
7	2.5	1.5
8		2
9		2.5

FIGURE 6: Comparison of reliability models established by the IMLE method in different a and b .

mean IMLE method in different a and b detailed in Table 3. “G” and “N” are the abbreviation of “Good” and “Normal,” respectively. Similar content can be explained in the same way for the similar pictures.

Figure 7 shows that the IMLE method has better modelling accuracy with $a = 1.5$ and $b = 2.5$ on the whole. In order to make the result more accurate and more intuitive, comparative modelling curves developed by the EMLE and IMLE methods are shown in Figure 8, respectively. For easy observation, the times of simulation are set as 10.

From Figure 8, we can see that the reliability modelling curves established by the IMLE method are more concentrated around the true curve than that of the EMLE method, so the IMLE method is more stable.

3.3. Verification by the Orthogonal Experiment. The number of CNC machine tools from different field tracking tests is changeable. And the range of parameters of Weibull distribution is always really large with $0.8 \leq \beta \leq 2$ and $800 \leq \eta \leq 2000$. But the IMLE method mentioned above is simulated only under the conditions with 10 CNC machine tools and 4 kinds of Weibull distributions. There are still some differences between the actual conditions and the simulation conditions. In order to verify the applicability of the IMLE and EMLE methods, four-factor and four-level orthogonal simulation test is carried out. The simulation conditions and results are shown in Table 4 and Figure 9, respectively.

FIGURE 7: Comparison of a and b in IMLE method in wide simulation conditions.

As shown in Table 4 and Figure 9, when the values of MRCT of conditions of 1, 2, 3, 4, 5, and 7 are between 0.75 and 0.90, the modelling accuracy of the IMLE method is higher than that of the EMLE method. Hence, we can come to a conclusion that the accuracy of the reliability model obtained by the IMLE method is higher than that of the EMLE method when $0.75 < \text{MRCT} \leq 0.9$ with no more than 10 CNC machine tools.

Seen from conditions of 6, 8, 11, 12, 15, and 16, when $\text{MRCT} < 0.75$, EMLE method is better than IMLE. The IMLE method is better than the EMLE method in conditions of 9 and 10, while the EMLE method is better than the IMLE method in condition of 13. Hence, the two methods are similar when $\text{MRCT} > 0.9$.

Therefore, the IMLE method can compensate the instability of the curves of the reliability model established by the EMLE method when $0.75 < \text{MRCT} \leq 0.9$ with no more than 10 CNC machine tools. The improved maximum likelihood estimation function is shown as

$$L(\theta) = \prod_{i=1}^{N-n_1-n_2} f(t_i, \theta) \prod_{j_1=1}^{n_1} f(1.5t_{j_1}, \theta) \prod_{j_2=1}^{n_2} f(2.5t_{j_2}, \theta). \quad (8)$$

4. Application

The IMLE method is used to evaluate the reliability of the key functional parts of CNC machine tools in order to verify it. The key functional parts are components that have high failure rate or that have poor maintainability. For example, tool rest has a higher failure rate compared to other functional parts in CNC machine tools, so it is regarded as a key functional part. Another example is motorized spindle because of its poor maintainability [32].

4.1. Verification. In order to validate whether the IMLE method can be applied to the key functional parts of CNC machine tools, tool rest, whose MTBF is about 5000 h, is selected as one example. So the simulation parameters are set as $0.8 \leq \beta \leq 1.6$ and $2000 \leq \eta \leq 6000$. Then the reliability models are established by the EMLE and IMLE

TABLE 4: Test parameters for four-factor and four-level orthogonal simulation conditions.

Number	Number of machine tools	Test time T/h	Ideal parameters		MRCT
			η	β	
1	5	1000	800	0.8	0.81
2	5	1400	1200	1.2	0.80
3	5	1800	1600	1.6	0.82
4	5	2200	2000	2.0	0.84
5	10	1000	1200	1.6	0.90
6	10	1400	800	2.0	0.67
7	10	1800	2000	0.8	0.84
8	10	2200	1600	1.2	0.74
9	20	1000	1600	2.0	0.95
10	20	1400	2000	1.6	0.91
11	20	1800	800	1.2	0.57
12	20	2200	1200	0.8	0.67
13	50	1000	2000	1.2	0.94
14	50	1400	1600	0.8	0.84
15	50	1800	1200	2.0	0.73
16	50	2200	800	1.6	0.49

TABLE 5: Test parameters for three-factor and three-level orthogonal simulation conditions.

Number	Ideal parameters		Test time T/h	MRCT
	β	η		
1	0.8	3000	6000	0.68
2	0.8	4500	5000	0.82
3	0.8	6000	4000	0.90
4	1.2	3000	5000	0.71
5	1.2	4500	4000	0.87
6	1.2	6000	6000	0.86
7	1.6	3000	4000	0.77
8	1.6	4500	6000	0.77
9	1.6	6000	5000	0.91

methods, respectively. Figures 10(a), 10(b), 10(c), and 10(d) are the contrast diagrams of the reliability models developed by the two methods in different situations with 10 samples.

It can be seen from Figure 10 that when truncated ratio and scale parameter are large, the accuracy of the model established by the IMLE method is higher and the stability is better compared to that of the EMLE method. Therefore, the IMLE method is also suitable for reliability modelling of the key functional components of CNC machine tools.

4.2. The Scope of Modelling Method. Due to great changes of $R(t)$, three levels of S need to be redefined that when $S \leq 50$, the accuracy level can be seen as “A”; when $50 < S \leq 250$, accuracy level can be seen as “B.” When the number of CNC machine tools is small as 5, the simulation test is conducted.

The simulation conditions and model validation results are shown in Table 5 and Figure 11, respectively.

As shown in Figure 11, models developed by the EMLE and IMLE methods both have low accuracy and poor stability. When $0.75 < \text{MRCT} \leq 0.9$, the IMLE method has higher modelling accuracy compared to the EMLE method in most of conditions. When sample size is increased to 10, the simulation test is conducted and the test results are shown in Figure 12.

As shown in Figure 12, when sample size, the scale parameter, and truncated ratio are large (sample size equals 10, $2000 \leq \eta \leq 6000$, and $0.75 < \text{MRCT} \leq 0.9$), modelling accuracy of the IMLE method is higher than that of the EMLE method in most of conditions.

Combining Figure 11 with Figure 12, a conclusion can be drawn that the IMLE method is better than the EMLE method when sample size is no more than 10, $2000 \leq \eta \leq 6000$, and $0.75 < \text{MRCT} < 0.9$.

5. Discussion

There is a large limitation when the IMLE method is used to estimate MTBF of CNC machine tools, but it truly improves modelling accuracy in the large MRCT condition. When it is applied to the key functional parts of CNC machine tools, the improvement of modelling accuracy is not really large due to the fact that values of a and b are obtained from the simulation process of establishing reliability models for CNC machine tools, rather than the key functional parts. If someone applies it to other areas for a higher accuracy in practice, it is better to obtain the optimal a and b first. In order to improve the proposed method, there is still a lot of further work to study. Firstly, the solution method of a and b is rude and it can be improved. Secondly, the data type of a and b

FIGURE 8: Comparison of modelling between EMLE and IMLE method.

can be changed from constant to random variable following a certain distribution in order to enlarge incomplete failure data more properly. Last but not least, the combination of the proposed method and Bayesian theory considering the more complex conditions would get a more reasonable result.

6. Summary and Conclusions

In this work, we have presented a novel improved maximum likelihood estimation method (IMLE) through enlarging censored failure data. Moreover, the correction factor of mean ratio to extend censored time has been designed. Verification by

the orthogonal experiment has been simulated to verify the proposed model. It is concluded the following.

(1) Compared to the ICM and MLE methods, the EMLE method is more suitable for the reliability modelling for CNC machine tools with a short test time and a large truncated ratio.

(2) When $0.75 < \text{MRCT} \leq 0.9$ with the number of CNC machine tools no more than 10, the IMLE method has higher accuracy and stability than that of the EMLE method. In other words, low accuracy and poor stability of the EMLE method under a large truncated ratio condition can be overcome by the IMLE method in a certain extent.

FIGURE 9: Verification results of the IMLE method.

FIGURE 10: Comparison of simulation with large scale parameter of Weibull distribution.

FIGURE 11: Application of IMLE method in 5 key functional parts.

FIGURE 12: Application of IMLE method in 10 key functional parts.

(3) When sample size is no more than 10 with a large truncated radio, the accuracy and stability of IMLE method for the key functional parts of CNC machine tools are higher than that of the EMLE method under most of conditions. In summary, the IMLE method is better than the EMLE method when $0.75 < MRCT \leq 0.9$ and sample size is no more than 10.

Conflicts of Interest

There are no conflicts of interest related to this paper.

Acknowledgments

This research is financially supported by National Natural Science Foundation of China (Grant nos. 51505186 and 51675227), Jilin Province Excellent Researcher Foundation (20170520103JH), Key Research and Development Plan of Jilin Province (20180201007GX), and CNC First Generation of Guangdong Province (2013B0110304006). The authors thank the authors of this paper's references whose works have contributed greatly to the completion of this thesis.

References

- [1] C. Drouillet, J. Karandikar, C. Nath, A.-C. Journeaux, M. El Mansori, and T. Kurfess, "Tool life predictions in milling using spindle power with the neural network technique," *Journal of Manufacturing Processes*, vol. 22, pp. 161–168, 2016.
- [2] T. Benkedjouh, K. Medjaher, N. Zerhouni, and S. Rechak, "Health assessment and life prediction of cutting tools based on support vector regression," *Journal of Intelligent Manufacturing*, vol. 26, no. 2, pp. 213–223, 2015.
- [3] J. Gokulachandran and K. Mohandas, "Comparative study of two soft computing techniques for the prediction of remaining useful life of cutting tools," *Journal of Intelligent Manufacturing*, 2013.
- [4] B. C. D. Santos, G. De Andrade, and E. G. Del Conte, "A method for monitoring and diagnosing the circular trajectory error in micromilling," *IEEE Latin America Transactions*, vol. 14, no. 12, pp. 4639–4645, 2016.
- [5] Y. A. Mir, J. R. R. Mayer, and C. Fortin, "Tool path error prediction of a five-axis machine tool with geometric errors," *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, vol. 216, no. 5, pp. 697–712, 2002.
- [6] A. P. Kuznetsov, "Evolution of methods of assessing the accuracy of metal-cutting machines. 2. Evolution of concepts and models used in assessing the accuracy of metal-cutting machines," *Russian Engineering Research*, vol. 37, no. 11, pp. 936–949, 2017.
- [7] R. Usubamatov, Z. M. Zain, and A. M. Ahmed, "Productivity rate of machine tools depending on the change of machining modes," *Proceedings of the Institution of Mechanical Engineers*,

- Part B: Journal of Engineering Manufacture*, vol. 225, no. 8, pp. 1447–1456, 2011.
- [8] R. Usubamatov, A. Bin Harun, and A. Bin Sanuddin, “Optimisation of machining parameters by criterion of maximum productivity,” *International Journal of Production Research*, vol. 52, no. 10, pp. 2946–2953, 2014.
 - [9] Z. Yang, C. Chen, F. Chen, and G. Li, “Progress in the research of reliability technology of machine tools,” *Journal of Mechanical Engineering*, vol. 49, no. 20, pp. 130–139, 2013.
 - [10] Z. Yang, X. Li, B. Xu, F. Chen, X. Zhu, and Q. Hao, “Time dynamic reliability modelling of machining center,” *Jixie Gongcheng Xuebao/Journal of Mechanical Engineering*, vol. 48, no. 2, pp. 16–22, 2012.
 - [11] Z. Yang, C. Chen, J. Wang, and G. Li, “Reliability Assessment of CNC Machining Center Based on Weibull Neural Network,” *Mathematical Problems in Engineering*, vol. 2015, Article ID 292197, 2015.
 - [12] A. K. Aggarwal, S. Kumar, and V. Singh, “Mathematical modeling and reliability analysis of the serial processes in feeding system of a sugar plant,” *International Journal of Systems Assurance Engineering and Management*, vol. 8, pp. 435–450, 2017.
 - [13] K.-W. Xia, M.-X. Liu, Z.-W. Zhang, and Y. Dong, “An approach to attribute reduction based on attribute similarity,” *Journal of Hebei University of Technology*, vol. 34, no. 4, pp. 20–23, 2005.
 - [14] S. Lee, S. Han, and H. Lee, “Assessment of the tool post reliability of a high-stiffness turning machine,” *Journal of Mechanical Science and Technology*, vol. 21, no. 8, pp. 1244–1252, 2007.
 - [15] Y. Dai, Y. F. Zhou, and Y. Z. Jia, “Distribution of time between failures of machining center based on type I censored data,” *Reliability Engineering & System Safety*, vol. 79, no. 3, pp. 377–379, 2003.
 - [16] Shik and Y. Chung, “Bayesian Inference of Three-parameter Exponentiated Weibull Distribution Based on Progressive Type-II Censoring,” *Journal of The Korean Data Analysis Society*, vol. 15, no. 2, pp. 585–591, 2013.
 - [17] W. Qiao, J. Jiao, and Y. Jia, “Research on the numerical control system reliability model using censored data,” in *Proceedings of the 2009 IEEE 16th International Conference on Industrial Engineering and Engineering Management, IE and EM 2009*, pp. 1204–1207, China, October 2009.
 - [18] Z. T. Wang and L. He, “Simulation analysis of random censoring data about reliability under Weibull distribution with two parameters,” *Reliability and Environment Test about Electronic Product*, vol. 5, p. 14, 1998.
 - [19] J. D. Chen and D. F. Li, “Maximum likelihood estimation of normal distribution in random censored cases,” *Journal of Applied Mathematics*, vol. 34, no. 6, pp. 961–975, 2011.
 - [20] S. D. Guikema and M. E. Paté-Cornell, “Bayesian Analysis of Launch Vehicle Success Rates,” *Journal of Spacecraft and Rockets*, vol. 41, no. 1, pp. 93–102, 2004.
 - [21] S. D. Guikema and M. E. Paté-Cornell, “Probability of infancy problems for space launch vehicles,” *Reliability Engineering & System Safety*, vol. 87, no. 3, pp. 303–314, 2005.
 - [22] J. Guo, Z. Steven Li, and J. Judy Jin, “System reliability assessment with multilevel information using the Bayesian melding method,” *Reliability Engineering & System Safety*, vol. 170, pp. 146–158, 2018.
 - [23] I. Tien and A. D. Kiureghian, “Reliability assessment of critical infrastructure using Bayesian networks,” *Journal of Infrastructure Systems*, vol. 23, no. 4, Article ID 04017025, 2017.
 - [24] A. Ciobanu, F. Munteanu, and C. Nemes, “Bayesian networks utilization for reliability evaluation of power systems,” in *Proceedings of the 9th International Conference and Exposition on Electrical and Power Engineering, EPE 2016*, pp. 837–841, Romania, October 2016.
 - [25] F. Munteanu, A. Ciobanu, and C. Nemes, “From technical design structures to Bayesian networks in power engineering,” in *Proceedings of the 2016 International Conference on Applied and Theoretical Electricity, ICATE 2016*, Romania, October 2016.
 - [26] W. K. Ni, F. B. Yu, and J. Q. Wei, “Comprehensive reliability evaluation of foreign high-end gantry machining Center,” *Machine Tool & Hydraulics*, vol. 43, no. 24, pp. 25–29, 2015.
 - [27] G. Ren, Z. Yang, and B. Meng, “Reliability evaluation on machining center based on three-parameter weibull distribution,” *Advanced Materials Research*, vol. 430–432, pp. 1645–1649, 2012.
 - [28] M. Nourbakhsh, Y. Mehrali, A. Jamalizadeh, and G. Yari, “On a selection Weibull distribution,” *Communications in Statistics—Theory and Methods*, vol. 44, no. 8, pp. 1640–1652, 2015.
 - [29] Z. T. Wang, “Digital simulation of field data about reliability,” *Journal of Harbin University of Science and Technology*, vol. 3, no. 4, pp. 30–35, 1998.
 - [30] M. Oguz, T. Bektas, and J. A. Bennell, “Multicommodity flows and Benders decomposition for restricted continuous location problems,” *European Journal of Operational Research*, vol. 266, no. 3, pp. 851–863, 2018.
 - [31] Y. H. Yang, Y. S. Wang, and Y. Z. Song, “A new local energy-preserving algorithm for the BBM equation,” *Applied Mathematics Computation*, vol. 324, pp. 119–130, 2018.
 - [32] T. H. Lee, “A Study on the Failure and Life Assessment of High Speed Spindle,” *Journal of the Korean Society for Precision Engineering*, vol. 31, no. 1, pp. 67–73, 2014.