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Dynamic Forecasting for Vibration of CNC Lathe using Grey Bootstrap Model

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Abstract: In order to realize online monitoring and forecasting of CNC lathe faults, firstly, grey bootstrap model is proposed to forecast vibration of tool rest; secondly, the vibration signal of CNC Lathe is collected, and the effectiveness of the model is verified . The experimental study is shown that grey bootstrap model possesses high forecast accuracy, and the maximum and the mean of the relative errors of the predicted results are respectively 7.61% and 2.64%, and the reliability of the predicted interval is proved to be 100%. The point forecasting and interval forecasting are actualized at the given time and the given confidence level, only with very small predicted errors. This can solve the problem of dynamic evaluation of vibration signal of CNC lathe.

Keywords: CNC lathe; Tool rest vibration; Grey bootstrap model; Point forecasting; Interval forecasting

I. INTRODUCTION

With the feature of high automaticity, high efficiency and the most widely used, CNC lathe once mal- functions, causing stopping production, it will cause a great loss to the enterprises. At present, the fault diagnosis of CNC lathe is still in the stage of breakdown maintenance. How to realize online monitoring and forecasting of CNC lathe becomes a current research focus. Based on vibration signal, short-term forecasting of CNC machine vibration trend was achieved ,but dynamic forecasting and interval forecasting wasn't achieved in literature[1,2]. Because of the complexity of the vibration signal, online monitoring system and fault diagnosis of machine vibration signals was researched and analyzed, but dynamic forecasting of fault cannot be realized in literature [3-5]. How to achieve long-term dynamic forecasting and interval forecasting of CNC lathe vibration is of great significance to realize online condition monitoring. Statistics show that failure frequency of tool rest system is up to 31.4%, whose failures occur most frequently in literature [1, 6], so the reliability of tool rest system determines the reliability of the whole machine. Therefore, in order to improve the reliability of CNC lathe, it is necessary to carry out on-line monitoring and forecasting of tool rest system, to further realize the fault diagnosis of CNC lathe.

Firstly , grey bootstrap model is proposed to forecast vibration of tool rest; secondly, the vibration signal of CNC Lathe is collected; Thirdly, using the grey bootstrap model, time series forecasting of tool rest vibration signal of CNC lathe is actualized by means of point estimation and interval estimation, so as to realize the online fault diagnosis of CNC lathe tool rest.

A. Grey Bootstrap Modeling

Suppose a vibrational time series of CNC lathe, which can be represented as a vector and can be given by

$$Y = \{y(t)\}; t = 1, 2, ... \quad (1)$$

where $y(t)$ stands for vibrational data of tool rest at time t. The current time t is constantly changing, and t=1,2,…,m,m+1,….Adopting the former m vibrational data of tool rest at current time t=m, the vibrational condition is predicted at time t+1.

At the time t , m data from series $\boldsymbol{Y}_m$ can form a sub- series $\boldsymbol{Y}_m$ as follows [6]:

$$Y_m = \{y_m(u)\}; u = t_0, t_0 + 1, t_0 + 2, ..., t-1, t \quad (2)$$

and

$$t = t - m + 1; t = m, m + 1, ... \quad (3)$$

Where m is the number of sub-series $\boldsymbol{Y}_m$ [7] .

According to the bootstrap methodology, B simulation samples of size m_D, namely the bootstrap resampling samples, can be obtained by an equiprobable sampling with replacement from Eq. (2), as follows:

$$G_{\mathbf{Bootstrap}} = (G_1, G_2, ..., G_b, ..., G_B) \quad (4)$$

where $\boldsymbol{G}_b$ is the bth bootstrap sample. It can be expressed as

$$G_b = \{g_b(u)\}; b = 1, 2, ..., B \qquad (5)$$

where $g_b(u)$ is the uth bootstrap resampling sample within $\boldsymbol{G}_b$ and B is the number of the bootstrap resampling samples.

According to the grey system theory [8], the first-order accumulated generating operation (1-AGO) of $\boldsymbol{G}_b$ is defined as

$$Y_b = \{y_b(u)\} = \{\sum_{j=t-m+1}^{u} g_b(j)\} \qquad (6)$$

grey generated model based on Eq. (6) can be described by the differential equation as follows:

$$\frac{dy_b(u)}{du} + c_1 y_b(u) = c_2 \qquad (7)$$

where u is regarded as a time variable, c_1 and c_2 are the coefficient to be estimated. Equation (7) is called the first-order grey differential equation and denoted by GM(1,1) where the first 1 stands for first-order derivative of 1-AGO series of $\boldsymbol{Y}_{Bb}$ and the second 1 stands for only 1 series having to do with the grey system. Substitute the increment with the differential, viz. where $Y_0(w)$ is the value predicted by the grey

$$\frac{dy_b(u)}{du} = \frac{\otimes y_b(u)}{\otimes u} = y_b(u+1) - y_b(u) = g_b(u+1) \qquad (8)$$

when Δu is equal to the unit interval, 1. Suppose the mean series is

$$\mathbf{Z}_b = \{z_b(u)\} = \{0.5\, y_b(u) + 0.5\, y_b(u-1)\}$$
$$u = t - m_D + 2, t - m_D + 3, ..., t \qquad (9)$$

The least-squares solution to Eq. (7) with the initial condition $y_b(t+m-1) = g_b(t+m-1)$ is

$$\hat{y}_b(j+1) = (g_b(1) - c_2/c_1)e^{-c_1 j} + c_2/c_1 \qquad (10)$$
$$j = t-1, t$$

where the coefficients, c_1 and c_2, are given by

$$(c_1, c_2)^T = (\mathbf{D}^T\mathbf{D})^{-1}\mathbf{D}^T(G_b)^T \qquad (11)$$
$$u = t - m_D + 2, t - m_D + 3, ..., t-1, t$$

and

$$\mathbf{D} = (-\mathbf{Z}_b, \mathbf{I})^T; \mathbf{I} = (1, 1, ..., 1) \qquad (12)$$

According to the inverse accumulated generating operation (IAGO) [9], the bth data at the forecasting time w can be given by

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$$\hat{g}_b(w) = \hat{v}_b(w) - \hat{v}_b(w-1); w = t+1 \quad (13)$$

$$\hat{Y}_w = (\hat{g}_1(m_D+1), \hat{g}_2(m_D+1), \ldots, \hat{g}_b(m_D+1), \ldots, \hat{g}_B(m_D+1)) \quad (14)$$

Using Eq. (14), a probability density function can be obtained as follows:

$$F_w = F_w(x_{m_w}) \quad (15)$$

where F_w is called the grey bootstrap probability density function.

For discrete variable, Eq. (15) can also be written by

$$Y_0 = Y_0(w) = \sum_{q=1}^{O} F(y_{wq})\, y_{wq} \quad (16)$$

where $Y_0(w)$ is the value predicted by the grey bootstrap fusion method, the fused value for short; Q is the number of groups ; q is the qth group, q=1,2,…,G; y_{wq} is the median of the qth group; and $F(y_{wq})$ is the value of the grey bootstrap probability at the point y_{wq}.

Let the significance level be α<[0,1], then the confidence level P can be given by

$$P = (1-\alpha) \times 100\% \quad (17)$$

At the confidence level P, the variation domain of is defined as

$$[Y_L, Y_U] = [Y_{\alpha/2}, Y_{1-\alpha/2}] \quad (18)$$

where $Y_{\alpha/2}$ is the value of the variable y_w corresponding to a probability $\alpha/2$, and $Y_{1-\alpha/2}$ is the value of the variable y_w corresponding to a probability $1-\alpha/2$. Y_L is the lower boundary of the estimated interval; and Y_U is the upper boundary of the estimated interval. Therefore, the weighted mean Y_0 is the predicted value of tool rest vibration at the time $w=t+1$, and the estimated interval $[Y_L, Y_U]$fiis the predicted interval of tool rest vibration at the time $w=t+1$.

If there are h data outside the estimated interval $[Y_L,$ $Y_U]$, a parameter P_B is defined as

$$P_B = (1 - h / m_D) \times 100\% \quad (19)$$

where P_B is the parameter about reliability of the estimated result at the given confidence level P, and it describes the reliability of the result estimated using the grey bootstrap fusion method.

II. EXPERIMENTAL INVESTIGATION AND DISCUSSION

Selecting vibration sensor, vibration signal of tool rest for CNC lathe can be obtained, and the measured principle diagram is shown in figure 1. The voltage signal is collected by the piezoelectric acceleration sensor, which is arranged on the tool rest. The preprocessed voltage signal by signal adjusting module is transmitted to a data-collecting card, which can convert the signals from analog format to digital.

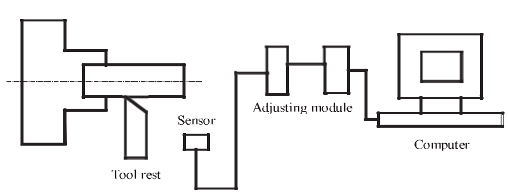

Fig.1 Measured principle diagram of Vibration signal

Process parameters of machining are given, including 6mm in diameter of aluminum blanks, hard alloy cutting tools, the spindle speed of CNC lathe 2000 r/min, and the feed rate 0.15mm/r. 40 parts is processed in equal condition. In order to verify the validity of established model, the peak value of tool

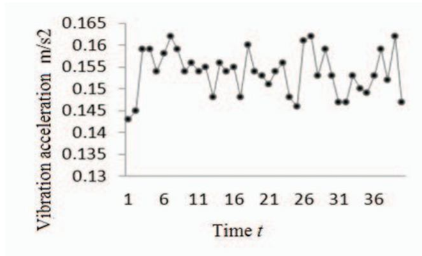

Fig.2 Test data

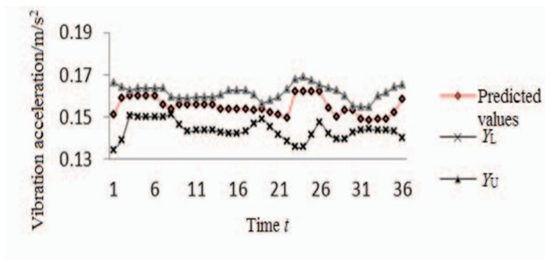

Fig.3 Predicted values and interval

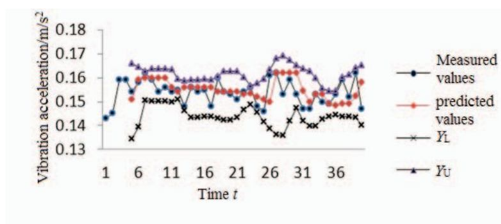

Fig.4 Comparison between predicted result and test data

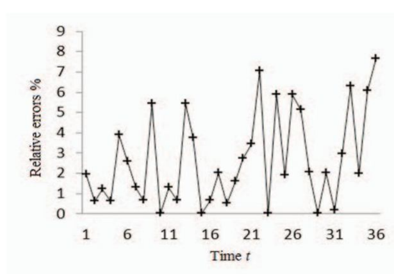

Fig.5 Predicted error

It can be seen from Fig. 2 that GBM(1,1) forecasting model can obtain multi-step predicted values, which can update the data; not only can the model predict the vibration values, but also predicts the estimated interval, having overwhelming advantages.

Fig.3 and Fig.4 are the estimated interval of the grey bootstrap forecasting method. The estimated interval, namely the predicted interval, can characterize the increasing and reducing trend of data fluctuation range at each time. It can be seen from Fig.3 and Fig.4 that the interval $[Y_L,Y_U]$ of the predicted true value can reliably be estimated by the grey bootstrap fusion method. And as shown in Fig.4, all measured values are in the predicted interval $[Y_L,Y_U]$ and the reliability the predicted results can therefore be up to P_B =100%. From Fig.5, using point estimation of the grey bootstrap forecasting method, the maximum and the mean of the relative errors of the predicted results are respectively 7.61% and 2.64%. This indicates that the grey bootstrap forecasting method is able to obtain reliable results, being propitious to long-term forecast of less data.

III. CONCLUSIONS

Using the grey bootstrap model proposed in the paper, time series forecasting of tool rest vibration signal of CNC llathe is actualized by means of point estimation and interval estimation at the given time and the given confidence level, only with very small predicted errors. This can solve the problem of dynamic evaluation of vibration signal of CNC lathe.

The grey bootstrap model proposed in the paper has three overwhelming advantages: high prediction accuracy, high reliability and suitable for less data. This solves the forecasting problem of poor information system with unknown probability distribution, and provides a new method for state monitoring and forecasting of CNC machine, and provides references for the further implementation of intelligent fault diagnosis of mechanical system for CNC machine.

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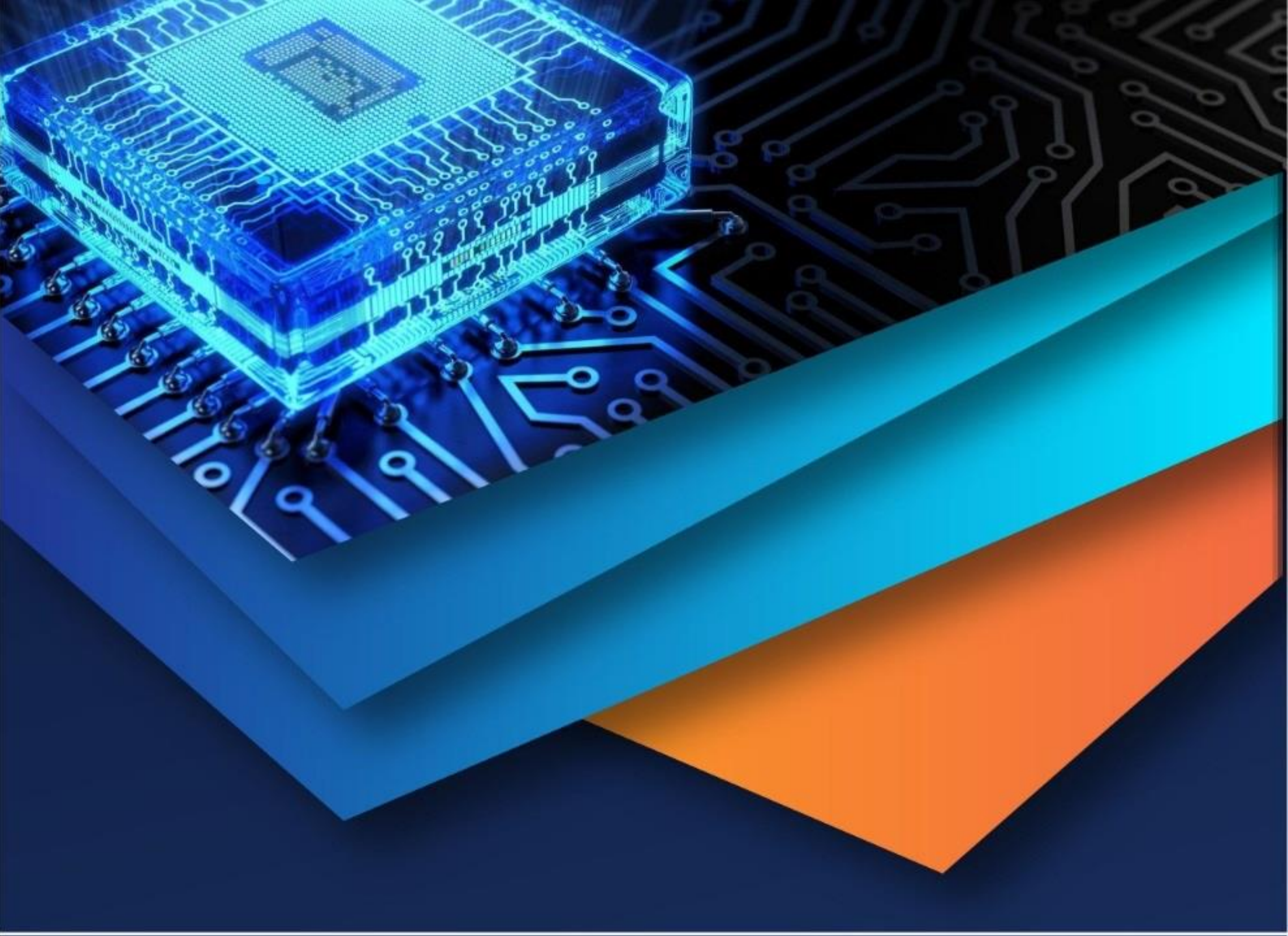

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