Adaptive Modification of Digital Twin Model of CNC Machine Tools Coordinately Driven by Mechanism Model and Data Model

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Abstract. The digital twin of CNC machine tools has become one of the important technical means to realize intelligent manufacturing. To reflect the real conditions of the whole life cycle of the machine tools, an adaptive modification method of the digital twin model of CNC machine tools coordinately driven by mechanism model and data model is proposed. Taking the dynamic stiffness of the CNC machine tool as the combined object, firstly the finite element method is used to establish the initial digital twin mechanism model, then the simulation data of the mechanism model is used to generate enough samples to establish a surrogate model to realize the construction of the initial data model. At different stages of the life cycle of CNC machine tools, the minimum deviation between the dynamic response obtained by the simulation of the digital twin model and the measured response is set as the objective function, and intelligent optimization algorithm is adopted to adaptively modify the digital twin model to ensure the consistency between the digital twin model and the physical object. The established digital twin model is used to predict the dynamic performance of CNC machine tools, which lays the foundation for the whole life cycle management decision of CNC machine tools.

1. Introduction
Digital twin (DT) is a kind of technical means which can realize the physical world and information world interaction and fusion [1-2]. As the working machine, CNC machine tools (CNCMT) in its life cycle have a significant impact on the entire manufacturing system.

Tao Fei et al. (2019) proposed a five-dimensional model of DT and its ten major applications, which greatly promoted the theoretical research and wide application of DT in the manufacturing field [3]. Sun Huibin et al. (2019) proposed a cutting tool DT model in the cutting process [4]. Yi Cai et al. (2017) took the development of a DT system for a three-axis vertical milling machine as an example to illustrate the construction of a DT virtual MT in cyber-physical manufacturing [5]. Luo Weichao et al. (2018) proposed a DT modeling and application framework for CNCMT, and established a DT model for predicting the life and maintenance strategy of the ball screw of a CNC milling machine [6]. Tong Xin et al. (2019) proposed an intelligent machine tool (IMT) DT model based on real-time data services, and proved the effectiveness of the IMT DT system development method [7].

This paper proposes an adaptive modification method of DT model of CNCMT driven by mechanism model and data model. Firstly, the finite element method is used to establish the initial DT mechanism model. At the same time, the simulation data is used to establish the initial data model. At
different stages of the whole life cycle, the model can be modified based on the measured data to realize self-adaptation and self-derivation of the DT virtual model [8].

2. Framework of DT model of CNC machine tools

Figure 1 shows the DT model framework of CNC machine tools. The DT model of a CNCMT is composed of a mechanism model and a data model, which can be simulated and calculated separately according to the measured data of the sensors. In the whole life cycle of the CNCMT, the DT model is constructed and modified under the coordinate drive of the mechanism model and the data model.

![Digital twin modeling framework of CNC machine tools.](image)

Figure 1. Digital twin modeling framework of CNC machine tools.

3. Construction of the initial mechanism model and initial data model

3.1. Initial mechanism model of dynamic stiffness of CNC machine tools

When the CNCMT is subjected to the excitation force \( F(t) \), the system vibration differential equation is:

\[
M\ddot{x} + C\dot{x} + Kx = F(t)
\]

where \( M \), \( C \), and \( K \) are the mass matrix, damping matrix and stiffness matrix of the system respectively.

As in equation (2), the frequency response function \( H(\omega) \) of the system in the frequency domain is:

\[
H(\omega) = \frac{1}{-\omega^2 M + j\omega C + K}
\]

The frequency response function characterizes the relationship between system output and input, and reflects the inherent dynamic characteristics of the system.
This paper uses the finite element method to establish the high-fidelity initial DT mechanism model of the inclined bed CNCMT as shown in figure 2.

![Figure 2. 3D model of CNCMT.](image)

1 bed; 2 large slider; 3 small slider

A FEA (Finite element analysis) model of the whole CNCMT is constructed using the identified stiffness and damping values $K_1, K_2, C_1$ and $C_2$. Where $K_1, K_2, C_1, C_2$ are the total stiffness or damping values of the two pairs of vertical and lateral sliding joint surfaces respectively. Taking the identification of the stiffness as an example, the stiffness is used as optimization variable, and the convergence analysis of the first four-order natural frequencies of the finite element model with experimental results is carried out to preliminarily determine the variation range. Then a method of MATLAB and ANSYS joint optimization and identification of joint surface parameters based on genetic algorithm is used to identify joint surface parameters.

As shown in figure 3, where the Spring2 unit connects the nodes between the two entities of the joint for equivalent simulation of the joint surface in Abaqus.

![Figure 3. FEA model of CNCMT.](image)

In this paper the tool tip is used as a reference point to measure its displacement-frequency curve to reflect the dynamic performance of the machine tool, as shown in figure 4.

![Figure 4. Tool tip displacement-frequency curve: (a) X-axis direction, (b) Y-axis direction, and (c) Z-axis direction.](image)
3.2. Initial data model of dynamic stiffness of CNC machine tools
As in equation (3), the exponential formula after cutting force experiment is:

\[ F_c = C_{F_c} a_p^x F_c y F_c^y v_c^n F_c K_{F_c} \] (3)

In the above equation, \( F_c \) is the main cutting force; \( C_{F_c} \) is the coefficient determined by the machining conditions; \( x_{F_c}, y_{F_c}, n_{F_c} \) are exponential values representing various factors on cutting force; and \( K_{F_c} \) is modification factor under different machining conditions; \( a_p, f \) and \( v_c \) are machining parameters.

The cutting parameters and the corresponding dynamic displacement response obtained by the FEA simulation are used as sample points, thus the surrogate model is constructed through the simulation data generated by the initial DT mechanism model [9]. When \( a_p, f \) and \( v_c \) acquired in the actual machining process are transmitted to the data model through the data interface, the surrogate model can calculate the corresponding dynamic displacement response at once.

As shown in figure 5, the 3D result graph of the Kriging surrogate model is finally generated, and the dynamic displacement response of the tool tip can be obtained for any combination of machining parameters \( a_p, f \) and \( v_c \).

\[ \text{Figure 5. 3D result graph in Isight.} \]

\[ \text{R}^2 \text{ error analysis in Isight can be used to verify the accuracy of the surrogate model. If the } \text{R}^2 \text{ value is close to 1.00, it means that the surrogate model has high credibility, generally the lowest limit of } \text{R}^2 \text{ is set to 0.9. As shown in Figure 6, the error } \text{R}^2 \text{ value of 0.947 in this example is within the acceptable range.} \]

\[ \text{Figure 6. Error analysis of data model} \]
3.3. Update of DT model of CNC machine tools

If the real-time detected displacement $X_R(t)$ is much more different from the displacement calculated by mechanism model $X_M(t)$ and data model $X_D(t)$, the DT model will need to be adaptively modified.

![Figure 7. Update mechanism of DT model.](image)

As shown in figure 7, taking the identification of the changed stiffness and damping parameters of the sliding joint surface of the bed-large slide plate as an example, the stiffness and damping values $K_1$, $K_2$, $C_1$, $C_2$ of the sliding guide joint surface in the mechanism model of the CNCMT are used as optimization variables. The data model is used to utilize the FEA simulation program in the mechanism model to construct a surrogate model, and then based on the established surrogate model to optimize the joint surface parameters.

As shown in figure 8, the DOE module of Isight performs Latin hypercube sampling of the joint surface stiffness and damping values $K_1$, $K_2$, $C_1$, $C_2$. The sampling data are transferred to the finite element program for analysis and calculation, and the surrogate model is built.

![Figure 8. Latin hypercube sampling process.](image)

The mathematical expression of the optimization model is shown in equation (4), which can be solved to obtain the stiffness and damping value of the joint surface at this time, thereby the initial digital twin mechanism model can be modified.

$$\min \begin{cases} E = X_M(t) - X_R(t) \\ \text{opt: Find: } K_1, K_2, C_1, C_2 \\ \text{S.T: } \Delta_{\min} \leq K_1, K_2, C_1, C_2 \leq \Delta_{\max} \end{cases}$$

(4)

Where $\Delta$ represents $K_1$, $K_2$, $C_1$ and $C_2$, and $\Delta_{\min}$, $\Delta_{\max}$ are the lower limit and upper limit of each parameters respectively.

For the initial data model, the historical data of the cutting force load $F(t)$ and displacement response $X(t)$ measured by the sensors are used as sample points to train, and the data model is updated.

4. Dynamic performance prediction method of CNC machine tools

In this paper, an ARMA model is established based on the historical data and the accuracy of the prediction model is verified.
The acceleration data obtained by the vibration acceleration sensor is shown in figure 9. The acceleration data of the tool holder in the turning state can be transmitted to the initial DT mechanism model and the initial data model in real time to modify the mechanism model and data model. This paper removes the average value from the original data to remove the linear trend, as shown in figure 10.

![Figure 9. Vibration acceleration data of tool holder in turning state.](image)

![Figure 10. Comparison before and after removing the linear trend.](image)

In order to determine the order of the AR model, FPE criterion, AIC criterion and BIC criterion of the Akaike information test criterion are needed to perform variance analysis for each order AR model. The specific method is to take the order 1 to 40 of AR in Matlab to model the data, and use the least square method to find the model parameters of each order, finally calculate with three criterion functions, and make the graph of each criterion as shown in Figure 11. It can be seen from the graph that when $n=24$, the FPE, AIC, and BIC values are the smallest, so the 24-order AR model is selected.

![Figure 11. The optimal model order $n$ determined by Akaike information test criterion.](image)

![Figure 12. Fitting graph of AR model: (a) 1-step prediction, (b) 2-step prediction, (c) 3-step prediction, and (d) 4-step prediction.](image)
It can be seen from Figure 12 that the fitting accuracy of one-step prediction reaches to 61.55%, and the fitting result graph roughly overlaps the real measurement result graph, indicating that the established prediction model is ideal.

5. Conclusion
This paper takes the DT model of the dynamic stiffness of the CNC machine tools as an example. Firstly, the realization framework of the DT model in the whole life cycle of the CNC machine tools driven by the mechanism model and the data model is proposed, and then the initial DT mechanism model and initial data model of the CNC machine tools are established. The adaptive modification method of the DT model is proposed to maintain the consistency between the DT model and the real machine. Finally, a method for predicting the dynamic performance of CNC machine tools based on time series analysis is proposed. The results show that the established AR model has high prediction accuracy and can realize the prediction of the dynamic performance of CNC machine tools. When predicted performance degrades, adaptive modification of the DT model and maintenance recommendations for machine tool dynamic stiffness can be carried out.

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