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Modeling and Real-time Compensation of Cutting Force-induced Errors on NC Turning Center

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Abstract. This paper systematically presents the relationship between cutting forced-induced errors and the spindle motor current basing on kinematic chain of NC machine tools. Constructs the model of cutting force-induced errors with BP Neural network, and develops the real-time error compensation system. The compensation effect of this system is verified through the experiment and the compensation system is of a great importance to precision manufacturing industry.

Introduction

With the wide use of precision machining processes, industry faces the growing demands for improving accuracy of NC machine tools. The cutting force-induced errors are more significant than before because of the increasing uses of hard machining and big feed machining processes. Error compensation is an effective technique and has achieved remarkable results in enhancing machine tool accuracy, especially as the real time compensation of geometric and thermal errors are concerned. Consequently, cutting force-induced error becomes a major source of errors in a machine tool after geometric and thermal errors are compensated for. Hence calling for calibration, modeling and compensation for forced-induced errors on NC machine tools.

Theoretical Background

Traditional means of measuring cutting force using sensors such as dynamometers, which are presently available, set many limits with respect to cost, installation and reliability. Increase of cutting forces causes increase of the drive motor current accounting for the increase in power. Therefore, monitoring the changes of the motor current can help obtain change of cutting force, and measuring of motor current is economical and convenient. Consequently, the method avoids the shortcomings of traditional measuring cutting force method. But the cutting force signals response measured through motor current lags behind the actual cutting force signals. This paper solves the problem when modeling using neural network with self-learning ability.

Kinematic Chain of Machine Tools. The kinematic chains of most NC machines tools are into categories: the direct motor spindle assembly and motor, belt drive with spindle assembly. Obviously, former assembly is the subset of the latter. Therefore, for the sake of generalizing, this paper considers the latter for general model. As shown in Fig.1, the spindle drive configuration is comprised of spindle motor, motor spindle, belt drive and spindle. The whole mechanical system of the machine tool is summed up in a module that are acted on by several forces including cutting force, electric magnetic force, bearing friction force, etc.

The equation of the whole mechanical system can be expressed as follows [1,2]:

$$J_s \frac{d\omega_s}{dt} = K_{\alpha s} I_s - B_s \cdot \omega_s - T_{ts} \tag{1}$$

where, ω_s: Angular speed of the machine spindle; J_s: Equivalent inertia seen by the motor; B_s: Equivalent viscous damping coefficient; T_{ts}: Total external torque applied to the spindle motor; I_s:

Armature current of the spindle drive motor; K_{as}: Motor constant of the spindle motor. A subscript "s" means the entire spindle drive.

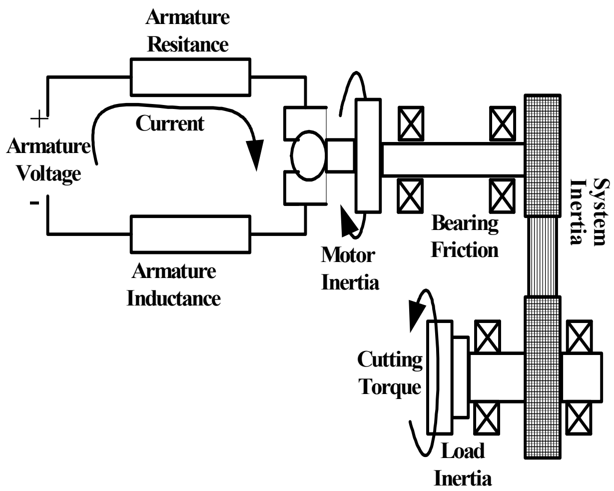


Fig.1 Schematic diagram of kinematic system for nc machine tool

T_{ts} is the total torque reference to the motor including the friction torque and the cutting torque, and is given by:

$$T_{ts} = T_{fs} + \delta T_{bs} + T_c \tag{2}$$

T_{fs}: Friction torque (= T_{fs0}+δT_{fs}); T_{fs0}: Friction torque at idle state; δT_{fs}: Additional coulombic friction torque due to cutting load; δT_{bs}: Additional viscous friction torque due to cutting load; T_c: Normal cutting torque.

The balance equation of the spindle drive system can be arrived at by merging Eq.1 and Eq.2:

$$J_s \frac{d\omega_s}{dt} = K_{\alpha s} I_s - B_s \cdot \omega_s - \left(T_{fs0} + \delta T_{fs} + \delta T_{bs} + T_c\right) \tag{3}$$

There is a linear relation between the cutting torque T_c and the cutting force F_c. The changes of cutting forces cause motor current change; therefore, the cutting forces can be obtained by monitoring of motor current signal.

Analysis of the Relationship Between the Motor Current and the Cutting Force-induced Error. The changes of motor current ΔI can be calculated as follows:

$$\Delta I = I_s - I_0 \tag{4}$$

I_s: Armature current of the spindle drive motor during cutting process; I_0: Armature current of the spindle drive motor at idle state.

At idle state, relationship between the armature current of the spindle drive motor I_0 and angular speed of the machine spindle ω is a linear [3]:

$$I_0 = m\omega_s + n \tag{5}$$

At idle state, T_c=0, δT_{fs}=δT_{bs}=0, $\frac{d\omega_s}{dt} = 0$, the Eq.3 can be simplified:

$$K_{\alpha s} \cdot I_0 = B_s \cdot \omega_s + T_{fs0} \tag{6}$$

Substituting Eq.6 into Eq.3 can be simplified as follows:

$$J_s \frac{d\omega_s}{dt} = K_{\alpha s}\Delta I - \left(\delta T_{fs} + \delta T_{bs} + T_c\right) \tag{7}$$

The equivalent inertia J_s can be calculated according to the physical dimensions of the concerned rotating components. The magnitude of δT_{fs} and δT_{bs} depends on the magnitude of F_c and ω_s and the cutting force-induced errors δF_C is related to the cutting force F_C. Therefore, can arrive at a function according to above analysis:

$$\delta F_c = F\left(\Delta I, \omega_s\right) \tag{8}$$

BP Neural Network Modeling. BP (Back Propagation) Neural Network has one or more hidden layers nodes besides input nodes and output nodes. The nodes in same layer have no coupling and its neuron transfer function usually is sigmoid. BP Neural Network can cope with data of a complex process and has ability of self-training, parallel processing and fault-tolerance to computing.

BP neural network's output varies continuously but not linearly as the input changes. It can be seen as a non-linear map function, F: $R_n \rightarrow R_m$, $f(X)=Y$. About sample set: the input x_i(□R_n)and y_i(□R_m), a map function g is presented:

$$g(x_i)= y_i \quad i=1, 2\ldots\ldots\ldots, n. \tag{9}$$

Usually using least square method, a map function f is got, which is optimally similar to the function g mentioned in Eq.9. Neural Network can be seen as a complex function, which is a multiple compound of simple linear functions.

Neural network modeling refers to training of the neural network using its input and output data and getting a certain neural network model which inputs and outputs is equivalent to the actual process at last. BP neural network is wide used to uncertain system's modeling.

Self-training of BP Neural Network. BP neural network has a significant property, which is self-training [4]. The aim of self-training ability is derivation of inherent rule from the specific observation data and determinate model in accordance with the statistical characteristic of sample. The back propagation involves performing of backward computations through the network. Therefore, the network weights and biases are updated on backward path. During the training process, the network weights are repeatedly modified and optimized according to predefined rule and input mode until the network can output precise outcome under definite sample condition. It is very important thing to determine the sample number of the self-training process. The performance of the network is poor if the sample numbers are too few during the training process. While processes of collecting sample and self-learning waste much time for the case of large number of the samples. The sample data must consider the potential random noise because the network has good interpolation performance but its extrapolation performance is poor.

Inputs and Outputs of the BP Neural Network. Can be known from the Eq.8, and since the cutting forced-induced errors depend on the changes of motor current ΔI and the angular speed of the spindle ω_s, therefore, select ΔI and ω_s as the inputs of the BP neural network. The outputs of the BP neural network are got from the compensations of the cutting forced-induced errors in x, z directions.

Structure of the BP Neural Network. This paper adopts a BP neural network with three layers. According to above analysis, it is can be determined that the input layer has two nodes and the output layer also has two nodes. The number of mid hidden layer nodes is closely related to the learning and calculating rate of the neural network and it is a key factor to the success of the network. The neural network can't handle complicated system if the number of mid hidden layer nodes are too few. The neural network will overwork and weaken its anti-interference capability if the number of mid hidden layer nodes are too large. Now, there are no perfect theories that can be used to direct us to determining of the number for mid hidden layer nodes. Therefore the general procedure is by tentatively choosing the number of hidden layers nodes in accordance with the actual condition, and then the number is gradually modified to the optimal value. Considering the error compensation system in this paper, the cutting force-induced errors are continuous functions of ΔI and ω_s. Therefore, we can determine the number of mid hidden layer nodes according to Kolmogorov theorem [5], as described below:

The mid layer has 2M+1 nodes, if the input layer has M nodes and the input layer has N nodes. Therefore the number of mid hidden layer nodes in this system should be: 2M+1=2×2+1=5 nodes. The structure of BP neural network in this system is shown in Fig.2.

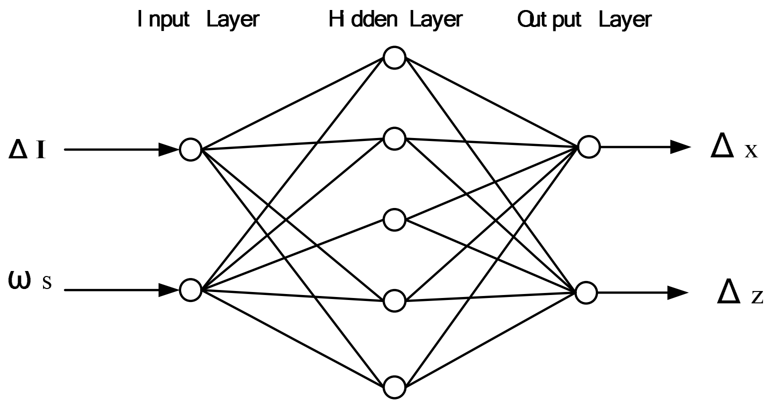


Fig.2 Neural network for the cutting force-induced error

Compensation System of Cutting Force-induced Errors

Modeling of Cutting Force-induced Errors Based on BP Neural Network. According to the above analysis, BP neural network has two input nodes. Ten values are given to each node and hundred input sample pairs are obtained through various combinations of those data.

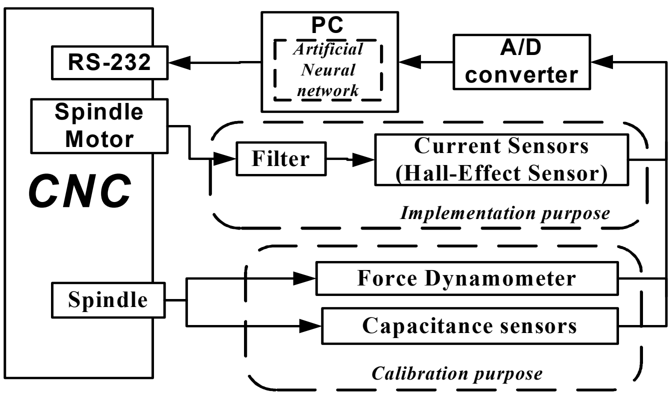


Fig.3 Schematic diagram for the experiment setup

The procedure of obtaining sample pairs is as follows: Firstly, measure the cutting force and corresponding value of driving motor current using sensors. Secondly, pick out ten current values according to the magnitude of the cutting force. Thirdly, get ten values of angular speed by adjusting angular speed of spindle. Fourthly, after hundred sample pairs are determined, then obtain weight of every node and fix the neural network through its self-training function. Finally, save the neural network model of the cutting force-induced errors into a computer, which can be used when the machine tool is real time compensated.

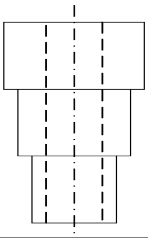
Principle and Structure for Compensation System of Cutting Forced-induced Errors. As shown in the schematic diagram in Fig.3: Variation of motor current signal is monitored and the analog to digital conversion is done. Followed by inputting of the data into the cutting forced-induced model to work out the compensation error. Then transfers the compensation error to

CNC controller and translates the reference origin of coordinate system. Finally the cutting force-induced errors are compensated by adding the compensation signal to the control signal.

Performance Evaluation of the Compensation System

A batch of shafts is produced on a vertical turning lathe, which has been compensated using the compensation system. The shafts are finished in three machining cuts. The dimensions and errors of the shafts shown in Table 1:

Table 1 Performance evaluation of compensation system for the cutting force-induced error

Type	Dimension without compensation [mm]	Dimension with compensation [mm]			Cutting parameter
		No.1	No.2	No.3	
 D1	29.2768	29.2897	29.2892	29.2883	n=750rpm f=143mm/min a_p =0.508mm, 1.016mm, 1.524mm
D2	29.2617	29.2761	29.2773	29.2759	
D3	29.2502	29.2862	29.2838	29.2832	
Error [mm]	0.0266	0.0136	0.0119	0.0124	

As shown in Table 1, the errors reduced by 49% as compared to errors without cutting force-induced errors compensation, hence the machining accuracy of turning lathe improves tremendously.

Summary

This paper describes a new technique of calibration and modeling of cutting force-induced machine tool errors basing on transmission system of machine tool and adaptive intelligent system. And develops a real-time cutting forced-induced error compensation system that can improve machining accuracy of NC machine tool. This compensation system is of a great importance to precision manufacturing industry.

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