Application of the digital model thermal errors of machine tools in automated production

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Abstract. The article presents a predicting method for a machine tool thermal error based on a nonlinear autoregressive neural network with an external input, as well as methods for smoothing experimental data obtained from measuring devices by approximation using polynomial regression and the gray systems theory. The development of accurate and robust thermal models is a critical step in achieving high productivity in thermal deformation reduction techniques on machine tools. Because thermal deformations of the machine structure caused by temperature increase often lead to thermal errors and reduce the accuracy of machining parts. The use of neural networks is a promising direction in solving forecasting problems. The authors propose a block diagram of a thermal process digital twin based on a neural network, which can be used in automated production. The results of the experiment carried out for the machine model 400V are obtained in the form of an assessment of approximation quality and accuracy of the forecasting model. The results show that the use of the proposed smoothing methods and a model for predicting a machine tool thermal error based on a neural network can improve the forecast accuracy.

1. Introduction
Currently, to produce component parts with high dimensional accuracy, enterprises require high-precision machine tools with numerical control. However, thermal deformations of the machine tool structure caused by temperature increase leads to thermal errors, amounting to 60-75% of the total error in processing parts [1, 2]. Therefore, the development of new methods for reducing thermal deformations is becoming one of the priority tasks for enterprises of automated production.

The effectiveness of reducing thermal deformations methods is largely influenced by accuracy and stability of models for predicting thermal error. Forecasting, in turn, is performed using many different modeling methods [3]. However, the most effective and promising solution is the use of artificial neural networks. For example, the model proposed by the authors of the work [4], using an intelligent optimization algorithm designed to improve the performance of the Back Propagation Neural Network (BP), allows predicting thermal errors in accordance with the nonlinear temperature characteristics of the machine. In the work [5], the authors presented a model based on the Bayesian Neural Network (BNN), which shows high prediction results for various operating conditions of the machine tool. The authors of the study [6] presented a model based on a Recurrent Neural Network (RNN), which also shows high prediction performance.

Today, the application of classical approaches to forecasting in the industry 4.0 environment is complicated by the fact that industrial big data must comply with the “5V” standard specifications, that is, “volume”, “velocity”, “variety”, “veracity” and “value”, this limits scope of traditional models. A
significant amount of information and heterogeneity of big data also complicate the choice of an effective modeling method [7]. Therefore, in this work, it is proposed to apply methods of smoothing experimental information and develop a forecasting model based on a neural network. Section 2 presents the smoothing methods and the forecasting model. Section 3 contains experimental studies, including analysis of results. Section 4 presents a block diagram of a digital model that can be used in automated production. Section 5 contains brief conclusions and summary.

2. Research methods
The smoothing procedure for the data obtained from the measuring devices improves the quality of the experimental information. Various data fitting methods can be used for smoothing. Therefore, the approximation of the measured data is an effective solution from the point of view of improving the thermal models’ accuracy and stability.

2.1. Temperature values approximation
A visual analysis of the graph (figure 1) of changes in temperature values over time shows that the data are stepwise since the measuring device operates on a discrete principle. The approximation of temperature values makes it possible to reveal the qualitative properties of the process stored in the measured data.

Horner’s method is used to calculate the values of the approximating function based on the power polynomial. This is efficient in comparison to calculating each monomial separately and then adding them together and using the formula:

$$P(x) = a_0 + x(a_1 + x(a_2 + \ldots x(a_{m-1} + a_m)\ldots)),$$

where $x$ is variable; $a$ – constant coefficients; $m$ – polynomial degree.

The determination of the optimal coefficients set for the equation (1) is performed using the least squares method. Since this method allows you to get the best approximation of the function to the original data.

2.2. Approximation of thermal displacement values
The measured values of thermal displacements can also contain various anomalies. For example, in the presence of a stable upward trend (figure 2), displacement level can jump when the spindle speed changes [8]. Therefore, approximation is a necessary procedure because thermal models should consider the patterns of process change, and not random phenomena.

The approximation is performed by Gray’s method with a convolution integral according to the formula:

$$\hat{X}(t) = X_1^{(0)}(1)e^{-at^2} + \frac{1}{2\sqrt{\pi}} \times e^{-at^2} \times f(t) + \sum_{\tau=2}^{\tau=n-1} \left[ e^{-a(t-\tau)} \times f(\tau) \right] + \frac{1}{2} \times f(t),$$

where $X_1^{(0)}$ – initial data; $X_1^{(1)}$ – converted data; $a$ – development rate; $b_i$ – impact value; $u$ – control parameter; $f(t) = \left[ \sum_{i=2}^{N} b_i X_i^{(1)}(t) \right] + u$ – single step function; $N$ – number of model inputs; $t = 2,3,\ldots,n$; $n$ – data volume.

This method is based on the principle of measured data linearization using accumulation generation operation, which allows transforming the original data set into a monotonically increasing sequence $X_1^{(1)}$. The model is multidimensional, which allows it to consider not only the displacement values $X_1^{(0)}$, but also the spindle speed $X_2^{(0)}$. Coefficients $a, b, u$ for the equation (2) are also calculated by the least squares’ method [9].
2.3. Estimation of approximation quality

The approximation quality is assessed using the coefficient of determination. Figure 1 and figure 2 shows the results of the experimental data approximation.

Figure 1. Temperature values approximation. Figure 2. Approximation of thermal displacement values.

The coefficient of determination is a positive indicator, which reflects consistency of model and measured data, the closer the indicator is to one, the higher the approximation quality. The results show that both models allow obtaining a qualitative set of experimental data due to the approximation. For temperature values using a 15-degree polynomial, formula (1), the coefficient of determination is \( R^2 = 0.9988 \), and for thermal displacements using the model GMC \( R^2 = 0.9868 \), formula (2), which confirms the high quality of the data approximation.

2.4. Thermal error prediction model

Since a model that can predict the thermal errors of a machine tool with high accuracy must consider the complex relationship between temperature and displacement values, it is proposed to use one of the feedforward network architectures as one of the effective tools for identifying the relationship.

Nonlinear Autoregressive Neural Network with External input (NARX) is one implementation of a feedforward network that can predict data using a regression method using the following formula:

\[
 y(t) = f\left[x(t-1), x(t-d_1), y(t-1), ..., y(t-d_2)\right]
\]

where \( x(t) \) and \( y(t) \) are network input and output respectively; \( t \) is variable, in this case time; \( d_1 \) and \( d_2 \) are input and output data delays, respectively; \( f \) is nonlinear fitting function.

Since it is noted in various sources that thermal errors are nonlinear and non-stationary [10], the use of this network is effective from the point of increasing the accuracy of the model. Input data are temperature values, \( T_e \) is the external temperature and \( T_{sp} \) is the spindle body temperature, and the target thermal displacement is \( \delta_z \), caused by displacement of the cutting tool along the axis Z. For the network, the delays \( d_1 = d_2 = 10 \) are set for the input and output data, respectively, as well as the number of neurons in the hidden layer equal to 15 neurons. The network is trained using the “trainlm” error backpropagation algorithm.

3. Experimental research

The experiment was carried out for a 400V machine model. The temperature was measured using a MIT12TP multichannel temperature meter. One of the sensors of the device was located near the front support of the spindle assembly, and the second measured the ambient temperature. Positioning
deviations of the drive, thermal drift of the machine spindle, along the Z axis were measured using a
digital displacement transducer. The data was recorded continuously while the machine was idling for
6 hours.

3.1. Thermal error prediction
The total amount of measured data in the experiment is 360 values, while the first part of the data (240
values) is used to train the network, and the second one (120 values), which is not involved in the training
process (33%), to assess the effectiveness of the prediction model. Figure 3 and figure 4 show the
prediction results.

![Figure 3. Prediction based on measured data.](image1)

![Figure 4. Prediction based on smoothed data.](image2)

It can be seen from the graphs that the model shows a qualitative predicting result based on the
measured data (figure 3). However, for smoothed data, the result turned out to be higher in terms of
prediction accuracy (figure 4). It is difficult to obtain such a high result using only classical modeling
methods.

3.2. Evaluating the effectiveness of prediction model
The criterion for evaluating the model effectiveness is the prediction accuracy, which is calculated using
the following formula:

$$\eta = 1 - \frac{\sum_{i=1}^{n}|x_i - y_i|}{\sum_{i=1}^{n}x_i} \times 100\%,$$

(4)

where $x_i$ is actual values; $y_i$ is forecast values; $n$ is data volume.

The prediction accuracy reflects the maximum approximation of the forecast values to the actual data
and is a positive indicator, that is, the higher this indicator, the more effective the prediction model.

The results show high values of the prediction accuracy, as for measured data $\eta = 94.75\%$, and for
smoothed data $\eta = 96.55\%$. However, the model accuracy based on smoothed data turned out to be
higher and, in addition, the model shows a smoother and more stable result (figure 4).

4. Digital modeling in automated production
Currently, digital modeling is one of the most promising areas for development of automated production
enterprises. For digital models’ development, the technology of creating Digital Twins (DT) is used, in
which simulation at the system level is performed in real time throughout the entire life cycle of the
machine [10]. Figure 5 shows a block diagram of DT using the developed model for predicting thermal
error based on a neural network. Various models can be introduced into the DT structure [11], as well as intelligent control algorithms that increase the accuracy of machining parts on machine tools due to compensation.

![Block diagram of a cyber-physical machine.](image)

**Figure 5.** Block diagram of a cyber-physical machine.

Development of cyber-physical systems concept is becoming necessary and has become widespread in industry. The use of artificial intelligence systems and cloud technologies in automated production can significantly increase productivity of modern precision machine tools.

5. Conclusion

Experimental data obtained from measuring devices are often intermittent and noisy. The smoothing procedure eliminates extreme fluctuations and noise, as well as obtains linear characteristics that simplify further modeling process.

The use of neural networks to solve the predicting problem improves accuracy and stability of the thermal models of the machine.

Studies in the field of cyber-physical production systems and cloud manufacturing show that the general trend in development strategy is clearly indicated, this is deep integration of the virtual world and physical automated production, as well as active introduction of artificial intelligence systems in enterprises.

Acknowledgement

The reported study was funded by RFBR according to the research project No. 20-38-90045.

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