A model for predicting the temperature of a machine tool structure by a neural network using the sliding window method

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Abstract. The paper studies a model for predicting the surface temperature of structural elements of a machine tool using artificial neural networks. A method of forming a training sample by the sliding window method for solving the problem of retrospective forecasting is presented. As applied to a neural network, the sliding window method is an algorithm for forming a training set from an initial set of experimental data necessary to build a forecasting model. Research was carried out for various types of neural networks, namely, generalized regression neural network, radial basis function network and feed forward network. Extrapolation was performed using multistep prediction, in which the predictive system uses the data obtained at the output of the neural network to predict subsequent values. The efficiency and practical suitability of neural network models for predicting the temperature of key heat sources located in certain areas of the machine structure was verified.

1. Introduction
A modern numerical control machine tool, as a typical technological equipment, is an important component in most mechanical engineering enterprises. Therefore, the quality indicators of machine tools largely determine the competitiveness of enterprises in the world market of high technology products. One of the quality criteria of modern machine tools is their accuracy. In this case, thermal deformations of the structural elements of the machine tool, which form thermal errors, can lead to a significant loss of machining accuracy. According to various sources [1-3], thermal errors are approximately 70 % of the total machining error.

Thermal errors can be reduced by making changes to the machine tool structure using advanced design methods and engineering solutions. For example, such as the implementation of structural symmetry or the use of cooling systems. In this case, methods of numerical analysis are used, such as the finite element method, the finite difference method [4, 5]. Extensive studies are also carried out in the field of thermal error compensation [6]. This approach is based on the correlation between measured temperature values and the resulting displacement of the machine tool functional point, for example, the tool center point (TCP). This allows you to evaluate the change in the relative position of the tool and workpiece. While all of these methods can provide acceptable results for some machine tool tests, improvements in predictive accuracy are still relevant. An accurate and reliable predictive model is the most important part of studying thermal processes in machine tools.

In recent years, it has been shown that temperature values can be successfully predicted using empirical modeling methods such as multiple regression analysis, various types of artificial neural
networks, and a combination of several modeling methods [7]. The combination of various numerical calculation methods and the advantages of an artificial neural network is the most reliable and effective tool for modeling thermal processes.

2. Materials and methods

Prediction of experimental values of temperatures is an important component of the study of thermal processes in machine tools. This information is very useful both at the design stage of the machine tool structure by refining thermal models, and at the operation stage, by increasing the accuracy of predicting the thermal error for compensation systems.

There are currently no absolutely reliable methods capable of predicting thermal characteristics, temperature field and thermal errors with extremely high accuracy. Therefore, many different methods are used to improve the temperature characteristics of the machine tool, which are most often divided into three main groups.

The first group is conventionally called the constructive method, which involves making changes to the design of the machine tool, for example, the use of heat pipes, cooling systems, various materials that are insusceptible to temperature changes. This approach is very expensive and ineffective in reducing the thermal error.

The second group of methods is based on compensation using a thermal error model embedded in a numerical control system, and is more efficient and economical. The model can be obtained using linear or multiple regression, artificial neural network, etc. [8] with a sufficient amount of experimental data.

The third group is based on finite element modeling, which allows thermal performance to be evaluated early in the design of a machine tool. This approach is the most economical since it does not require continuous full-scale experiments.

However, all of these methods assume an accurate and reliable mathematical model for predicting temperature. The implementation of the principle of extrapolation by the sliding window method allows obtaining predicted temperature values for a pre-emptive time period.

2.1. Using the sliding window method

As applied to a neural network, the sliding window method [9] is an algorithm for forming a training set from an initial set of experimental data necessary to build a model for predicting the thermal characteristics of a machine tool.

In this case, a window is understood as a time interval containing a set of values required to form a training example. During the operation of the algorithm, the window is shifted in the original sequence by one observation unit, and each position of the window forms one example.

A time series $\{X(t)\}$ is a set of values of a certain quantity $x(t)$ at successive times:

$$X(t) = \{x(t_0 - m\delta), \ldots, x(t_0 - \delta), x(t_0), x(t_0 + \delta), \ldots, x(t_0 + k\delta)\},$$

where $t_0$ is current time; $\delta$ is prediction interval; $m$ is immersion depth; $k$ is forecast horizon.

The prediction task for a time series $\chi(t)$ on an interval $t = 1, n$, is to find the continuation of the time series on an unknown interval. This means that it is necessary to determine $x(n + 1), x(n + 2), x(n + 3), \ldots, x(n + k)$. The set of known values of the time series forms a training sample, the dimension of which is characterized by the value $n$ and $k$ the forecasting horizon. In addition, the method is also characterized by the width of the sliding window with a dimension $m$ equal to the number of time series elements simultaneously fed to the input of the neural network.

To build a sliding window, a certain segment of the time series is selected and several observations are selected from it, which will represent the input vector (Inputs) of the neural network. The desired output (Targets) in the tutorial example will be the following observation in order.
2.2. Neural network training

The sliding window method assumes the presence of two windows $W_i$ and $W_o$ with dimensions $m$ and $s$, respectively, which move along the time sequence of the initial experimental data with a certain sliding step $\delta$.

Thus, the sequence of pairs $W_i$ and $W_o$ forms the training sample, which is used to train the neural network in forecasting. After training, the network must predict a time series for a forward period of time [10].

In this case, the training set can be represented as a matrix, the rows of which are vectors fed to the input of the neural network and the vector of target values:

\[
W_i = \begin{bmatrix}
  x(1) & x(2) & \ldots & x(n-m) \\
  x(2) & x(3) & \ldots & x(n-m+1) \\
  \vdots & \vdots & \ddots & \vdots \\
  x(m) & x(m+1) & \ldots & x(n-1)
\end{bmatrix},
\]

\[
W_o = [x(m+1), x(m+2), \ldots, x(n)],
\]

where $W_i$ – input data matrix; $W_o$ – target vector; $m$ – sliding window width; $n$ – training sample size.

The proposition that the sliding window method is characterized by a window width equal to the number of time series elements simultaneously fed to the network input determines the structure of the neural network, which includes distributed neurons and one output neuron (figure 1).

2.3. Implementation of the extrapolation principle

Recently, it has been established that neural networks do a good job of approximating experimental data from thermal tests of machine tools [11]. But for forecasting, it is necessary to realize the possibility of continuing the time series for an anticipatory period of time, that is, the principle of extrapolation.

To implement the principle of extrapolation, the window is shifted one position in the direction of increasing time, and the process of forming the next pair of training sample is repeated. When constructing a sliding window, data is taken from the table of the relative change in the predicted value. At the next step, the obtained predicted value is added to the original sequence and a new input data matrix is formed.

Long-term forecasting is carried out using multi-step forecasting, in which the forecasting system uses the obtained forecast values (output data) to predict subsequent values.

The proposed forecasting model was implemented in the MATLAB system using the Neural Network Toolbox application package. The following is the sequence of execution of the forecasting algorithm, which is written as follows:

Step 1: formation of a set of initial experimental data $N$.

Step 2: forming a training sample $P$. MATLAB uses a cell array that defines a matrix of training sample sequences and is given by the following expression:

\[
P[i] = \{N(i:m+i)\},
\]

where $i$ – cyclic variable, $i = 1,2,3,\ldots,n-m$; $n$ – training sample size; $m$ – sliding window width.

The input array of the neural network $X$ is the first $m$ values of the matrix columns, and the target output vector $T$ is the $m+1$ column. In this case, the values $X$ and $T$ are set by the following expressions:

\[
X[i] = P[i](1:m); T[i] = P[i](;m+1), i = 1,2,\ldots,n-m,
\]
Step 3: train the neural network. At this stage, the network is trained based on the training example formed in the previous step.

Step 4: determine the forecast values. Forecasting is carried out similarly to the process of forming a training sample. After training, the last of the known samples is fed to the input of the network, and one predicted value $x(t_n + \delta)$ for the initial time series is formed at the output of the network. After that, the obtained predicted value is added to the sequence and the input data matrix is formed again. The procedure is repeated until the forecast horizon is reached $k$.

Step 5: forming a sequence of predicted values.

The presented algorithm for the formation of a training sample of a neural network and realizing the principle of extrapolation by the sliding window method allows predicting the values of the thermal characteristics of the machine tool for a pre-emptive period of time.

3. Experimental research

The experiments were carried out on vertical machine tool model 400V (Russia). To determine the temperature, a multichannel temperature meter was used, the sensors of which were located on the surface of the spindle assembly. As a result, a sample of temperature values in the volume of 406 elements was formed.

MATLAB functions were developed to analyze and predict temperature data near the front spindle bearing. These functions include the implementation of the algorithm for the formation of the training sample by the sliding window method and the implementation of the algorithm for extrapolation of experimental data.

Prediction was carried out using three types of neural networks, namely: Generalized Regression Neural Network, Radial Basis Function Network, and Feedforward Neural Network. Figure 1 shows the block diagrams of neural networks implemented in the MATLAB system.

![Figure 1. Block diagrams of neural networks: a – generalized regression neural network; b – radial basis function network; c – feedforward neural network.](image-url)
For all neural networks, the same parameters were set, namely: the volume of the initial experimental data \( n = 300 \), the width of the sliding window \( m = 50 \), the forecasting horizon \( k = 106 \). The number of neurons in the hidden layer for the feedforward network was set to 50 neurons, which was trained using a standard learning algorithm.

It is proposed to evaluate the accuracy of the forecasting model using retrospective forecast. In this case, forecasting is carried out for a certain moment in the past, for which the actual data are already known.

To do this, we divide the initial experimental data into two parts. The first one will cover earlier data (300 nodes), with their help we will form a training sample for artificial neural networks. Based on the later data (106 nodes), we will form a test sample designed to obtain retrospective forecast values and check the correctness of the networks.

Figure 2 shows the results of the retrospective forecasting procedure.

**Figure 2.** Forecasting results: a – initial experimental data; b – generalized regression neural network; c – radial basis function network; d – feedforward neural network.

On the graphs (figure 2), the abscissa shows the node numbers, and the ordinate shows the temperature values. The solid line denotes the initial experimental data; the dashed line indicates the predicted values of thermal characteristics.

The accuracy of the forecast can be judged by the magnitude of the error between the predicted and actual values of the experimental data [12].

4. Conclusion

Thus, the proposed method for forming a training sample allows you to create data arrays for training a model based on the mathematical apparatus of artificial neural networks, as well as to predict thermal characteristics beyond the set of initial experimental data obtained at the stage of machine tool operation.

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