Approximation of machine tool experimental thermal characteristics by neural network

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Abstract. The article evaluates the effectiveness of an artificial neural network use for mathematical processing of the machine tool experimental thermal characteristics. To improve the quality of approximation and the accuracy of forecasting, two types of neural networks were used, namely a network of radially basis functions and a generalized regression neural network. The results of a full-scale thermal experiment of the idling 400V machine tool are presented. Computational experiments of the thermal testing results of a metal cutting machine were carried out to build and test the models under study. The results showed that neural networks perform better than the classical power polynomial model in terms of accuracy and approximation quality. Thus, neural networks can be used to approximate the experimental thermal characteristics of the machine tool in real time.

1. Introduction
Currently, the demand for precision machining equipment is rapidly growing. This is due to the ever-increasing need for machined parts of complex geometry and high dimensional accuracy. A lot of research is being done to reduce part-processing errors. The error, which is most often caused by thermal influences, is one of the main sources of violation of the accuracy of the machine tool [1]. Therefore, effective control of thermal deformations is a prerequisite for improving the accuracy of modern machine tools.

An effective diagnostic system for the thermal state of the machine tool should include reliable measuring equipment, a high-precision measurement method and a thermal error model. Various methods are used to construct models of thermal error, for example, the least square method [2], the finite element method [3], artificial neural networks [4], etc. Applications developed on the basis of these modelling methods can be found both in research laboratories and at industrial enterprises [5].

Recently, an artificial neural network (ANN) is often used in cases where it is necessary to solve problems of modelling, approximation or forecasting. To simulate thermal errors, many different types of ANNs are being developed, for example, the Integrated Recurrent Neural Network (IRNN) [6], the Radial Basis Function Network (RBFN) [7], and the General Regression Neural Network (GRNN), Gray Neural Network (GNN) [8], etc. In this work, a study was conducted to evaluate the effectiveness of using ANN to approximate experimental data in comparison with the classical method. In further sections, two types of ANNs are presented and analysed, namely RBFN and GRNN, as well as an approximate calculation method based on a power polynomial.
2. The use of neural networks for approximation

When solving the problems of approximating experimental information by a neural network, the problem of choosing its architecture becomes especially acute. This is due to the fact that solving this problem with the help of various types of ANN; we can get the same result in the end. Therefore, the conditions of the task will determine which type of ANN will be more effective. We will try to approximate the initial data set with two types of ANN, namely RBFN and GRNN.

In most cases, ANNs represent output values in a certain range. Therefore, first it is necessary to normalize the initial set of experimental data by the formula:

\[
\hat{y}_i = y_i - My / (Dy)^{1/2},
\]

where \( \hat{y}_i \) is a new variable value; \( y_i, (i = 1, N) \) - initial data; \( My = \sum y_i / n \) - expected value; \( Dy = \sum (y_i - My)^2 / n - 1 \) - dispersion.

As a result of this procedure, training becomes better. The problem statement for ANN can be formulated as follows. There is an initial set of function values in nodes, weighting coefficients, and also basic functions. It is necessary to select such coefficients for the basis functions, so that the combination of these weighting coefficients allows one to obtain a dependence that effectively approximates the set of values of the response function. This process is called supervised learning of the neural network.

2.1. Radial Basis Function Network (RBFN)

The RBFN network is a standard two-layer feedback-free neural network. The inner layer of such a network is completely associated with the output, and the synaptic weights of the neurons (figure 1) of the hidden layer will be equal to unity. The hidden layer contains radially symmetric activation functions (Figure 2). This function is usually a Gaussian function, which is calculated by the formula:

\[
\varphi(s) = \exp(-s^2 / 2\sigma^2),
\]

where \( \sigma \) is the width of activation function.

RBFNs can model an arbitrary nonlinear function with just one middle layer. The parameters of the linear combination of functions of the output layer can be optimized by standard linear modelling methods. For example, one can take a weighted sum of Gauss functions. Then the output layer will contain linear activation functions:

\[
\varphi(s) = ks,
\]

where \( k \) is angular coefficient.

![Figure 1. Radial basis neuron.](image1.png)

![Figure 2. Radially symmetric activation function.](image2.png)
2.1.1. **RBFN neural network training.** The teaching process consists of two stages. At the first stage, the centres of basis functions are tuned (2). The second one optimizes the parameters of the linear output layer. Considering that only the output layer is optimized, training of such a network is fast enough.

2.2. **General Regression Neural Network (GRNN)**

The GRNN network is very similar in structure to the RBFN one except that it contains a line layer. To evaluate the response at arbitrary nodes, this network is able to copy training observations inside itself, and its final output estimate is the weighted average of all these observations. The nodes located closer to the training observations make the largest contribution to the assessment, since the values of the weights reflect the distance from the observations to the estimated node.

GRNN networks are capable of solving the problems of generalized regression, approximation of functions, and time series analysis. They represent the implementation of nuclear approximation methods, that is, the method of approximating the probability density by a Gaussian function, designed in the form of a neural network.

2.2.1. **GRNN neural network training.** GRNN training is similar to RBFN training. First, the centres of the basis functions are tuned (2). Then, with fixed parameters of the RBF neurons, the output layer is trained.

2.3. **Neural network with radial basis elements**

The structure of the two types of neural networks described above is largely the same. Figure 3 shows a diagram of a neural network of a radial basis function.

The number of input elements for the two types of networks will be the same \( R = 1 \). The number of neurons in the second layer will also coincide \( S_2 = 1 \), taking into account the fact that only one output value needs to be estimated for approximation. The number of neurons in the first layer \( S_1 \) for each type of neural network was determined individually.

It should be noted here that in order to get the network output, it is necessary to perform the inverse transformation according to the formula:

\[
y_n^* = y_n^* (D_y)^{1/2} + M_y,
\]

where \( y_n^* \) - converted network output; \( y_n^* \) - initial network output; \( D_y \) - dispersion; \( M_y \) - expected value. As a result, we obtain the network output corresponding to the real data scale.

3. **The experimental part**

The experiment was conducted for a model 400V metalworking machine tool. As the initial experimental data, we took the temperature values that were read from the MIT12TP multichannel
temperature meter. The sensors of the device were installed on the elements of the carrier system of the machine. To improve the quality of experimental information, and then the accuracy of forecasting models, intelligent data processing methods in real time were used. The following are the simulation results and a method for assessing the quality of approximation.

3.1. Measurement and simulation results
Let us analyse the results of approximation of experimental data by the analytical modelling method. We will take a power polynomial as a model:

\[ y_i = a_0 + a_1t + \ldots + a_{n-1}t^{n-1} + a_nt^n, \]  

where \( t \) is the time of the experiment in minutes; \( n \) is degree of polynomial; \( a \) - coefficients.

The coefficients of the equation were calculated using the classical least squares method.

Figures 4 and 5 show the results of approximating the thermal characteristics of the machine tool of the first and second measuring channel, respectively.

![Figure 4. The results of the first channel data approximation.](image)

For the polynomial model, several degree parameters from 3 to 24 were studied. Figures 4 and 5 show the fifth degree polynomial. The volume of the source data constituted 1,053 nodes, which corresponds to 470 minutes. The time of the experiment in minutes was taken as input elements for neural networks, and the output temperature indicators were taken in Celsius degrees. Allowable root mean square error \( E(\omega) = 0.3 \) for RBFN and the influence parameter is one. For the GRNN network, zero error \( E(\omega) = 0 \) and a smoothing factor of one were set.

It is clearly seen from the graphs that all models show good results of approximating the data of the first measuring channel (figure 4). However, for the second measuring channel (figure 5), approximating curves constructed using neural networks are located closer to the original nodes. This is mainly due to the presence of a hidden layer in RBFN and GRNN neural networks with nonlinear radially basis activation functions. These neurons allow you to track the slightest changes in the behaviour of the investigated object. It is very difficult to get such a high result using classical methods. Of course, increasing the degree of the polynomial will make it possible to approximate the values of the approximating function to the original nodes, but this will negatively affect the construction of forecast models in the process of extrapolation.
Figure 5. The results of the second channel data approximation.

3.2. Approximation quality assessment

It is possible to evaluate neural network approximation algorithms using the test (Competition on Artificial Time Series, CATS) [9]. However, this test cannot be considered universal, since neural network solutions developed for a specific task can show poor results of this test [10]. In addition, in this paper, the quality of approximation by a neural network and a power polynomial is estimated. Therefore, the quality of the approximation was estimated using the coefficient of determination (table 1).

Table 1. The values of the determination coefficient.

|               | Polynomial | RBFN  | GRNN  |
|---------------|------------|-------|-------|
| 1 (R²) Channel| 0.8949     | 0.995 | 0.9843|
| 2 (R²) Channel| 0.6514     | 0.9918| 0.9795|

According to the data presented in table 1, we can conclude that the use of neural networks can significantly improve the quality of approximation of experimental data, which, in turn, determines the accuracy of forecasting models built on the basis of these approximation methods.

4. Conclusion

Each set of experimental data contains a random component. However, when forecasting, it is necessary to take into account the patterns of change, and not random phenomena. Therefore, the most appropriate models to identify a general trend are neural networks. They provide high quality approximations and show trends in the indicator over the longest periods of time.

Thus, neural networks can significantly improve the quality of approximation, and can be used to build models for predicting the thermal characteristics of the machine in real time.

Acknowledgements

The reported study was funded by RFBR and the Orenburg Region according to the research project № 19-48-560001 and the Ministry of Education of the Orenburg Region as part of the research (project № 24 on 16 July 2019).
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