Prediction of cutting force during hard turning of 105WCr6 steel using artificial neural network and neuro-fuzzy modeling

D A Rastorguev and A A Sevastyanov
Togliatti State University, Belarusian Street, 14, Togliatti City, 445020, Samara Region, Russian Federation

E-mail: alex-119977@yandex.ru

Abstract. In this work research of correlation between mean value and range of cutting force and processing modes during hard turning of 105WCr6 steel is presented. The results of three-factor experiment on end face cutting of ring workpieces hardened to 55 HRC are presented. During experiment cutting speed, feed and cutting depth are varied. The value of the cutting force is estimated indirectly by the value of current load of the main drive motor. For the development of the model which can predict the value of cutting force at given cutting modes feed-forward neural network trained using Bayesian regularization algorithm and adaptive neuro-fuzzy inference system are used. Developed mathematical models can predict cutting force parameters with high accuracy.

1. Introduction
The task of determining the technological parameters at the machining passes, comprehensively providing accuracy, surface quality, tool operability, has always been one of the most important tasks in the design of technological operations. In the present time it is especially actual due to continuously developed new materials and technological methods for their machining. One of these methods is hard turning.

The integral parameter which characterize the machining process is cutting force. The direct control of this force using dynamometric tools is difficult and require the machine modernization. The indirect control of cutting force i.e. using current load in the main motion drive circuit is structurally simpler and cheaper in making. However, selection of informative features from common signal which correlate with interested parameters of cutting process is more difficult. It is necessary to separate them from common signal and consider processes which correlate with losses in machine kinematic chain registered during machine idle running. Cutting forces prediction in view of cutting modes is a difficult problem considering nonlinear relations in chip formation zone, elastic technological system closed through cutting process and effects of random uncontrolled factors influence.

Artificial neural network (ANN) is a powerful tool for modeling nonlinear correlation between input and output parameters. The efficiency of such networks grows when the amount of data for their training increases. Neural networks are often used for prediction of different machining process parameters. In work [1] multi-layer perceptron (MLP) and radial-basis neural network (RBF) are used to predict dimensional error during ball-end milling of inclined surfaces. The last network showed more precise results. For tool wear monitoring during milling convolutional neural network can be used to analyze...
signal features in different domains: time, frequency and time-frequency [2]. Subtype of radial-basis network called general regression network (GRNN, General regression neural network) are used in research [3] to predict cutting forces, surface roughness and tool wear in depending for cutting speed during turning of titanium alloy. Feed-forward neural network trained with back propagation error algorithm can predict with high precision machined surface roughness and root mean square speed of workpiece vibrations during boring of AISI 1040 [4]. Comparative analysis of different methods of tool wear online monitoring during turning of SAE4140 steel which include artificial neural network, fuzzy logic and least square method is described in [5]. According to results, neural network predicts tool wear more precisely, but in case of less amount of experimental data fuzzy logic is more precise. Research [6] is also devoted to comparison of different algorithms for prediction and optimization of machined surface roughness and cutting forces during slot milling of aluminum alloy 7075-T6. In this work regression analysis, support vector machine (SVM) and neural network integrated with genetic algorithm for search of optimal solutions are compared. Results show obvious superiority of neural network in comparison with other methods, but in case of enough amount of training data.

For solving the problem of approximation of fuzzy, noisy functions such as functions of cutting forces from technological parameters hybrid neuro-fuzzy networks can be used. Neuro-fuzzy networks use supervised learning algorithms, which means that training data is necessary to form the network parameters. Learning quality depends on amount of this data. During practical modeling of manufacturing problems, a good set of input – output data i.e. got from full factor experiment can’t be always got. Usage in such cases of hybrid Adaptive Neuro-Fuzzy Inference System (ANFIS) allows to get higher accuracy of data approximation. For example, in [7] during modeling roughness parameters, cutting forces and temperature in the milling zone regression method, feed-forward network and ANFIS model were compared. The last model was showed maximum accuracy which proved its good generalization capability on limited learning data. In [8] similar problem was solved for turning. One of the features of ANFIS model was fuzzification of input parameters by only two membership functions and method of setting of model parameters – Particle swarm optimization algorithm. In [9] relation surfaces of roughness and wear or cutting force [10] during turning have smooth character. However, in [11] during modeling the dependence of roughness from lubrication materials parameters relation surfaces have essentially nonlinear character.

This work is devoted to development of models based on feed-forward neural network and neuro-fuzzy system for prediction cutting force during hard turning of 105WCr6 steel.

2. Experimental technique

The experimental technique is described in details by authors in article [12]. The experiment was carried out on a lathe model 16B16T1C1 with CNC system Flex NC. Workpieces were rings made of 105WCr6 steel and hardened to 55 HRC with geometrical parameters: outer diameter 55 mm, inner diameter 30 mm, thickness 20 mm. 105WCr6 steel is used in manufacturing of cutting and measuring tools with high requirements in terms of dimensional accuracy and lack of distortion after heat treatment. No coolant was used during machining. End face cutting of samples was performed using PCLNR 2525M 12 plate NP-CNGA120404GA2 Mitsubishi, the plate material cubic boron nitride (CBN). Cutting modes were as follows: cutting speed – 150, 250, 300, 400 m / min; feed – 0.1; 0.2; 0.3 mm / rev; cutting depth – 0.1; 0.2; 0.3; 0.4 mm. The signals of the diagnostic system of the CNC machine were recorded, in particular, the values of the current of the main motion drive with a sampling frequency of 227 Hz were obtained. These values are further used to estimate the value of the cutting force during processing. A detailed statistical analysis of the results is given by the authors in the article [13].

3. Neural network modeling

The authors earlier in [14] successfully applied various architectures of neural networks to solve the problem of classification of processing modes according to the criteria of surface quality and chip type obtained during hard turning.
In this work, a two-layer feed-forward neural network is used to predict the parameters of the cutting force at different cutting modes. The hidden layer of the network consists of sigmoidal neurons, and the output layer consists of a linear neuron. The scheme of the neural network is shown in figure 1.

![Feed-forward neural network](image)

**Figure 1.** Feed-forward neural network.

Training of the neural network was performed by Bayesian regularization algorithm to improve the accuracy of the modeling. In this case, the validation set was used to stop the network learning early if the learning rate stopped improving or if it remained unchanged for a certain number of consecutive epochs. A test set was used to test network performance.

Inputs of the trained network are cutting modes (speed, feed, depth) and outputs are the mean value or the range of the cutting force. To use the ANN for modelling according to experimental data it is necessary to do the following steps. Input data (cutting speed, cutting depth, feed) form an input vector \( X \) of dimension \( k = 3 \). The output vector \( Y \) of the corresponding values of the cutting force parameters is formed. The dataset must be randomized and normalized. After that, it is divided into training, test and validation samples. The initial data for 48 experiments are divided into three groups: training, validation and testing in the proportion of 70-15-15 \%. Normalization of the initial data is necessary to reduce the various parameters to the same scale and is carried out according to the formula:

\[
x_i = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}},
\]

where \( X_i \) – actual value of normalized parameter, \( X_{\min}, X_{\max} \) – minimum and maximum values of the parameter, \( x_i \) – the value of the parameter after normalization.

Then it is necessary to choose the number of neurons of the hidden layer of the network, which is usually done empirically. For each selected number of neurons, a network is trained, and then one with minimal error is selected from the trained networks. Thus, the optimal number of neurons for this task was 25 for mean cutting force and 100 for range. Hidden layer neurons have a symmetric sigmoidal activation function described by the formula:

\[
y = \frac{2}{1 + e^{-2z}} - 1.
\]

Before submitting the initial data to the input of the sigmoidal activation function, the data must be row-by-row normalized, reducing all values to the segment \([-1; 1]\), according to the formula:

\[
z = (z_{\max} - z_{\min})x_i + z_{\min},
\]

where \( z_{\min} = -1, z_{\max} = 1 \), \( x \) is the parameter value before normalization, \( x_{\min}, x_{\max} \) – minimum and maximum parameter values before normalization.

The normalized input data is weighted, summed with a bias, and fed to the symmetric sigmoid input. This happens in all 25 neurons of the hidden layer. The hidden layer data is then fed into the output
layer, where it is weighed, and then a bias is added to the weighted sum. The resulting value is the output of the neural network.

4. ANFIS modeling
Another approach to approximating nonlinear dependencies is to use a hybrid fuzzy network. ANFIS hybrid fuzzy network is used for parameter analysis. ANFIS is a fuzzy inference system by Sugeno method.

The method of setting up this system is presented as an iterative procedure for finding the parameters of the fuzzy inference system using a hybrid algorithm. It is used to configure parameters of the membership function of input variables and coefficients of rule conclusions. The setup is done by a combination of the back propagation error method and the least squares method. The network has five layers. Three inputs (depth of cut, feed and cutting speed), each of which is divided into a number of terms – membership functions (Fig. 2). Their number changed from 2 to 4. The shape of the selected membership functions is a bell curve, which is given by the formula:

$$
\mu_{k,j}(x_i) = \frac{1}{1 + \left| \frac{x_i - c}{a} \right|^b},
$$

(4)

where $a$, $b$, $c$ – tunable parameters of a membership function; $j$ – number of terms. In the second layer, the number of nodes corresponds to the number of rules, which are formulated in the form of fuzzy rules on the principle of "IF... - THEN...", fully reflecting the influence of changes in the input vector $x$ on the output of the model $y$. The output of this layer is the degree to which each of the rules $m$ is executed as an expression

$$
w_m = \mu_{1,n}(V) \times \mu_{2,l}(S) \times \mu_{3,p}(I),
$$

(5)

where $n$, $l$, $p$ – number of corresponding membership function in one of the rules. In this expression, the $t$ – norm is implemented when the operation is «And». In the third layer, the relative degree of rule execution is calculated in each of the nodes whose number is equal to the number of rules:

$$
\bar{w}_m = \frac{w_m}{\sum_{v=1,m} w_v}.
$$

(6)

In each of the nodes of the fourth layer, the number of which remains equal to $m$, the contribution of each fuzzy rule to the output of the network is calculated:

$$
y = b_{m,0} + b_{m,1}x_1 + b_{m,2}x_2 + b_{m,3}x_3,
$$

(7)

where $b_{m,k}$ – coefficients. In the output layer contributions of all rules are summed:

$$
y = y_1 + y_2 + y_3.
$$

(8)

The process of setting the parameters of the first and fourth layers stops when the required error of learning the settings or after the specified number of iterations.
5. Results

When modeling the parameters of the cutting process the trained feed-forward networks predict the mean cutting force with a relative error of 4-6% and the range with a relative error of 10-13%. This happens because the range value of the cutting force is noisier than mean value. Neural networks are usually very sensitive to noise in data. The resulting system of fuzzy inference after learning is reflected in the linguistic rules of inference. This makes the influence of input factors on output transparent. The learning result is also available as three-dimensional output surfaces (figures 3, 4).

As can be seen from the figures with the output surfaces, the dependencies of the cutting forces ranges are essentially nonlinear. This is due to abrupt changes in the nature of chip formation. When changing processing modes, there was a transition from ribbon chips to saw-tooth chips and then to discontinuous chips. Moreover, these transitions were in a complex relationship with the processing parameters. This led to the same drastic change in the scope of the cutting force. The maximum errors during testing have always been related to the data obtained during elemental chip formation. The dependence of the mean cutting force (figure 4, a) is smoother and the error of training on these data is less.

The error after training varies depending on the number of terms in the input layer. For a 3-3-3 structure, the learning error is 0.08%. On the test set – 26%. For a 4-4-4 structure, the learning error is 0.001%. On the test set – 25.5%. Increasing the complexity of the network, the number of its parameters leads to a decrease in learning errors in the training set with a decrease in generalizing ability and the formation of a large error in the test set (figure 4, b). For optimal network structure ANFIS 2-3-2 training error 2.5%, on test set 7.2%.

![Figure 4. Inference surfaces for mean cutting force in coordinates feed – cutting speed: a – for network structure on input terms 2-3-2; b – for network structure on input terms 4-4-4.](image-url)
6. Results and conclusions
As shown by the results of modeling based on neural networks, the dependencies of the cutting force parameters on the processing modes during hard turning are predicted with very high accuracy. Feed-forward neural network showed higher accuracy when compared with the results of modeling using neuro-fuzzy network ANFIS. But the last can be used more effectively with small amounts of training data, and also makes a visual representation of the obtained dependencies. With the joint use of these networks, the accuracy of forecasting will increase, which will have a positive impact on the quality of the design of technological operations.

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