Empirical modeling of cutting force from technological factors in hard turning of 105WCr6 steel

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Abstract. The article is devoted to the mechanical load determination on process constants during hard turning of 105WCr6 instrumental steel. The work contains the results of three-factor laboratory experiment on end face turning. The blanks were rings, hardened to a hardness of 55 HRC. Their outer diameter was about 50 mm. During the experiment, the basic process parameters, namely cutting modes, were varied. Semiproducts were turned on a Russian CNC lathe modification 16B16T1C1. The system includes integrated diagnostic subsystem with encoders and current sensors. These sensors allowed using indirect method for mechanical loads assessment. To mathematically explain the force level statistical methods are used. They were linear regression for exponential formula and decision trees. The results of the mathematical investigation and the future review of the studied correlations are given. The results are compared with previously developed machine learning models.

1. Introduction

Hard turning is a finish processing of blanks, which hardness is higher than 47 HRC. One of the restraining factors on the way of mass application of new technology is the absence of background data and calculation instructions for the mode’s definition. It makes new studies very actual for both scientists and manufacturers.

The mechanical load factor is dominant in hard cutting processes. Its assessment from the processing conditions allows calculating of the necessary drive power of the machine equipment when introducing into production. Moreover, the magnitude of the elastic displacements directly relies on the magnitude of loads, which directly influences the dimensional precision of the semiprodut. In hard turning, it is essential to guarantee high rigidity in all directions to neutralize oscillations. Besides, in-process programmable observation of the mechanical load is commonly utilized for diagnostics purposes [1].

For mathematical description of the mechanical load’s behavior in different technological conditions, regression formulas are utilized by many researchers [2, 3]. Based on their basis experiential formulas can explain the affecting of large amount of reasons on mechanical load. So, in work [4] not only cutting modes varied, but also the cutter geometry and the semiproduct hardness.

Artificial neural networks (ANNs) and fuzzy logic (FL) are effectively utilized to approximate complex nonlinear functions [5, 6]. They are extremely popular nowadays due to achievements in pattern recognition tasks. The built program based on artificial intelligence allows virtual simulation of manufacturing process [7].
The target of this article is to determine the intercorrelations between mechanical loads and modes in hard turning of instrumental steel 105WCr6.

2. Experimental procedure
The laboratory setup is fully described in [8]. The CNC lathe modification 16B16T1C1 was utilized for dry hard turning. The semipродuct had a circular form and was made of instrumental steel 105WCr6 with hardness 55 HRC. End face was processed utilizing the plate made of cubic boron nitride. The time rows of the lathe diagnostic subsystem sensors were analyzed. So then, the current loads of the lathe spindle drive were recorded using PMAC Plot software. The sampling frequency of the analog-digital converter (ADC) was 227 Hz. The way of mechanical load assessment by current signals is mentioned in [9]. ANN and FL approximations are investigated in [9, 10].

3. Modeling
Apparently, there is a strong correlation between inputs t, s, v and the output Pz. The task is to build up correct mathematical formula, which represents laboratory data with desired accuracy. The formula should be simple for practical usage by manufacturers. The force Pz relies on modes t, s, v were simulated out using two methods: linear regressions (LR) for the exponential function and regression trees. Both methods are rather popular and simple enough to interpret by engineers.

3.1. Power dependence
The relation of the tangential component of the mechanical load from the modes can be represented by the traditional formula used in many reference books for engineers-technologists

$$P_z = Ct^x s^y v^u,$$

where C is the correction coefficient for Pz; x, y, u – exponents of the relevant parameters (t, s, v). After taking the logarithm of (1) we get:

$$\ln P_z = \ln C + x \ln t + y \ln s + u \ln v.$$  \hspace{1cm} (2)

Replace \( y = \ln P_z, b_0 = \ln C, b_1 = x, x_1 = \ln t, b_2 = y, x_2 = \ln s, b_3 = u, x_3 = \ln v \).

Then the formula (2) takes the following form:

$$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3.$$  \hspace{1cm} (3)

The calculation of the unknown constants of (3) produced via the programming language "R" (table 1). The assessment of significance levels of the LR coefficients was carried out using analysis of variance (ANOVA).

| Coefficients | Value  | Std. Error | t-value | Pr(>|t|) | Significance |
|--------------|--------|------------|---------|----------|--------------|
| b_0          | -1.22  | 3.0e-01    | -4.01   | 2.36e-04 | VS^a         |
| b_1          | 2.6e-01| 4.0e-02    | 7.19    | 6.82e-09 | VS           |
| b_2          | 2.2e-01| 4.0e-02    | 5.36    | 3.11e-06 | VS           |
| b_3          | 3.4e-01| 5.0e-02    | 25.72   | <2e-16   | VS           |

^a VS – very significant

For the calculated model criteria \( R^2 = 0.95 \); adjusted \( R^2_{\text{adj}} = 0.94 \), indicating its correctness.

The resulting mathematical formula has the form:

$$P_z = 0.295 t^{0.26} s^{0.22} v^{1.34}.$$  \hspace{1cm} (4)
As can be seen from table 2, all the constants of a LR formula have a high significance. It means that all modes affect the load.

Figure 1 represents both laboratory and calculated load plots. The dashed graphs plotted for the lowest and biggest values of the formula constants respectively. As graphs show, the approximation generally adequately describes the laboratory results. The error was about 18% in the most intensive modes, where the features of element chip formation led to a significant rise in the dynamic part of displacements and loads. This is also reflected in a rise in the variance in the spread of mechanical load values. The range of mechanical loads formed for the 95% confidence interval includes all experimental points. Even though the formula leads to high level of mistakes during direct calculation, it has advantages. First, the interval of loads are convenient enough to utilize by engineers in practice because this information is easy to interpret and the knowledge about possible offsets in the load can be very useful in process design task. Second, the variance distribution correlates with physical behavior of natural process, which is another proof of the model’s correctness.

3.2. Regression trees
Another method of developing mathematical approximations for test data is the method of regression trees (or decision trees). Decision trees are very popular because their structure and the way of information representation are easy to interpret. This method utilizes recursive division of the sample into groups with more and more homogeneous data. Because of such partition, a hierarchical structure forms resembling a tree. "Leaves" of the tree are determined by the subsets of explanatory variables, which are the most necessary for the dependent variable forecasting and its value itself. Described structure is relatively easy to interpret, does not require the alleged information about the data distribution and is robust to outliers. However, decision trees use the "naive approach", initially suggesting low multicollinearity of the analyzed variables. In our case this suggestion is obviously correct.

Figure 2 presents the decision tree splitting the original data into groups relying on the speed values. Figure 3 shows the same tree after the pruning procedure.

![Graph showing experimental and calculated values of the mechanical loads.](image-url)
"Branches" of the tree contain information about intervals of cutting speed that are used to split the data into groups. In turn, the tree nodal points contain the average mechanical loads in these groups and the number of laboratory tests in each set.

Figure 4 shows a relative errors function graph from the tree nodal points number. According to the graph, the optimal tree structure is selected. This structure is a compromise between accuracy, difficulty and generalization feature of the mathematical model.
Next, the way of building up trees via the procedure of the conditional inference is utilized. This way allows abandoning of tree pruning procedure. Figure 6 presents the conditional inference tree. Tree nodal points consist levels of relevant group significance. At this tree, the laboratory data is split by two main criterions: speed and depth of cut. At high speed, the laboratory data is grouped by depth of cut, at low speed — by speed ranges. The technologist is able to utilize such interpretation for simplified assessment of the loads level for choosing of modes levels. Consequently, despite the lack of deterministic function of mechanical loads from the modes, this tree allows to approximate the statistical characteristics of the load function and simply display them in a hierarchy, which is very practical.

![Conditional inference tree](image)

Figure 6. Conditional inference tree.

4. Summary and conclusions
Mathematical approximation, which describes the mechanical load behavior in different processing conditions, is developed. Built formula in the format of an exponential formula allows predicting values of loads with an error of up to 18%. Decision trees provide qualitative information containing not the specific values of the mechanical load, but their distribution in groups. This approach is visual and practical, because it provides information on the various physical parameters leverage on magnitude of loads. The authors previously obtained models of the mechanical load utilizing ANN and FL. These approximations simulate the desired function within the error of 4-6%, which indicates higher precision of machine learning methods in approximating nonlinear functions in conditions of small sample size (the total amount of laboratory tests is less than 50). Besides, fuzzy logic mathematics was more precise, simple to utilize and simple to interpret.

Statistical formulas allow drawing conclusions about the importance and influencing on mechanical load the specific parameters and their combinations, which is an important factor in the calculating of the finish machining operations. However, despite the advantages both approaches have the same problem with overlearning. Adding more coefficients in statistical formula acts like increasing the amount of neurons in the middle layer of ANN. The precision of the approximation will be higher, but in case of using new experimental data such formulas will make large mistakes on completely new values of independent variables. It means that the developer of the model should find a compromise between high accuracy and generalization capability.
Another aspect of such approximations is their empirical basis. The physical theory of the research object is not built yet. Therefore, it is impossible to calculate the result via analytical formula without any practical tests. Thus, empirical approximations are the best way to solve the task because of their simplicity and reliability. On the other side, the finite-element method (FEM) is a very powerful and popular way of solving such difficult physical and engineering tasks. However, the negative side of this way is the necessity to do all calculations for each new case from start point. It makes calculations time and resource consuming, which is unacceptable for practical conditions.

ANNs also require high computing power for learning. Huge networks with millions of nodes and thousands of layers called deep networks are very precise and useful in case of raw time rows investigation. They need powerful graphical processors for learning and work. In recent years productive electronics became cheaper and affordable for enterprises. The pluses of such mathematics include its capability of taking raw time row as input and drawing conclusions without expert intervention. This makes such mathematics free of human factor. In other words, system becomes much more objective. Its practical usage can be very promising even in the near future. For example, sound and image recognition tasks solved via deep networks lead to principally new approach to programmable mechanical diagnostics with high frequency state updating. Such way of mechanical load observation developed in laboratory conditions should become very popular on firms due to its simplicity, universality and precision qualities. This fact explains why both scientists and entrepreneurs are interested in new mathematical and computer technology described. Its evolution provides new opportunities for manufacturing effectiveness rise and better resource utilizing. The complex technology usually called digital twin makes creating virtual firms and assessment of new technological ways real. Thus, developing of mathematical instruments mentioned here possibly lead to new production reality.

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