MONITORING AND NEURAL NETWORK MODELING OF CUTTING TEMPERATURE DURING TURNING HARD STEEL

by

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In this study, cutting tools average temperature was investigated by using thermal imaging camera of FLIR E50-type. The cubic boron nitride inserts with zero and negative rake angles were taken as cutting tools and round bar of EN 90MnCrV8 hardened steel was used as the workpiece. Since the life of the cutting tool material strongly depends upon cutting temperature, it is important to predict heat generation in the tool with intelligent techniques. This paper proposes a method for the identification of cutting parameters using neural network. The model for determining the cutting temperature of hard steel, was trained and tested by using the experimental data. The test results showed that the proposed neural network model can be used successfully for machinability data selection. The effect on the cutting temperature of machining parameters and their interactions in machining were analyzed in detail and presented in this study.

Key words: *cutting temperature, turning, hard steel, neural network*

Introduction

In the hard machining process, cutting temperature is often of great concern due to its impact on the product performance. Cutting temperature in the metal cutting process is a very important factor affecting production optimization [1]. Therefore, for a desired part performance, it is important to predict and control the development of this cutting temperature as a function of the hard machining parameters. The importance of temperature prediction for the machining processes has been well recognized in the machining research community, firstly, due to its effects on tool wear and its constraints on the productivity, and secondly, due to a significant impact it has on the integrity of workpiece surface such as residual stress, hardness, and surface roughness [2].

An important advantage in meeting this new challenge is being able to quickly acquire information on specific machining operations [3, 4]. Cutting temperature is the commonest index for determining tool wear [5]. Ay and Yang [6] monitored time wise change in the temperature of the work piece by using infrared thermovision to determine the effect of heat transfer on the tool. They concluded that if the tool's temperature is increased that leads to the acceleration

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of the wearing process. The high cost of specific cutting tools and the cost of downtime for tool changing must be minimized [7]. Tool wear plays a key role in the economy of machining operations. Jawahir *et al.* [8] maintain that knowing the optimum machining parameters is vital.

Various researchers involved with the modeling of cutting temperature have at their disposal a number of options. For a variety of reasons, one particular option has been largely investigated in the literature, the use of artificial neural networks (ANN) [9, 10]. This method of artificial intelligence, is claimed by Zuperl *et al.* [11] and Ambrogio *et al.* [12] to have many attractive properties for modeling complex production systems. Petković *et al.* [13] developed an ANN model which can be used successfully for the accurate prediction of cutting temperature while performing the turning of the biomedical stainless steel. These include universal optimization algorithm to ensure simple, fast and efficient optimization of all important machining parameters, accommodation of multiple non-linear variables with unknown interactions, and good generalization capability.

Over the past few years, the growth of automated industries has prompted the use of artificial intelligence techniques, such as the neural networks (NN) [14]. The ANN are among the most powerful computer modelling techniques, based on statistical approach, currently being used in many fields of engineering for modelling complex relationships which are difficult to describe with physical models [15]. The ANN have been extensively applied in modelling many metal cutting operations such as turning, milling, and drilling [9, 10, 16]. The ANN models proved to be very effective in analyzing the effects of cutting conditions and predicting the output characteristics of the process.

Hard turning has been receiving increased attention because it offers many possible benefits over grinding in machining hardened steel [17]. The cubic boron nitride inserts are commonly used in hard turning, because of the high cost of cubic boron nitride (CBN) inserts. It is minimized cutting temperature which directly influences the tool wear. In turning process, cutting temperature depends on the options and the suitability of different cutting speeds, feeds, cutting depth and it also affects the durability of the cutting tool [18]. Due to these aspects, measuring procedures are necessary as they permit one to establish the real state of tool wear and to manufacture parts with higher accuracy [19]. The thermographic technique has commonly been used to measure the temperature of the cutting tool. Muller-Hummel *et a1.* [20] measured the temperature distribution on the rake face of the diamond coated tool in turning using a thermographic technique. This technique is used for researching the correlations between cutting parameters and temperature distribution in the zone of cutting.

However, this study was inspired by a very limited or no work on the application of ANN in modelling the relationship between cutting conditions and the cutting temperature during machining of hardened steel, EN 90MnCrV8, alloy. Hardened steel is usually machined by grinding process and here is used the turning process which is a more effective machining process with a satisfied quality. Cutting temperature is an important issue in the machining processes and it is influenced by the process parameters such as tool geometry (*i. e.* nose radius, edge geometry, rake angle, tool tip radius, chamfer thickness, *etc.*), cutting conditions (cutting speed, feed, depth of cut, *etc.*) and workpiece properties. Contribution of this paper is seen in the fact that not only modeling is done by NN, but the comparison of two CBN inserts with different tool geometry, a negative rake angle and zero angle, is shown. Comparative observation showed that zero angle gives slightly smaller deviation in the cutting temperature values than the negative rake angle.

The present work is focused on the modeling of cutting temperature in turning using NN methods. In this work, an experimental investigation was carried out using a lathe for the turning of hard steel. The important input turning parameters chosen were cutting speed, feed rate and the depth of cut. The response considered was cutting temperature. An ANN was developed for the prediction of cutting temperature values in hardened steel after the turning machining process. Obtained model gave a significant relationship between cutting temperature and cutting parameters in order for the improvement of cutting tools work efficiency.

Experimental set-up

The main aim of the experiments was to determine cutting temperature in the turning of cold working hardened steel. This steel was heat treated and hardness of 55 HRC was obtained in the machining zone of every workpiece. Machining was performed without cooling and lubrication agents. Turning operations were realized with five different cutting speeds, *v*, feed, *f*, and the depth of cut, *a*, using CBN tool, tab. 1.

Table 1. Turning conditions

v_c [m min^{-1}]	f [mm rev^{-1}]	a [mm]
80	0.045	0.07
90	0.05	0.1
120	0.1	0.22
160	0.2	0.5
180	0.25	0.7

The workpiece material was EN 90MnCrV8 cold working tool steel with the following chemical composition: 0.90%C, 0.20%Si, 2.00%Mn, 0.40%Cr, and 0.10%V. Turning test was performed in longitudinal turning on the round bar with 34 mm diameters and 500 mm length using conventional lathe with 10 kW spindle power. There are three types of rake angles: positive, negative, and zero. During the turning test, for zero and negative tool rake angle, cutting temperatures were recorded. A FLIR E50 thermal imaging camera was used to measure the cutting temperatures. Thermal camera was positioned and fixed on a tool holder. The camera moved with the tool and monitored the same area on it. The emission factor of 0.95 for steel was adopted as the highest temperature on the chip was measured. The thermal camera measured maximal temperature, minimal temperature, and average temperature in the selected area. The temperature in the pointed spot on the tool was also measured and this temperature was used in calculations by ANN modeling. The temperature was monitored during the machining of one whole section on the workpiece and the value obtained after 5 seconds was used for the calculation.

Two types of CBN inserts were used in these tests: CNMA120404 and CCMW120404 (tabs. 1 and 2). Through the use of tool holders, a negative rake angle $y = -6°$ was obtained for the tool holder PCLNR2525M12 and zero angle $y = 0°$ was obtained for the tool holder SCLCR2525M12, respectively. In planning and conducting the experiment, three factorial central compositional experimental plans were used. Selected factors of experiment have changed in five levels of value, authors used in [3, 4]. This method allows investigating the wider interval of parameters and the predicted model is more reliable, tab. 3.

Table 2. Specifications of tool insert

Inserts	γ [°]	α [°]	λ [°]	κ [°]	κ_1 [°]	r [mm]
CNMA120404	-6	6	-6	91	5	0.4
CCMW120404	0	7	-6	91	5	0.4

Artificial neural network modelling

The ANN method is becoming useful as the alternative approach to conventional techniques, or as the component of integrated systems. It is an attempt to predict, within a specialized software, the multiple layers of a number of elementary units called neurons [14]. The MATLAB software, NN toolbox function, was used to create, train, validate, and predict the different ANN reported in this research.

Table 3. Experimental plan and modeled data

No	v_c [mmin^{-1}]	f [mmrev^{-1}]	a [mm]	θ [°C]	θ NN [°C]	θ [°C]	θ NN [°C]
				Negative rake angle		Zero rake angle	
Training data							
1	90	0.05	0.1	100	98.268	104	103.978
2	160	0.05	0.1	105	106.999	119	119.465
3	120	0.25	0.22	108	97.086	130	126.467
4	160	0.2	0.1	135	137.895	169	169.471
5	90	0.05	0.5	154	152.445	108	108.084
6	180	0.1	0.22	128	129.756	102	112.383
7	90	0.2	0.5	167	165.357	143	141.468
8	160	0.2	0.5	201	200.762	138	132.748
9	80	0.1	0.22	169	172.443	145	139.992
10	120	0.1	0.22	155	154.911	130	124.194
11	120	0.1	0.22	141	154.387	131	123.291
12	120	0.1	0.22	140	153.866	120	122.269
13	80	0.1	0.22	165	164.194	105	105.272
14	180	0.1	0.22	170	170.367	137	137.357
15	120	0.045	0.22	130	129.393	113	112.281
16	120	0.1	0.7	160	164.494	115	105.966
17	120	0.1	0.07	96	97.008	130	129.212
18	120	0.1	0.7	180	184.262	155	154.125
Average error of training data [%]:				1.32		2.34	
Test data							
19	160	0.05	0.5	118	117.628	187	186.333
20	120	0.1	0.22	121	124.966	153	155.436
21	120	0.25	0.22	139	138.503	151	150.959
Average error of test data[%]:				2.24		1.98	
Validation data							
22	90	0.2	0.1	120	129.967	121	121.163
23	120	0.045	0.22	156	151.060	145	139.411
24	120	0.1	0.07	164	183.557	165	157.024
Average error of validation data [%]:				5.48		1.74	

In this work, one of the most popular feed-forward networks was selected. This network is a multi-layer architecture proving to be an excellent universal approximation of non-linear functions. The feed-forward NN was trained by TRAINLM algorithms. The TRAINLM is a network training function that updates weight and bias values to Levenberg-Marquardt optimization.

Learning is a process by which the free parameters of the NN are adapted through a continuous process of simulation by the environment in which the network is embedded [21]. The learning function can be applied to individual weights and biases within the network. The LEARNGDM learning algorithms in feed-forward networks are used to adapt networks. Gradient descent method (GDM) was used to minimize the mean squared error between the network output and the actual error rate. It trains the network with gradient descent with the momentum back-propagation method. The back-propagation learning in feed-forward networks belongs to the real of supervised learning, in which the pairs of input and output values are fed into the network for many cycles, so that the network *learns* the relationship between the input and the output.

For this study, feed-forward network was selected since this architecture interactively creates one neuron at a time. This is an optimization procedure based on the gradient descent rule which adjusts the weights of the network to reduce the system error is hierarchical. The network always consists of at least three layers of neurons: the input, output, and middle hidden layer neurons. The input layer has inputs, which are: v [m min^{-1}] the cutting speed, f [mm rev^{-1}] – the feed, and a [mm] – the depth of cut. The outputs are the values of cutting temperatures for both inserts, fig. 1. Three parameters were set to optimize the network performance: the number of hidden layers is 12, the number of iterations is 100 and the number of neurons in the hidden layer is 20.

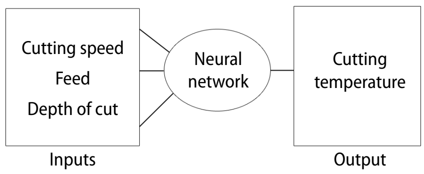

Figure 1. Network input and output layer

In this study, a part of the experimental data was used for training and the remaining data was used for testing the network. Each input has an associated weight that determines its intensity. The network can be trained to perform certain tasks where the data is fed into the network through an input layer.

This is processed through one or more intermediate hidden layers and finally it is fed out to the network through an output layer as shown in fig. 2. It must be highlighted that the best network architecture is reached by trial and error after considering different combinations of the number of neurons in the hidden layer, the number of hidden layers, spread parameter, and learning rate, depending on the type of NN being used.

Results and discussion

The regression plot of the ANN for zero angle for predicted cutting temperature is shown in fig. 3. The regression plots display the network outputs with respect to targets for training, validation, and test sets. From this plot, the value of the regression coefficient is found to be more than 97.7% which strongly justifies the acceptability in the prediction capability of the models. In case of the dry ANN model, the regression coefficient has a higher value. Hence, it can be concluded that this model is accurate.

Three different sets of data patterns were prepared for NN model development; the first set was comprised of 18 patterns for training, the second set was comprised of 3 patterns (15% of total patterns) for validation and the third set was comprised of 3 patterns (15% of total patterns) for the testing of network, fig. 3 and tab. 3. The parameters used in this testing and validation data were different from the data collected for the experiment.

Table 3 shows the compared values obtained by the experiment and the NN model. The average deviations of the ANN model for training parameters are 2.34% for zero rake angle

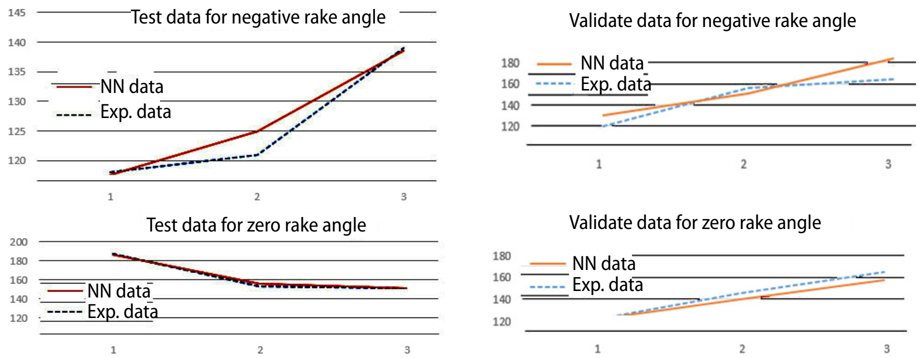

Figure 2. Error diagrams adopted for model test and validation

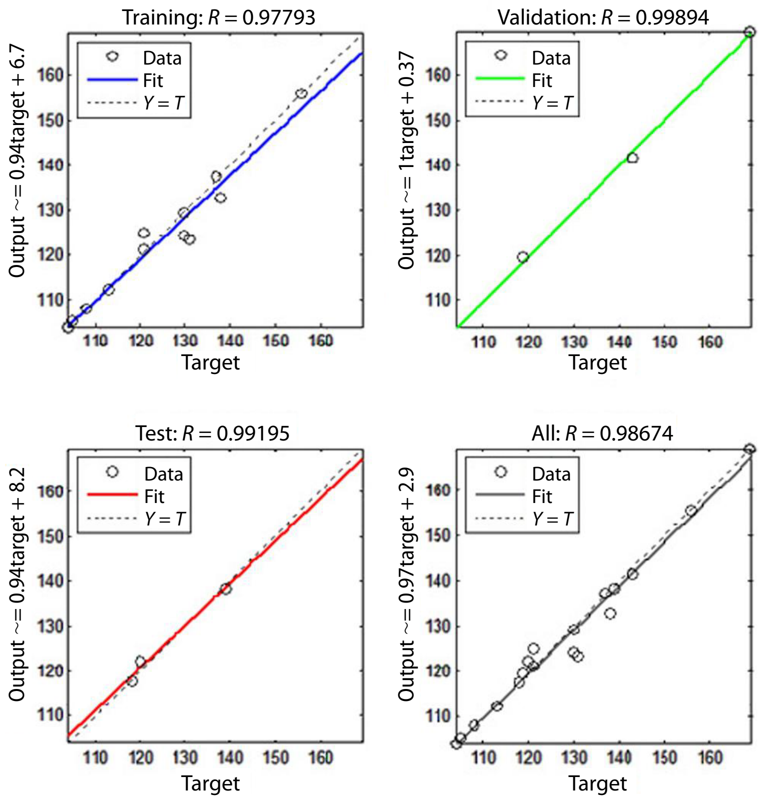

Figure 3. Linear regressions for actual and ANN predicted temperature for negative rake angle

and 1.32% for negative rake angle. The results obtained by the feed-forward network, using TRAINLM algorithms for training and LEARNGDM algorithms for learning, show agreement with the experimental data. This shows that the selected parameters to optimize the network performance were a good choice. The average deviations of the testing data for cutting temperature are 1.74% for zero angle and 5.48% for negative rake angle. Research showed that NN model gives accurate, precise prediction on cutting temperature, fig. 2.

Figure 4 shows the response surface graph of the analyzed variables in terms of the parameters selected from the turning process. These types of graphics allow us to know the way in which the temperature is at the same time influenced by two parameters.

Looking at the graphs, we can see that the highest temperature values for both rake angles were obtained for the depth of cut and feed values. For the maximum temperatures, if the response surface graph was observed, then cutting speed was the only variable that had a significant effect on the cutting temperature.

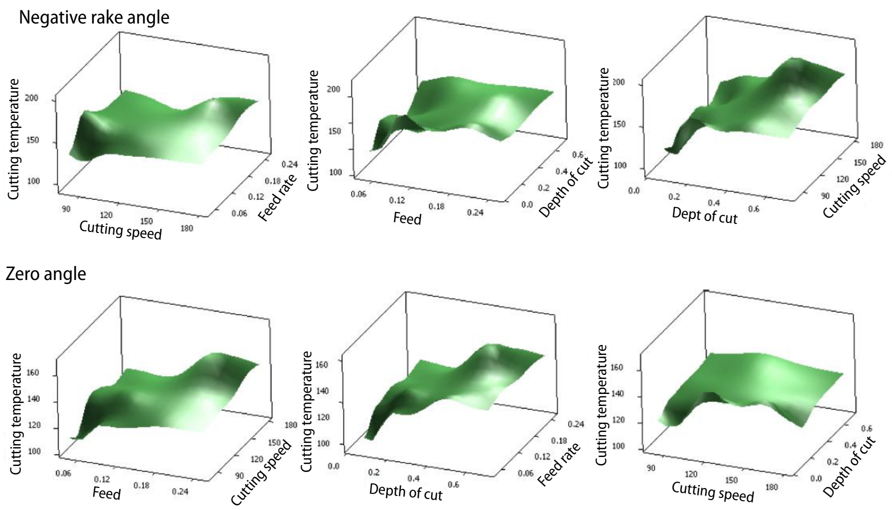

Figure 4. Response surface graph for cutting temperature
(*for color image see journal web site*)

The main effects plots represent the data means of each input variable level. Another type of graph that allows us to know about the behavior of different turning parameters is the main effects of plot. This plot depicts the way in which one of the input variables affects the temperature results. The influence of each input variable on the temperature values is shown in fig. 5. The tool temperature increases with the increase of cutting speed, feed and depth of cut for the negative rake angle. The influence of these machining parameters of the negative rake angle is higher than the influence of the same parameters of the zero angle.

Cutting speed for both rake angles has a similar effect on the cutting temperature, although somewhat higher temperature is obviously obtained when using the negative rake angle. Cutting speed for both rake angles has a similar effect on the cutting temperature, although somewhat higher temperature is obviously obtained when using the negative rake angle. Therefore, as expected, the higher the cutting parameters values, the higher the temperatures obtained.

Rake angle is a parameter used in various cutting and machining processes, describing the angle of the cutting face relative to the work. An insert with a zero rake angle reduces cutting temperature by allowing the chips to flow more freely across the rake surface.

With increases feed and depth of cut at negative rake angles, it is clear that the cutting temperature increase. This is due to the fact that the volume of work material coming in contact with the tool or the volume of material being removed also increases with the increase in feed rate. It can also be observed from fig. 5 that the cutting temperature continuously increase with feed, the increase is more prominent at negative rake angles while less at zero rake angles. This

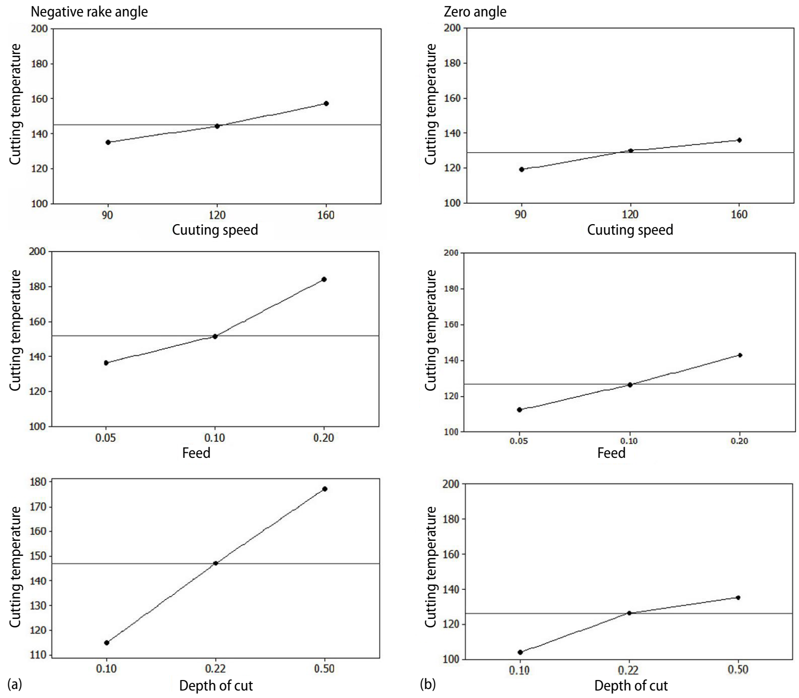

Figure 5. Effects of machining parameters on cutting temperature

is because the plunging effect of the tool into the workpiece material at a negative rake angle overshadows the effect of increase in cutting temperature with increase in feed at negative rake angles.

Rake angle have a great effect on the cutting temperature. Increasing and decreasing or keeping the rake angle negative and zero the cutting temperature thereby increases and decreases, respectively. When the negative rake angle is used, the shear strain is more, but for practical range, the negative rake angle has higher cutting temperature than zero rake angles, fig. 6.

The temperature distribution along the cutting edge at the tool-work contact area is shown in fig. 7. Temperatures on the rake face are measured by thermographic camera

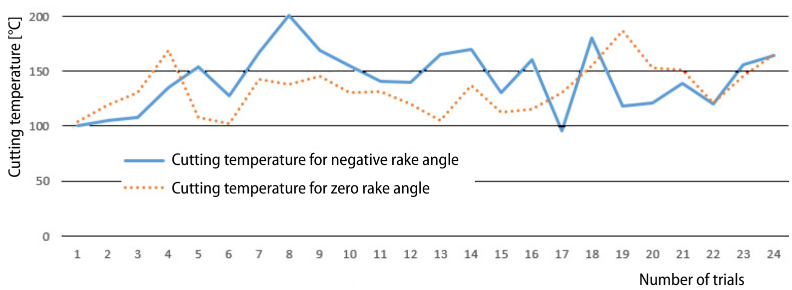

Figure 6. Comparison of cutting temperature for negative and zero rake angles

FLIR E50. In the figure, the temperature distribution is almost constant, but the temperatures at the negative rake angle are slightly higher. It is well known that the wear of the flank land is accelerated at points A and B. The temperature is much lower outside the contact area.

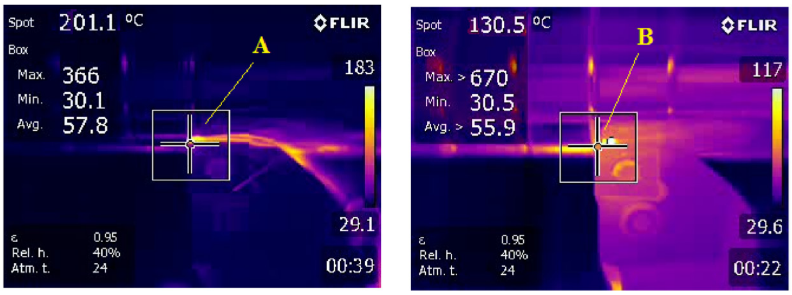

Figure 7. Values of cutting temperature for 160 m/min, 0.2 mm/rev, and 0.5 mm; (a) negative rake angle and (b) zero angle
(*for color image see journal web site*)

Conclusion

In this paper a NN system for the selection of the turning parameters has been introduced. The ANN model was developed based on the turning of cold work hard steel EN 90MnCrV8. Observations indicate that the ANN modeling results of turning were in good agreement with the experimental findings, demonstrating that approximately 95% of the predictions were achieved. Experimental results showed that, in machining without cooling and lubrication of hard steel EN 90MnCrV8 the cutting temperature increased with the increase in feed and depth of cut for the negative rake angle. The cutting speed has an influence on the cutting temperature for both angles. Negative rake angle have a higher effect than zero rake angle on the cutting temperature. The cutting temperature increase with decrease in rake angle from 0° to –6°. The comparison and validation of ANN results with the experiment findings verified the high accuracy of the models. The NN modeling technique could be an economical and successful method for the prediction of turning output parameters according to the input variables.

Nomenclature

a – depth of cut, [mm]
f – feed, [mmrev^{-1}]
r – nose radius, [mm]
v_c – cutting speed, [mmin^{-1}]

Greek symbols

α – back angle, [°]
γ – rake angle, [°]
θ – cutting temperature [°C]
κ, κ_1 – tool cutting edge angles, [°]
λ – cutting edge inclination angle, [°]

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