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DEVELOPMENT AND ANALYSIS OF ANN MODEL FOR TOOL LIFE PREDICTION IN DRY TURNING OF S355JR UNALLOYED STEEL

Abstract: *Assessment of tool life is of prime importance in machining process planning. The present study is focused on the development of tool life prediction model using artificial neural network (ANN). Data for model development were obtained using a tool and cutting data recommendation system of the cutting tool manufacturer and by applying full factorial design. The ANN prediction model was developed in terms of five input parameters, three parameters related to the machining process (depth of cut, feed rate and cutting speed) and two related to the cutting tool geometry (rake angle and cutting edge angle). Dry longitudinal single-pass turning of S355JR unalloyed steel using coated carbide tools was considered in the analysis. The adequacy of the developed ANN model was confirmed by considering the estimation of mean absolute percentage error and correlation coefficient, as well as residual analysis. In order to analyse and evaluate effects of considered input parameters on the tool life, sensitivity analysis of developed ANN model was conducted. Additional cutting data proved the generalization capability of the developed ANN model and its high prediction accuracy.*

Key words: *tool life, turning, ANN, sensitivity analysis, S355JR unalloyed steel, coated carbide tool*

1. INTRODUCTION

Tool life is one of the most significant criteria for assessment of cutting tool performance and machinability of materials [1]. It may be defined as the ability to preserve the tool cutting characteristics in certain operating conditions, while its assessment can be made with respect to effective cutting time, volume of removed chips, number of machined workpieces or total cutting length [2]. Most standard tool life tests use flank wear as criterion to define the end of tool life [1].

Reliable and accurate predictions of tool life is essential in manufacturing practice given that knowledge of tool wear and life can be helpful in multiple ways, such as process optimization regarding productivity, costs and scheduling, fulfilment of required tolerances, decrease of scrap, energy consumption [3,4,5]. In open literature and industrial practice one can find different methods and approaches for estimation of the tool wear and tool life. Among these, one can distinguish between model-based and data-driven methods (empirical mathematical modelling and use of AI), which belong to the in-direct methods, and direct methods, which use image recognition and deep learning to predict remaining tool life [6].

Choudhury and El-Baradie [7] applied experimental design method to develop first- and second-order tool-life models. Rao et al. [8] developed the extended Taylor model to predict tool life. Qehaja et al. [9] developed power model in terms of cutting speed, feed rate, depth of cut and tool flank wear. Laghari et al. [10] developed ANN model to predict tool life in SiCp/Al turning in terms of cutting speed, feed rate and depth of cut. Ojha and Dixit [11] proposed an economical and reliable procedure for the estimation of the tool life including the methodology for tool usage monitoring based on the shopfloor feedback, and approach for updating Taylor's tool life exponents. Królczyk et al. [12] proposed a second-order polynomial model to study the effects of depth of cut, feed rate and cutting speed on tool life. An approach for prediction of tool life in turning based on ANN models, which uses wear parameters, obtained by image processing, as model inputs was presented by Mikołajczyk et al. [5]. Bagga et al. [3] proposed a computer vision-based tool wear monitoring and tool life prediction system using machine learning methods. Gradient-boosted trees and support vector machine methods were also used for the prediction of tool life. Gao et al. [13] proposed reliability Taylor tool life equation in which approximate Bayesian theory was used to update reliability model parameters. Albertelli et al. [14] developed a generalized tool life model for considering non-stationary cutting conditions. A stochastic Markov model for prediction of remaining tool life was discussed by Mishra and Bhardwaj [15]. Hage et al. [16] proposed a novel combination of a tabu search algorithm with the regression analysis for the development of tool life prediction models in terms of spindle speed, depth of cut and feed rate. Karkalos and Markopoulos [17] analysed applicability of different experimental designs and ANN for prediction of tool life using CBN tools for a wide range of cutting speeds.

Given that the determination of the effect of each parameter on tool life is of crucial importance when designing the manufacturing process of a product in order to select suitable process parameter values and tool types [17], the present research deals the analysis of the effects of three parameters related to the machining process (depth of cut, feed rate and cutting speed) and two related to the cutting tool geometry (rake angle and cutting edge angle) on the tool life in dry longitudinal single-pass turning of S355JR unalloyed steel using coated carbide tools. Data for the analysis were obtained using a tool and cutting data recommendation system of the cutting tool manufacturer [18] and were modelled using ANN.

2. EXPERIMENTAL DATA

The start diameter for longitudinal single-pass turning was 120 mm, while the machined length was 60 mm. The workpiece material was S355JR unalloyed medium-carbon structural steel (hardness 161 HB). It is used for medium to high strength non-vital machine parts, with good toughness and easy formability. The machine tool was the CNC lathe with the motor power of P_m = 37 kW, the maximum spindle speed of n_{max} = 2000 rpm, and the maximum torque of M_{cmax} = 4200 Nm.

Walter was selected as cutting tool manufacturer. The cutting tools were toolholders DDJNR2525M15 (cutting edge angle of κ = 93°, rake angle of γ_{oh} = -6°) and DDNNN2525M15 (κ = 62.5°, γ_{oh} = -6°), with DNMG150612-MP3 WPP10G (γ_{oi} = 22.5°) and DNMG150612-MP5 WPP10G (γ_{oi} = 15°) coated carbide inserts for medium machining. Cutting parameter ranges and levels were selected considering availability and capabilities of the tool and cutting data recommendation system of the cutting tool manufacturer and recommended cutting conditions for the inserts. For the DNMG150612-MP3 WPP10G insert, the minimal and maximal depth of cut values were set to 1.2 and 3.5 mm, respectively, the minimal and maximal feed rate values were set to 0.16 and 0.40 mm/rev, respectively, while the cutting tool rake angle was 16.5°. For the DNMG150612-MP5 WPP10G insert, the minimal and maximal depth of cut values were set to 1.2 and 5.0 mm, respectively, the minimal and maximal feed rate values were set to 0.20 and 0.40 mm/rev, respectively, while the cutting tool rake angle was 9°. The cutting speed values for both inserts were selected considering availability and capabilities of the tool and cutting data recommendation system of the cutting tool manufacturer. It allows selection of values for the cutting speed from ranges that are different for different feed rate values, due to power limitation (e.g., for the feed rate value of f = 0.16 mm/rev the cutting speed value can be selected from the range of 351 – 550 m/min, while for the feed rate value of f = 0.40 mm/rev the cutting speed value can be selected from the range of 269 – 421 m/min). For the DNMG150612-MP3 WPP10G insert, the minimal and maximal selected cutting speed values were 269 and 550 m/min, respectively. For the DNMG150612-MP5 WPP10G insert, the minimal and maximal selected cutting speed values were 269 and 525 m/min, respectively. The cutting edge angles were 62.5° and 93° for both inserts. Data for the analysis were obtained using a tool and cutting data recommendation system of the cutting tool manufacturer [18]. The total number of different cutting conditions that were attempted in the virtual experiment was 108.

3. TOOL LIFE MODEL

To establish mathematical relationship between inputs and output, a multi layer perceptron (MLP) ANN architecture was chosen for its exceptional ability to approximate arbitrary functional dependencies. The number of hidden neurons was determined considering the number of ANN hyper-parameters (weights and biases) to be determined in the training process, and the number of available data. Linear transfer function and tangent sigmoid transfer function were used in the output and hidden layer, respectively. The entire set of cutting data was randomly divided into the data set for training (60% of data), used to develop ANN model, the data set for validation (20% of data), used to handle bias-variance trade-off and validate developed ANN model, and testing set (20% of data), for statistical assessment of the generalization capability of the developed model. The specified ANN model was trained using Levenberg-Marquardt algorithm due to its high accuracy and fast convergence [19]. Only fourteen epochs were sufficient for training process as no further improvement in ANN model performance was achieved. The mean absolute percentage error between ANN model predictions and the tool life values on the entire set of data was found to be 1.85%, which indicated the validity of the developed model. ANN model prediction results in relation to the experimental data are given in Figure 1. As could be observed, there exists perfect correlation for the entire set of gathered cutting data, thus confirming high performance capability of the developed ANN model. Residual analysis was also performed in order to further validate the appropriateness of the developed model for the prediction tool life (Figure 2). Residuals are scattered around zero with mean value close to zero, indicating closeness of predicted and observed values and unbiased prediction capability of the ANN model. Absence of obvious patterns also confirms the adequacy of the proposed prediction model. Finally, approximately even spread of the residuals across fitted values of tool life means that the model fits consistently in all regions of the covered experimental hyper-space.

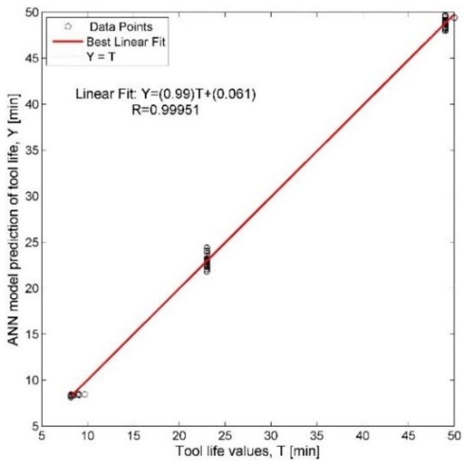

Fig. 1. Performance of ANN tool life prediction model

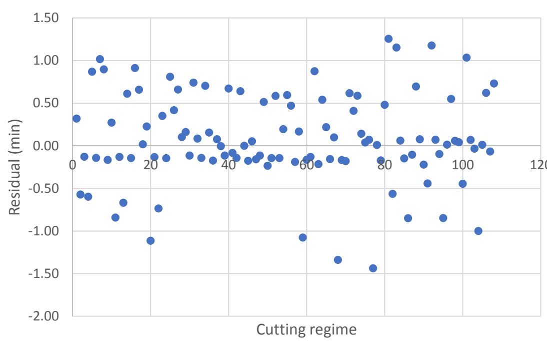

Fig. 2. Scatter plot of ANN models' residuals

4. RESULTS AND DISCUSSION

Sensitivity analysis is a very popular approach for knowledge extraction when using ANN. The idea of this approach is to simulate trained ANN model with different input data patterns and record how inputs affect output values over a range of values [20]. In the present study, four parameters were kept constant (at low, medium, and high level), while the fifth input parameter was varied at three levels (low, medium, and high). Subsequently, by ANN model simulation it was possible to observe the change in tool life values as the difference between maximal and minimal values (Figure 3).

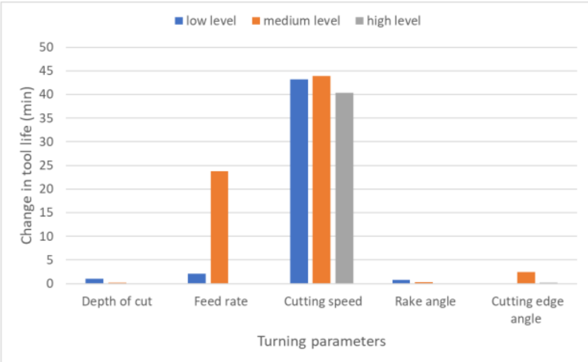

Fig. 3. Main effects of turning parameters on tool life

As could be observed, irrespective of whether other turning parameters are set at low, medium, or high level, cutting speed has the most significant effect on tool life. The effect of feed rate is also pronounced, particularly when all other turning parameters are set at medium level. Effects of cutting edge angle, depth of cut and rake angle on tool life are negligible. Based on performed analysis in general, there exist indirect relationships between feed rate, cutting speed, rake angle, cutting edge angle and resulting tool life. It is interesting to note that with an increase in depth of cut, one may observe insignificant change in tool life or even a slight increase. In sum, if one tends to extend tool life, cutting tool with rake angle of 16.5° and cutting edge angle of 93° is to be used under the following cutting conditions: depth of cut 5 mm, feed rate 0.16 mm/rev and cutting speed of 269 m/min. Under this cutting regime ANN model predicts tool life of 51.28 min.

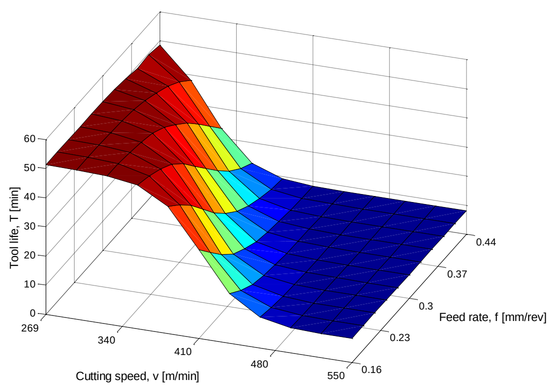

Fig. 4. Interaction effect of two most significant parameters on tool life (constant parameters: a_p = 5 mm, κ = 93°, γ = 16.5°)

Given that cutting speed and feed rate are the most significant turning parameters affecting tool life, it was decided to analyse their combined effect by developing 3D surface plot (Figure 4). As could be observed from Figure 4, there is no significant interaction effect, however, one can observe that at high feed rates, an increase in cutting speed leads to a faster decrease in tool life. It is interesting to note that for maximization of the tool utilization cutting regime with the highest possible tool life may not be, as a rule, the best solution, given that resulting material removal rates may differ for the same value of the tool life.

Given the high dimensionality of the input data, novel data from the tool and cutting data recommendation system of the cutting tool manufacturer [18], which were not used previously, were used to further assess model performance generalization capability. Four cutting regimes and tool geometry specifications were considered, as given in Table 1. With a mean absolute percentage error below 5% one can argue that ANN model proved to be able to adequately model tool life in five-dimensional hyper-space.

Cutting data	Trial 1	Trial 2	Trial 3	Trial 4
f (mm/rev)	0.34	0.22	0.25	0.36
a_p (mm)	1.8	3	2.1	4
v (m/min)	317	468	408	305
γ_o (°)	16.5	16.5	9	9
κ (°)	93	62.5	93	62.5
T (min) [18]	33	13	18	42
T (min) ANN model	34.76	13.75	17.5	39.59

Table 1. Additional cutting data for assessment of ANN model performance

5. CONCLUSION

The present study was focused on the development of ANN model for tool life prediction in dry longitudinal single-pass turning of S355JR unalloyed steel using coated carbide tools. Unlike traditional and extended Taylor's tool life models, the derived model was developed in terms of three parameters related to the machining process (depth of cut, feed rate and cutting speed) and two related to the cutting tool geometry (rake angle and cutting edge angle). It was observed that ANN model with 5-4-1 architecture, trained with Levenberg-Marquardt algorithm, proved to be able to capture the underlying dependencies between inputs and output with high accuracy and also showed very good generalization capability. Analysis of obtained results indicated the dominant effect of cutting speed on tool life, followed by the effect of feed rate, while the effects of cutting edge angle, depth of cut and rake angle on tool life are negligible. Analysis of interaction effect of the two most significant parameters (cutting speed and feed rate) indicated that there is no qualitative change in parameter effects. However, more comprehensive analysis, which included the consideration of MRR, indicated that some cutting conditions having lower tool life may be preferable given that these conditions enable removal of higher volume of material (chip).

The derived prediction model can be used in formulation of turning optimization problems to select the most appropriate cutting parameter values with respect to different objective functions, such as machining time, production costs, etc. Future work will consider application of connection weight approach for ranking the importance of considered input variables and dual-response approach for simultaneous analysis of tool life and material removal rates.

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