23rd ABCM International Congress of Mechanical Engineering
December 6-11, 2015, Rio de Janeiro, RJ, Brazil

APPLICATION OF INTELLIGENT TECHNIQUES AND REGRESSION ANALYSIS FOR MODELLING CUTTING TEMPERATURE IN FACE MILLING

Pavel Kovač
Dragan Rodić
Vladimir Pucovsky
Borislav Savković
Marin Gostimirović
Milenko Sekulić
University of Novi Sad, Faculty of Technical Sciences, Institute for Production Engineering, Trg Dositeja obradovića 6, Novi Sad, Serbia
pkovac@uns.ac.rs
rodicdr@uns.ac.rs
pucovski@uns.ac.rs
savkovic@uns.ac.rs
maring@uns.ac.rs
milenkos@uns.ac.rs
Ildiko Mankova
Technical University of Košice, Faculty of Mechanical engineering, Masiarska 74, 04001 Kosice, Slovakia
ildiko.mankova@tuke.sk

Abstract. *A new approach in modelling cutting temperature which uses artificial intelligence tools is described in this paper. This paper proposes a methods for developing empirical models using neural network and regression analysis. The neural network model for determining the cutting temperature of steel AISI 1060, was trained and tested by using the experimental data. The values of cutting temperature predicted by these models are then compared. All models show good agreement with experimental results. The results indicate that the neural network modelling technique can be effectively used for the prediction of cutting temperature in face milling.*

Keywords: *neural network, regression analysis, cutting temperature, face milling*

1. INTRODUCTION

Cutting temperature in the metal cutting process are very important factors affecting production optimization. The importance of temperature prediction for the machining processes has been well recognized in the machining research community primarily due to its effects on tool wear and its constraints on the productivity "Usui, *et al*., 1978". Temperature modelling of any manufacturing process is usually a difficult task. The modelling techniques of input–output and in–process parameter relationships are mainly based on statistical methods and artificial intelligence tools "Rajmohana, *et al*., 2013 ". This paper focuses on an approach using the neural network and regression analysis for modelling of cutting temperature in face milling, without the application of cooling and lubricating agents. Different of analytically methods were also developed and used for predicting cutting temperature. "Wanigarathne *et al.*, 2005" examined the cutting tool–wear progression through an experimental study focusing on cutting temperatures and progressive tool–wear. "Recent work Grzesik and Luttervelt, 2005" predict the temperature fields in uncoated and coated carbide cutting tools. Numerical computations are supported by the experimentally/analytically obtained values of the contact length, the total heat flux and the heat partitioning. "Recent work Lazoglu and Altintas, 2002" have applied the finite difference method, for the first time for the prediction of steady-state tool and chip temperature fields in continuous machining and transient temperature variation in interrupted cutting (milling) of different materials such as steels and aluminum alloys. Unfortunately, most analytical studies thus far were focused on thermal modelling only for fresh tools. One of the important aims of this paper is to examine the influence of flank wear on cutting temperature in face milling.

Neural network (NN) is a theory used for describing the relationship between system inputs and outputs. It is widely used to develop rule–based expert systems in complex process modelling that are difficult to be modelled analytically under various assumptions "Rodic, *et al*, 2014". There have been many successful applications of neural network in metal machining. "Recent work Tanikic *et al.*, 2010 " presented the application of artificial neural networks and a hybrid, neuro–fuzzy model in the prediction of a workpiece temperature and surface roughness. "Recent work Aydin *et al.*, 2012 " presented an approach for modeling and prediction of both surface roughness and cutting zone temperature in turning of austenitic stainless steel using multi–layer coated tungsten carbide tools. "Recent work Adesta *et al.,* 2012 " applied neural network as an effective tool for modelling and predicting the cutting temperature in machining of hardened steel at high cutting speeds produces high temperatures in the cutting zone, which affects the surface quality and cutting tool life. "Recent work Savkovic *et al.,* 2013" developed neural network model on the face milling machining processes where is aimed to produce the relationship of cutting force versus instantaneous angle φ. The research conducted in the paper allows solving the problem that is difficult to define and mathematically modelled.

In this study, cutting speed, feed rate, depth of cut and width of flank wear land as machining conditions were selected. A neural network and regression models were developed and compared using these cutting parameters. Contribution of this paper is that not only modelling is done by neural network but comparison of two modelling methodologies, the classical regression method and neural network, is shown. As addition in the proposed model tool wear is also included because it is influential parameter in cutting temperature modelling. Inclusion of the wear in the model requires a much longer and more expensive experimental study, because it has to monitor the wear and cutting temperature parameters to the end of tool life. Comparative observation showed that the neural network model gives slightly smaller deviation of the measured values of model than regression method.

2. DESIGN OF EXPERIMENTS

The experiments have been carried out on steel AISI 1060 in normalized condition. The working material was a block of 100x120x600 mm of above steel and was fixed on milling machine table. The single tooth face milling cutter of 125 mm diameter, with plates of hard metal SPAN 12 03 ER, quality P25 were used as tool. The investigations have been carried out on the vertical milling machine, with driving power of 14 kW. All the investigations have been carried out without the application of cooling and lubricating agents. The measurement of temperature change on flank surface was performed by a standard thermocouple Cr–Ni built in cutting tool.

In planning and conducting the experiment, four factorial 2k central compositional experimental plans were used. Selected factors of experiment have changed in five levels of value. This method allows investigating the wider interval of parameters and the predicted mathematical model is more reliable. The experiment was carried out for different combinations of cutting speed (v) [m / s], feed per tooth (f) [mm / tooth], or the appropriate machines speed [mm / min], cutting depth (a) [mm], flank wear land (VB) [mm] according to the planning of experiment.

3. MODELING TECHNIQUES

3.1 Neural networks

A multilayer feed-forward network has been used, and the back-propagation training algorithm has been employed to train the network. Back-propagation is a systematic method for training multilayer NN. A back-propagation network is a multilayer feed-forward network which uses gradient-descent method to minimize the total squared error of the output computed by the net. The training algorithm of back-propagation involves four stages which are initialization of weights, feed-forward, back-propagation of errors, and updating the weights and biases [8]. Modelling of cutting temperature with feed forward neural network is composed of two stages: training and testing of the network with experimental machining data. The scale of the input and output data is an important matter to consider, especially when the operating ranges of process parameters are different. The scaling or normalization ensures that the NN will be trained effectively without any particular variable skewing the results significantly. As a result, all the input parameters are equally important in the training of network. The architecture of the designed network comprises four input neurons corresponding to one input parameters, an output layer with one neuron corresponding to one output parameter at a time, and a single hidden layer of neurons. The transfer functions which have been used are tansig and purelin in hidden and output layers, respectively. The transfer function tansig is a hyperbolic tangent sigmoid transfer function, and purelin is a linear transfer function. With the help of back propagation training data set (Input parameters related to output parameters) is set to utilize to train the neural network. Two input parameters and one output parameter are considered. The selected input parameters should be easily variable and can be easily changed by the operator. Selected input parameters are: of cutting speed (v) [m / s], feed per tooth (f) [mm / tooth] or the appropriate machines speed [mm / min], cutting depth (a) [mm], flank wear land (VB) [mm] and output parameter is: Cutting temperature θ [°C]

A good number of experiments have been performed, and their results have been used for training and testing of the network. Randomly selected results (75%) have been used for training, and the rest of the results (25%) have been used for testing.

3.2 Regression analysis

In order to establish the effectiveness of neural network model, it is necessary to employ a theoretical model for prediction purposes by using conventional techniques (regression modelling) to modelling cutting temperature. These adequate regression models were obtained as follows:

$$T = 139{,}4950 \cdot v^{0,4515} \cdot f^{0,2726} \cdot a^{0,4326} \cdot VB^{0,1969} \tag{1}$$

where θ – cutting temperature [°C], T – tool life [min], v – cutting speed in m/s, f – feed [mm/tooth], a – depth of cut in [mm] and VB – flank wear land in [mm].

4. RESULTS

Comparative observation showed that the neural network model gives a slightly smaller deviation of the measured model values than the regression method. Table 1 shows the compared values obtained by the experiment, and estimated by the models of neural network and regression analysis.

Table 1. Test results.

Cutting speed (v) [m / s]	Feed per tooth (ft) [mm / t]	Cutting depth (a) [mm]	Flank wear (VB) [mm]	Cutting temperature		
				Exp. θ [°C]	NN θ [°C]	Reg. θ [°C]
2,32	0,178	2,25	0,12	115	115,0054	119,2
3,67	0,280	1	0,28	147	146,9957	122
3,67	0,178	2,25	0,28	161	160,9894	173,2
1,83	0,223	1,5	0,18	117	100,9889	103,5
2,95	0,351	1,5	0,18	157	157,0071	145,3
Average error [%]					2,7407	9,3385

The average deviation of the neural network for cutting temperature is 2,74%, while the average deviation of the regression model for cutting temperature is 9,34%. Research showed that the neural network model gives a more accurate prediction of cutting temperature.

In Fig. 1 we plotted the main effects for cutting temperature. This figure displays the effect of machining parameters and their interaction on cutting temperature. The influence of feed rate on cutting temperature change is similar to the impact of cutting speed. Fig. 1 displays value of cutting temperature increases with the increase of cutting speed and feed rate. The most significant factor on the cutting temperature is the depth of cut. It is clearly observed that the depth of cut strongly affects cutting temperature parameters. The depth of cut has an increasing effect.

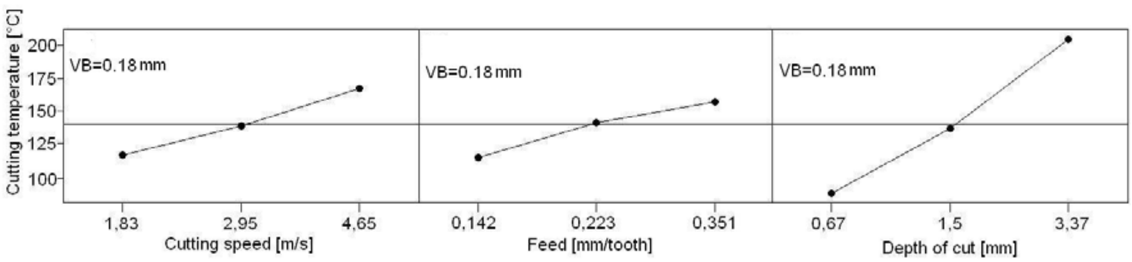

Figure 1. Influence machining conditions on cutting temperature

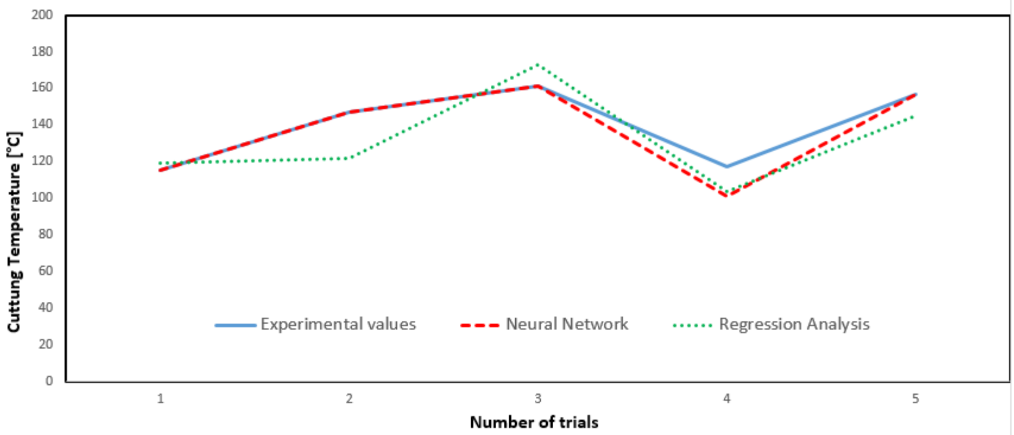

Figure 2. Correlation between experimental, neural network and regression analysis cutting temperature value

Results obtained by back-propagation training algorithm, using multilayer feed-forward network, show agreement with experiment. This shows that the selected types of neural network are a good choice (Fig. 2).

5. CONCLUSIONS

This optional section must be placed before the list of references. This paper suggests a neural network for selecting the introduced face milling parameters. The neural network model was developed based on the face milling of correction steel AISI 1060. The adequacy of the model is checked and is found to be adequate at 90% confidence level and the model can be used for predicting the cutting temperature and in machining of AISI 1060. Experimental results showed that, in machining of correction steel AISI 1060 the cutting temperature increased with an increase in depth of cut. The remaining parameters have less influence on the cutting temperature. Although neural network model is a bit complicated to develop than regression model (need of experience and knowledge). Comparison and validation of neural network results with experiment findings verified the high accuracy of models. The neural network modelling technique could be an economical and successful method for prediction of face milling output parameters according to input variables.

6. ACKNOWLEDGEMENTS

The paper is the result of the research within the project TR 35015 financed by the ministry of science and technological development of the republic of Serbia and CEEPUS project.

7. REFERENCES

Aydın, M., Karakuzu, C., Ucar, M., Cengiz, A. and Cavuslu, M.A., 2012. "Prediction of surface roughness and cutting zone temperature in dry turning processes of AISI304 stainless steel using ANFIS with PSO learning". International Journal of Advanced Manufacturing Technology, Vol. 64, p. 1045.

Erry, Y.T. Adesta, Muataz, H.F., Al Hazza Suprianto, M. and Muhammad, R., 2012. "Prediction of Cutting Temperatures By Using Back Propagation Neural Network Modeling When Cutting Hardened H-13 Steel in CNC End Milling". Advanced Materials Research, Vol. 576, p. 91.

Grzesik, W. and Luttervelt, V., 2005. "Analytical models based on composite layer for computation of tool- chip interface temperatures in machining steels with multilayer coated cutting tool", (Annals of CIRP), Vol. 54, p. 91.

Lazoglu, I. and Altintas, Y., 2002. "Prediction of tool and chip temperature in continuous and interrupted machining". *International Journal of Machine Tools & Manufacture*, Vol. 42, p. 1011.

Rajmohana, T., Palanikumar, K. and Prakashc, S., 2013. "Grey–fuzzy algorithm to optimise machining parameters in drilling of hybrid metal matrix composites". Composites Part B: Engineering, Vol.50, p. 297.

Rodic, D., Gostimirovic, M., Kovac, P., Radovanovic, M. and Savkovic, B., 2014. "Comparison of fuzzy logic and neural network for modelling surface roughness in EDM". International Journal of Recent advances in Mechanical Engineering, Vol. 3, p. 69.

Savković, B., Kovač, P., Gerić, K., Sekulić, M. and Rokosz, K., 2013. " Application of neural network for determination of cutting force changes versus instantaneous angle in face milling", Journal of Production Engineering, Vol. 16, p. 25.

Tanikic, D., Manic, M., Devedzic, G. and Stevic, Z., 2010. "Modelling Metal Cutting Parameters Using Intelligent Techniques", Journal of Mechanical Engineering, Vol. 56, p. 52.

Tsai, K.M. and Wang, P.J., 2001. "Predictions on surface finish in electrical discharge machining based upon neural network models". Int J Mach Tools Manuf, Vol. 41, p. 1385.

Usui, E., Hirota, A. and Masuko, M., 1978. "Analytical prediction of three dimensional cutting process, Part 3: Cutting temperature and crater wear of carbide tool". Journal of Manufacturing Science and Engineering, Vol.100, p. 236.

Wanigarathne, P.C., Kardekar, A.D., Dillon, O.W., Poulachon, G., and Jawahir, I.S., 2005. "Progressive tool–wear in machining with coated grooved tools and its correlation with cutting temperature". Wear, Vol. 259, p. 1215.

8. RESPONSIBILITY NOTICE

The authors are the only responsible for the printed material included in this paper.