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Article in *Solid State Phenomena* · March 2013

DOI: 10.4028/www.scientific.net/SSP.199.371

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Wear Model in Milling Compacted Graphite Iron with Different Lead Angle Using Ceramic Cutting Tools

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Keywords: compacted graphite iron (CGI), tool life, flank wear (VB), milling, ANN, regression analysis.

Abstract. The objective of this study is to reveal the influence of the lead angle variation on tool wear in the process of face milling of compacted graphite iron with ceramic cutting tools. To achieve this goal, 36 milling experiments were carried out with different lead angles, cutting speeds and feed rates at the 2.5 mm constant depth of cut. The tool flank wear was strongly affected by the lead angle variations. SEM analyses of the cutting inserts were performed and experimental results have been modelled with artificial neural networks (ANN) and regression analysis. A comparison of ANN model with regression model is also carried out. The R^2 values for testing data were calculated as 0.992 for ANN and 0.998 for regression respectively. This study is considered to be helpful in predicting the wear mechanism of the ceramic cutting tool in the machining of compacted graphite iron. A quicker method for the estimation of tool life is proposed, which requires less consumption of workpiece material and tools.

Introduction

Compacted graphite iron (CGI) is an attractive material for automotive industry, because it combines the thermal properties of lamellar cast iron [1] with the mechanical strength of spheroidal graphite iron [2]. However, the machinability of CGI is poor when compared to grey cast iron [3], and it is the main restriction for a large scale production of CGI. An important aspect of machinability of workpiece material is the tool wear. High wear rates of tool material are usually associated with a poor machinability [4]. Schmitt and Schulz carried out some turning and milling test. During the milling tests the cutter was equipped with only two inserts. The turning test pieces were machined by longitudinal turning with a single insert. Test results show that low cutting speeds (150-250 m/min) with conventional coated carbide tools provide approximately 50 % of the tool life of gray cast iron in both milling and turning. Similarly, milling at high cutting speeds (400-800 m/min) with ceramic or polycrystalline cubic boron nitride also provides approximately 50 % of the gray iron tool life [5,6]. Ceramic materials generally have good properties as cutting tools, such as high hot hardness, good abrasion resistance, low-thermal conductivity and excellent chemical stability [7-10]. In the field of process engineering, ANN is a good alternative to conventional empirical modeling based on polynomial and linear regressions. The analysis of engineering systems is generally based on numerical solution methods. For this purpose, regression analysis method also has been used in this study. The aim of the presented study is to develop a new approach based on ANNs and regression analysis to determine the effect of the lead angle on the wear mechanism when milling CGI various cutting speed and feed rates. This study consists of two phases: (1) the experimental analysis to determine the wear mechanism of the ceramic insert was performed 36 wear experiments at various cutting conditions respect to different lead angle, cutting speed and feed rates in the machining of CGI while maintaining a constant metal removal rate; (2) The mathematical modeling analysis has been developed by the ANN and regression analysis model using results of experimental data. The research literature shows that many studies focus on investigation the difference in machinability of CGI. In this study, the effects of lead angle variation and different cutting parameters on the wear behavior of ceramic inserts in CGI machining are studied.

Material and methods

The experiments were carried out on a very rigid Jhonford VMC550 CNC milling machine tool using with 45°, 60°, 75°, and 88° lead angle cutters. Two inserts were used equally spaced at 180° in the milling cutter in dry cutting conditions and down milling was used in the experiments. Rectangular blocks of 200 x 200 x 100 mm CGI were used for experiments. The chemical compositions of the CGI were obtained during the casting process for 9 lt. motor blocks is given in a Table 1 and mechanical properties of CGI is given in a Table 2 respectively. The milling cutter diameter had 63 mm and cutting width is 40 mm. The ceramic CC6090 inserts were used Si₃N₄-based (Sialon) with ISO code R245-12 T3 E 6090. The cutter and insert assembly provide a positive geometry. Maximum chip thickness (h_{ex}) values of 0.07, 0.084 and 0.1008 mm and cutting speeds of 400, 460 and 530 m/min were used for all milling trials.

Tab. 1. Chemical composition of CGI (wt%)

C	Si	Mn	P	S	Cr	Ni	Mo
3.82	1.804	0.337	0.031	0.015	0.074	0.013	0.002
Cu	Mg	Sn	Ti	Al	Zn	Bi	Fe
0.879	0,014	0.092	0.0203	0.008	0.082	0.007	residual

Tab. 2. Mechanical properties of CGI

Ultimate Tensile Strength (MPa)	% 0.2 Yield Strength (MPa)	Elongation (%)	Typical Hardness,HV	Impact test (Joule)
502.7	284.3	1.8	280	8.6

A total of 36 tests were given by a combination of these parameters for tool life experiments. Various feed rates were used in the experimental trials depending on the $h_{ex} = f_z \times \sin \kappa_r$ equation. The tool life was evaluated according to removed material volume (500 cm³) and the tool rejection criteria for the cutting experiments were the flank wear $VB \geq 0.3$ mm.

Estimation of tool life by ANN

To estimate the output value of the wear rate, a multi layer feed –forward network is trained with 36 data obtained from experimental results and tested for its ability to generalization and interpolation in this study. The used architecture of ANN that estimates the flank wears (VB) is shown in Fig.2. In the training step, an input is introduced to the network together with the desired output. The weights and bias values are initially chosen randomly, so the weights are adjusted to produce the desired output in the network attempts. While the weights are random and have no meaning before training, they contain meaningful information after training. The prediction performance of the developed ANN model is determined by applying different error analysis methods. These methods are the coefficient of determination (R^2), root mean square error (RMSE) and mean absolute percentage error (MAPE). These parameters are defined and calculated as follows:

$$R^2 = 1 - \left(\frac{\sum (VB_i - VB_{ANN,i})^2}{\sum (VB_{ANN,i})^2} \right) \quad (1)$$

$$RMSE = \sqrt{\left(\frac{1}{n} \sum_{i=1}^n |VB_{ANN,i} - VB_i|^2 \right)} \quad (2)$$

$$MAPE = \sqrt{\left(\frac{VB_{ANN} - VB}{VB_{ANN}} \times 100 \right)} \quad (3)$$

The back-propagation learning algorithm has been used in the feed forward work with four hidden layers having fourteen neurons. Inputs and outputs are normalized in the (-1,1) range. The Fermi transfer function has been used in eq. (4)

$$N(z) = \frac{1}{1 + e^{-4(z-0.5)}} \quad (4)$$

Where z is weighted sum of the input, Pythia-neural network designer software has been used as an ANN computer program. Fig.2 shows the four hidden- layer ANN architecture used in application. After the training step was completed, it was compared with 8 test data to check the accuracy of the network. The new formula of output as the best algorithm LM with fifteen neurons is given in Eq. (5). This equation can be used to estimate flank wear rate when milling CGI where the lead angle, cutting speed (V_c), maximum chip thickness (h_{ex}) and table feed rate (V_f), are the known input parameters. Each of the input values is multiplied by connection weights. Weighted input values are added linearly and they are converted to the output values. These outputs are used as the input values for the other neurons as shown in Fig.2.

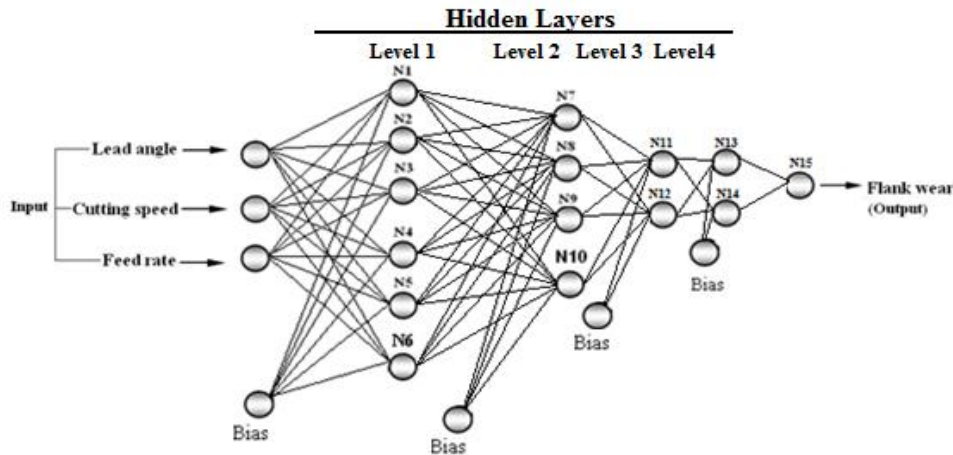


Fig. 2. ANN structure in LM algorithm with fifteen neurons

$$N_{15}(VB) = \frac{1}{1 + e^{-4(2.68484 * N_{13} - 2.264778 * N_{14} - 0.5)}} \tag{5}$$

In Eq. (5), N_6 to N_9 values are calculated according to this rule. For each of the hidden layer levels E_i are calculated according to the level neurons.

$$N_{(i)} = \frac{1}{1 + e^{-4 * (E_i - 0.5)}} \tag{6}$$

The neurons 1–5 E_i are calculated using the Eq. (7). In this equation i represent the neuron number. Obtained constants are given in Table 3.

$$E_i = w_{1i} * V_c + w_{2i} * \kappa_r + w_{3i} * V_f \tag{7}$$

Tab. 3. Constants used in eq. (7) from neurons 1-5

i	Constants		
	w_{1i}	w_{2i}	w_{3i}
1	0.722765	0.057003	-0.218459
2	0.051442	-0.162736	-0.416983
3	-0.319189	-0.096655	1.327603
4	-0.346647	0.132961	-0.092823
5	-1.643332	-0.223513	-0.056815
6	0.911424	0.134206	-0.38016

The neurons 7–10 E_i are calculated using the Eq. (8), the neurons 11-12 E_i are calculated using the Eq. (9) and the neurons 13-14 E_i are calculated using the Eq. (10). Obtained constants are given in Table 4, Table 5 and Table 6 respectively.

$$E_i = w_{1i} * N_1 + w_{2i} * N_2 + w_{3i} * N_3 + w_{4i} * N_4 + w_{5i} * N_5 + w_{6i} * N_6 \tag{8}$$

$$E_i = w_{1i} * N_7 + w_{2i} * N_8 + w_{3i} * N_9 + w_{4i} * N_{10} \tag{9}$$

$$E_i = w_{1i} * N_{11} + w_{2i} * N_{12} \tag{10}$$

Tab. 4. Constants used in eq. (8) from neurons 7-10

<i>i</i>	Constants					
	w_{1i}	w_{2i}	w_{3i}	w_{4i}	w_{5i}	w_{6i}
7	0.218985	-0.626447	0.477632	-1.210188	-1.333063	0.294570
8	0.307321	0.188230	0.059982	0.340966	1.963849	-0.901311
9	0.231298	0.660768	-0.085428	0.146600	-0.829829	-0.201232
10	0.819858	-1.017972	0.182591	-1.351522	-1.057759	-0.019937

Tab. 5. Constants used in eq. (9) from neurons 11-12

<i>i</i>	Constants			
	w_{1i}	w_{2i}	w_{3i}	w_{4i}
11	-1.792269	1.341304	-0.104920	-0.265596
12	0.423498	-1.946949	-0.268216	0.633974

Tab. 6. Constants used in eq. (10) from neurons 13-14.

<i>i</i>	Constants	
	w_{1i}	w_{2i}
13	-0.917143	1.072589
14	1.803513	-1.736131

The input and output layers are normalized in (-1,1) or (0,1) range.

$$V_N = \frac{V_R - V_{min}}{V_{max} - V_{min}} \quad (10)$$

Determination of the regression analysis model for VB

In order to make a comparison with the multiple regression analysis, all 36 data were used to fit the regression equation. In this study, the prediction of tool wear is performed by calculating tool life according to experiment and empirical tool life equations such as Taylor's equation or its extension versions. The coefficients of regression and correlation have been obtained in Minitab software. The tool wear is obtained as follows:

$$VB = -1.33 + 0.0198 \times K_r + 0.000403 \times V_c + 4.68 \times h_{ex} \quad (13)$$

The multiple regression coefficient of the first order model was found to be 0.989. This indicates that the first order model can explain the variation to the extent of 96.5 % in eq.13. While VB is dependent variable, the lead angle (K_r), cutting speed (V_c) and maximum chip thickness (h_{ex}) are independent variables, respectively. The equation shows that the flank wear rate increased with the increase of lead angle, cutting speed and maximum chip thickness. K_r has the most dominant effect on the flank wear value.

Results and discussion

In the experiments, the machining performance was affected by the cutter lead angle. Feed rates and tool life are all affected by the lead angle. Decreasing the lead angle for a given chip thickness and cutting speed, increases the feed rates, the productivity and the tool life. The longest tool life was obtained when the machined CGI with lower lead angle. The best value for the flank wear rate VB 0.11 mm was obtained when the cutting parameters are $K_r=45^\circ$, $V_c=400$ m/min and $V_f=400$ mm/min. The maximum value for the flank wear rate VB 0.87 mm was obtained when the cutting parameters are $K_r=88^\circ$, $V_c=530$ m/min and $V_f=540$ mm/min. These results may be related to smaller leading angles as they provide a more gradual entry into the cut, reducing radial pressure and protecting the cutting edge. Fig. 3 shows a plot of average flank wear against constant chip removal rate (500 cm^3) for various lead angles, cutting speeds and maximum chip thickness.

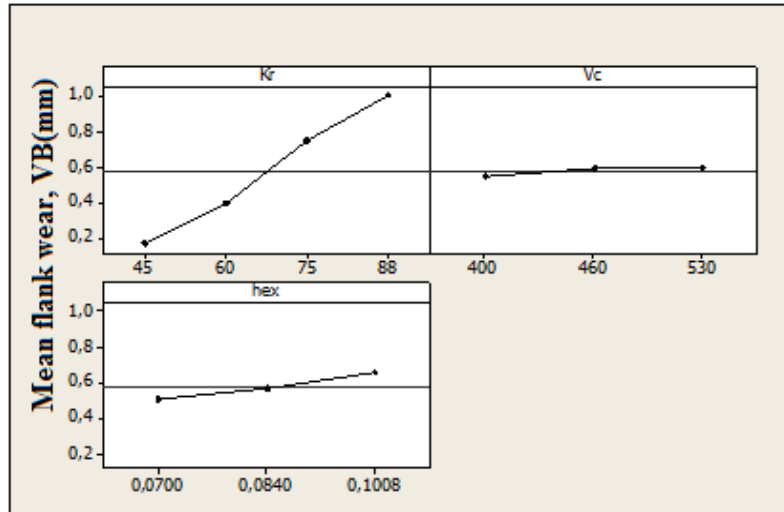


Fig. 3. The effects of the cutting parameters on the tool wear

As it is shown in Fig. 3, the flank wear is increased rapidly with the high lead angle under dry cutting condition. This situation can be explained as follows: when lead angle decreases, the chip width increases correspondingly because the active part of the cutting edge increases. As a result, because the heat is removed from the tool easily, the tool life increases.

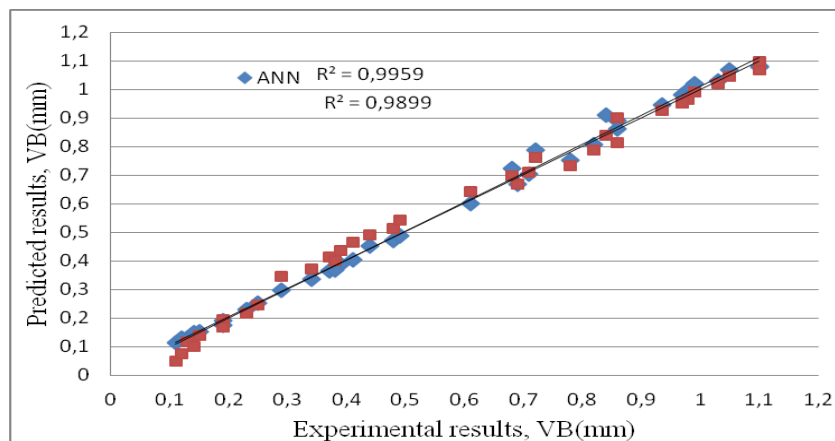


Fig. 4. Comparison of training data result with the ANN model and regression model

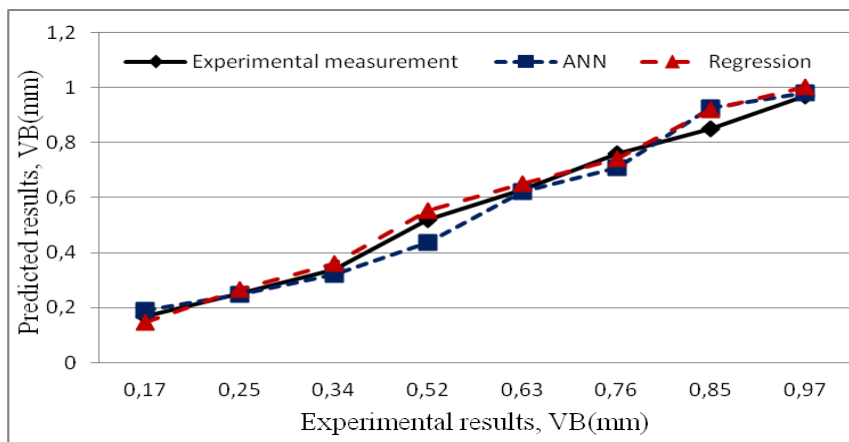


Fig. 5. Comparison of test data with the ANN model and regression model

After having finished the ANN train and regression analysis, ANN and regression analysis equations were tested by using the experimental results. The experimental results have been graphically compared with the results obtained from training network and regression analysis equation. The scatter diagrams of the predicted values and measurement values of the flank wear

rate as shown in Fig.4. Coefficient of determination value R^2 for ANN and regression analysis were obtained 0,977 and 0,993 respectively. Fig.5 compares the predicted values and measurement values of the flank wear rates of a set of 8 testing data after obtained mathematical equations by ANN and regression analysis. The predicted flank wear rates are very close to measured values for all the cutting parameters.

Conclusions

There is significant (95.87%) relationship between tool life and lead angle while milling CGI by the ceramic insert. The results have shown that a higher productivity and a higher tool life were obtained in milling of CGI with small lead angle. Smooth wear pattern on the flank face was widely observed in machining CGI at low cutting conditions with small lead angles. The tool life decreased when the lead angle, cutting speed and maximum chip thickness increased. The experimentally obtained flank wear rate results have been compared with the results which have been by ANN and regression model. Predictive models are found to be capable of better predictions for flank wear within the range used in network training. The R^2 values for testing data were calculated as 0.977 for ANN and 0.993 for regression respectively. According to the results of experiments, it can be concluded that Predictive models reduce the disadvantages of time and cost of material and machining.

Acknowledgements

The authors thank to University of Gazi for the financial support with project number 07/2010-33.

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