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Influence of Lead Angle Variation on the Coated Carbide Inserts Wear when Milling CGI and Modeling by Artificial Neural Networks and Regression Analysis Method

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

Abstract. The aim of this research is to investigate the influence of lead angle, cutting speed and the maximum chip thickness on tool wear in face milling process of compacted graphite iron. Tool failure modes and wear mechanisms for all cutting tools were examined in respect of various cutting parameters and were evaluated on the base of the flank wear. 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. Predictive ANN model is found to be capable of better predictions for flank wear within the range used in network training. The R2 values for testing data were calculated as 0.992 for ANN and 0.998 for regression analysis, respectively. This study is considered to be helpful in predicting the wear mechanism of the coated carbide insert in the machining of compacted graphite iron.

Introduction

Compacted graphite iron (CGI) is the material for the upcoming new generation of high power diesel-engines for cars. Due to its increased strength compared to grey cast iron (CI), it allows an increase in the cylinder-pressures and, therefore, a better fuel economy and a higher power output would also be possible [1], [2]. An increasing environmental legislation on engines' emission rates has forced the automotive and heavy truck industry to find new material solutions for their diesel engines. One of the most interesting candidates for replacing gray iron is Compacted Graphite Iron which can better withstand the higher combustion pressure [3], [4]. The reason why CGI was not used up to now in large scale production in the automotive industry is its difficult machinability as compared to CI, especially at high cutting speeds which are mandatory for large scale automotive production lines [5], [6]. The difference in tool life of gray cast iron and CGI generally depends on the mechanical properties of the workpiece material. According to many investigations, shorter tool life is expected when machining CGI compared to gray iron [7], [8]. Schmitt and Schulz carried out some turning and milling test. 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. Under these circumstances, the difference in tool life of gray cast iron and CGI generally depends on the increase of mechanical properties of the workpiece material [9], [10]. The aim of the presented study is to develop a new approach based on artificial neural network (ANNs) and regression analysis to determine the effect of the lead angle on the coated carbide insert wear mechanism when milling compacted graphite iron various cutting speed and feed rates. 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 coated carbide inserts in CGI machining were studied.

Experimental Procedures

CGI was machined on Jhonford VMC550 CNC milling machine tool. Rectangular blocks of 200 × 200 × 100 mm CGI were used for the experiments. The chemical compositions of the CGI are given in a Table 1 and mechanical properties of CGI is given Table 2 respectively.

Table 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

Table 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

The experiments were carried out with 45°, 60°, 75°, and 88° lead angle cutters and two inserts were used equally spaced at 180° in the milling cutter. The AISI code of the tools which were used during the tests was SAE 4340. Cutter diameter is 63 mm. A carbide-grade GC 3040 coated with Al_2O_3 and Ti(C, N) was used as the cutting tool (ISO grade N331.1D-136520E-PM 3040). A constant cut depth of 2.5 mm was used in all machining trials. Maximum chip thickness (h_{ex}) values of 0.16, 0.20 and 0.24 mm and cutting speeds of 215, 250 and 290 m/min were used for all milling trials. Milling tests were carried out in dry cutting conditions. Total 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 flank wear was measured by an optical microscope with a measurement precision of 0.001 and it was photographed by a Digital Scanning Electron Microscope JEOL JSM-6060 LV. The tool life was evaluated according to removed material volume (500 cm^3) and the tool rejection criteria for the cutting experiments were the flank wear VB ≥ 0.3 mm. The experiments were repeated twice times upon the same conditions and the data was compared. As the result of comparison, the experiments whose results were different were repeated again by checking experiment parameters and vibration stemming from cutting insert. The average results were taken in consideration.

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 Figure 1. The hidden layers have totally fourteen neurons in four levels and the input layer has three neurons. There is only one output neuron, which gives the value of flank wear rate VB. 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. In Pythia-neural network designer software when a satisfactory level of performance is reached, the training stops, and the network uses the weights to make decision. 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:

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

$$RMSE = \sqrt{\left(1/n \sum_{i=1}^{n} \left| \mathrm{VB}_{\mathrm{ANN,i}} - \mathrm{VB}_{,\mathrm{i}} \right|^2 \right)} \quad (2)$$

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

The back-propagation learning algorithm has been used in the feed forward work with single hidden layer having fifteen neurons. Inputs and outputs are normalized in the (–1, 1) range. The Fermi transfer function has been used in Eq. (4):

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

here z is weighted sum of the input, Pythia-neural network designer software has been used as an ANN computer program. Figure 1 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 (Vc), maximum chip thickness (h_{ex}) and table feed rate (Vf), are the known input parameters.

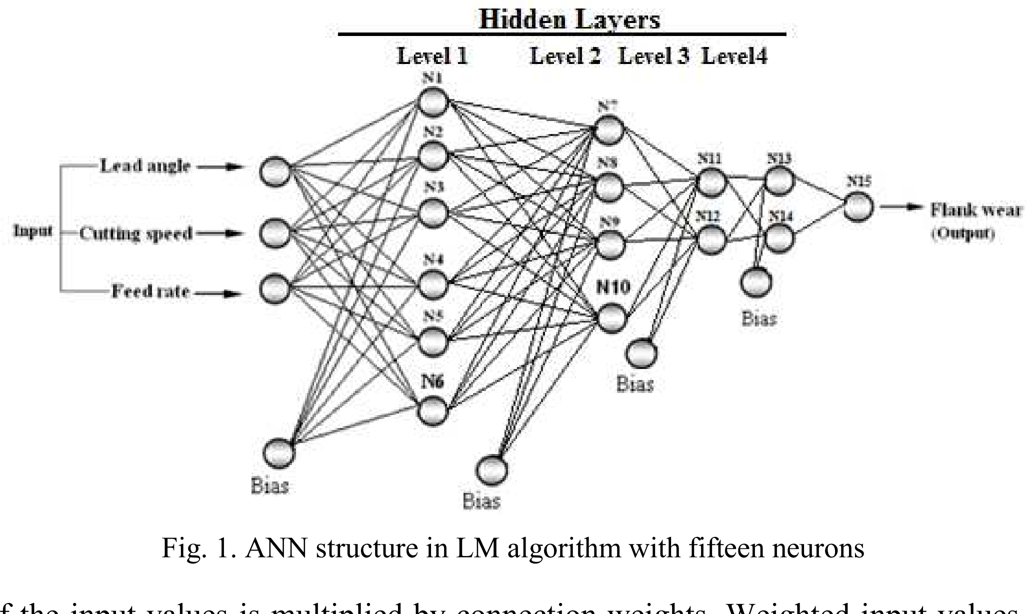

Fig. 1. ANN structure in LM algorithm with fifteen neurons

Each of the input values is multiplied by connection weights. Weighted input values are added linearly and they are converted into the output values. These outputs are used as the input values for the other neurons as shown in Figure1.

$$N_{15(VB)} = \frac{1}{1 + e^{-4(-1{,}522117 * \mathrm{N}_{13} + 1{,}512718 * \mathrm{N}_{14} - 0{,}5)}} \, . \quad (5)$$

In Eq. (5), N6 to N9 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 represents the neuron number. Obtained constants are given in Table 3.

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

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). The obtained constants are given in Table 4, Table 5 and Table 6, respectively.

Table 3. Constants used in Eq. (7) from neurons 1–5

i	Constants		
	w_{1i}	w_{2i}	w_{3i}
1	–0.628341	1.428712	–0.199413
2	0.508838	–0.461154	0.820906
3	–0.264352	–0.556014	0.176622
4	–0.714426	–0.350457	0.464586
5	–1.454960	1.374410	–0.315752
6	–0.222364	–0.939458	0.317280

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

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

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

Table 4. Constants used in Eq. (8) from neurons 7–10

i	Constants					
	w_{1i}	w_{2i}	w_{3i}	w_{4i}	w_{5i}	w_{6i}
7	0.919471	–0.155158	–0.925898	–1.178296	–0.310877	–1.120616
8	–0.269901	1.077365	–1.617829	–0.962827	–1.192473	–1.711635
9	–0.791579	–1.184605	1.976912	0.000275	0.948232	1.701282
10	–0.819206	0.251331	–0.465790	–0.057604	–0.563909	0.010288

Table 5. Constants used in Eq. (9) from neurons 11–12

i	Constants			
	w_{1i}	w_{2i}	w_{3i}	w_{4i}
11	1.726836	0.494352	–0.773293	–0.185145
12	1.247775	–1.740483	1.760649	–0.312200

Table 6. Constants used in Eq. (10) from neurons 13–14

i	Constants	
	w_{1i}	w_{2i}
13	–1.941718	1.156224
14	0.987498	–0.813027

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

$$V_N = \frac{V_R - V_{min}}{V_{max} - V_{min}} \tag{10}$$

Determination of the regression analysis model for VB

The regression analysis method is mostly used to obtain the tool life equation. Many researchers have successfully used this method [11]. The regression coefficients are estimated by using the experimental data. According to the tool life equation, which was developed by Taylor, the tool life depending on cutting conditions is expressed as follows [12]:

$$V_c T^n = C, \tag{11}$$

$$C = V_c T^n \times d^x f^y, \tag{12}$$

here V_c is cutting speed, T is tool life, d is depth of cut, f is feed rate, x and y are determined experimentally n and C are constants found by experimentation or published data; they are properties of tool material, work piece and feed rate. 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:

$$VB = -1{,}14369 + 0{,}00997637 \times \kappa_r + 0{,}00318761 \times V_c + 0{,}000195358 \times V_f\,. \tag{13}$$

The multiple regression coefficient of the first order model was found to be 0.965. 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, κ_r, Vc and hex 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. The lead angle (κ_r) has the most dominant effect on the flank wear value. The experimental values are very close to the predicted value (Fig. 5). The analysis of variance (ANOVA) was used to check the adequacy of the first and second order model. The P-value of the predictive model is calculated to determine the significance of the factors. According to the P-value, quadratic and interaction effects are not significant for second order model. Therefore, the first order model was used for the flank wear prediction (Table 7). The analysis of variance (ANOVA) of machining independent variables results show that the lead angle has the most significant effect 60.57% on the tool life when used the carbide insert tools, followed by cutting speed 35.67% and lastly maximum chip thickness 1.12% and average error is around 2.62%. So, the feed rates have little effect on the cutting insert wear when milling of CGI using carbide insert (Fig. 2.).

Table 7. Analysis of Variance for VB

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Kr	1	0.76143	1.2240	0.582931	395.244	0.000000
Vc	1	0.44845	0.58293	0.229666	564.707	0.000000
hex	1	0.01412	0.01412	0.014119	222.486	0.0008105
Error	32	0.03303	0.03303	0.001032	13.678	
Total	35	1.25703				

The evaluation of the results

The longest tool life was obtained for the machined CGI with lower lead angle. The best value for the flank wear rate VB 0.12 mm was obtained when the cutting parameters are κ_r = 45°, Vc = 215 m/min and h_{ex} = 0.16 mm (Vf = 492 mm/min). The maximum value for the flank wear rate VB 0.87 mm was obtained when the cutting parameters are κ_r = 88º, Vc = 290 m/min and h_{ex} = 0.24 mm (Vf = 704 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. Figure 2 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. As shown in Figure 2, the flank wear increased rapidly with the high lead angle under dry cutting condition. However, the tool wear decreased under low cutting conditions such as lead angles and cutting speeds, especially when using 45° and 60° lead angles. The smallest flank wears were obtained from the experiments for 45° and 60° lead angles under low cutting conditions. 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.

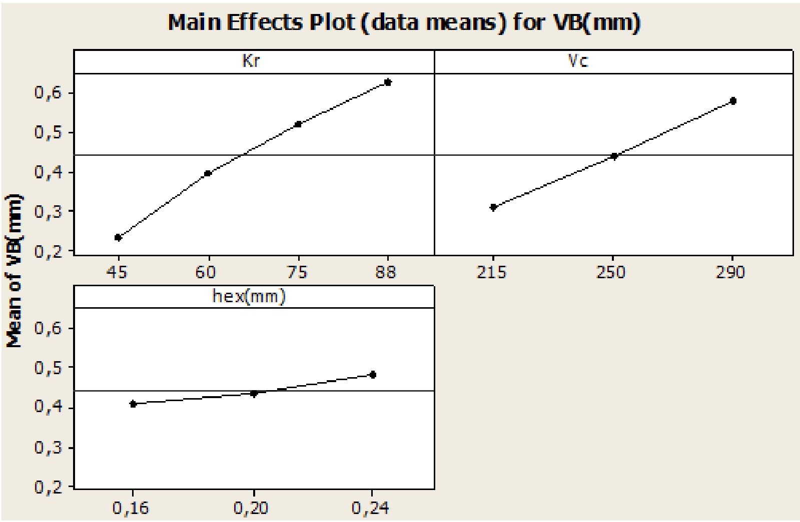

Fig. 2. The effects of the cutting parameters on the tool wear

The experimental results have shown that localized flank wear VB on tool cutting edge is the dominant wear determining factor for the tool life. Flank wear was the main type of wear for all cutting conditions.

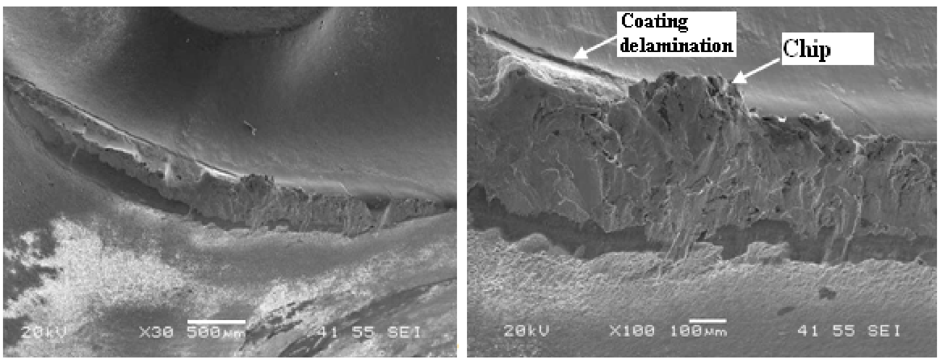

Fig. 3. Lead angle κ_r = 60°, Vc = 290 m/min, Vf = 813 mm/min

The tool cutting edge is confronted to different thermal and mechanical loads for every engagement of the tool in the milling CGI. The wear mechanisms observed at the cutting conditions were abrasion, adhesion, cracking, chipping and a coating delamination. Edge chipping was common problem in the experiments. The main reason of this problem is the first contact of tool to the part or its exit from the part. Adhesion was the main wear mechanism at higher cutting parameters. Adhesion wear was caused by the mechanical removal of the tool material parts when the adhesive materials are broken as shown Figure 3. Adhesion of workpiece material onto the flank face of tool was observed under some cutting conditions. Figure 3 shows an example of adhered workpiece material on the flank face of tool, and it indicates that there is a strong adhesion at tool-workpiece interface. 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 Figure4. Coefficient of determination value R^2 for ANN and regression analysis were obtained 0.994 and 0.973 respectively. Figure 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 (Fig. 5).

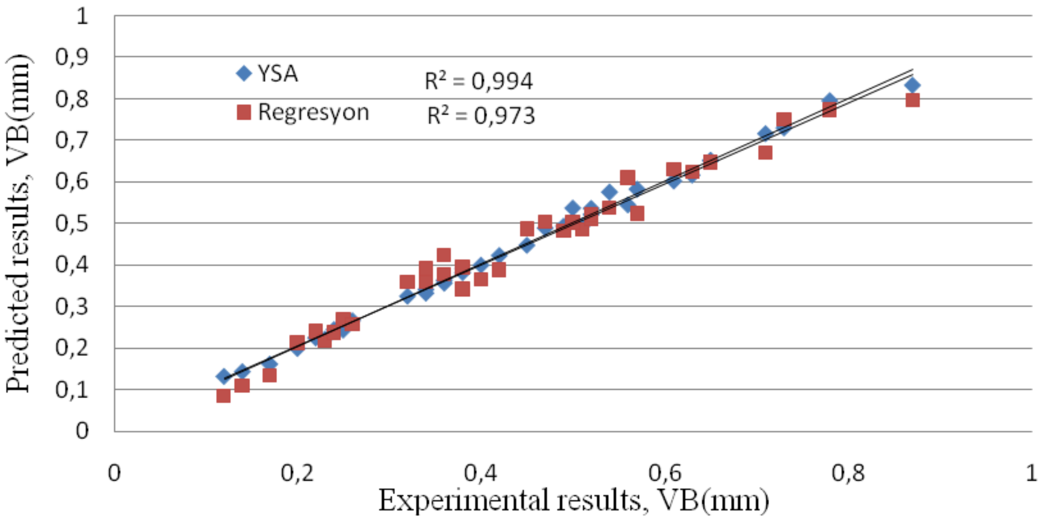

Fig. 4. Comparison of training data result with the ANN model and regression model

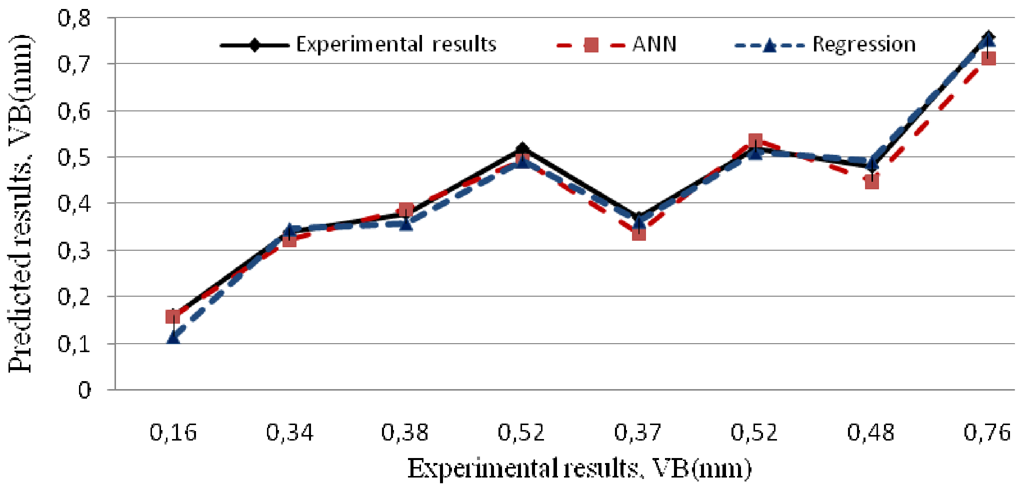

Fig. 5. Comparison of test data with the ANN model and regression model

Conclusions

There is significant (60.57%) relationship between tool life and lead angle while milling compacted graphite iron by the coated carbide insert. The tool life decreased when the lead angle, cutting speed and maximum chip thickness increased. The results indicate that ANNs were giving better result with respect to regression analysis method. The experimentally obtained flank wear rate results have been compared with the results which have been by ANN and regression model. Predictive ANN model is 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 0.992 for ANN and 0.998 for regression respectively. According to the results of experiments, it can be concluded that ANN reduces disadvantages of machining time, cost of material and machining.

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References

[1] U. Reuter, H. Schulz, M. McDonald, Compact and bijou – the problems associated with CGI can be overcome, Engine Technology International (1999) 58–60.

[2] M. McDonald, M. Dawson, Compacted graphite iron and current trends in engine design, Engine Technology International (1999).

[3] S. Dawson, Practical Applications for Compacted Graphite Iron, AFS Transactions, (2004) 813–821.

[4] W. Guesser, Production experience with compacted graphite iron automotive components, AFS Transactions (2001).

[5] U. Reuter, Wear mechanisms of the machining of cast iron with PCBN-tools: Ph.D. thesis, Faculty of Mechanical Engineering, Darmstadt University of Technology, 2001.

[6] S. Dawson, The effect of metallurgical variables on the machinability of compacted graphite iron, in: Proceedings of the Compacted Graphite Iron Design and Machining Workshop, 1999.

[7] A. Berglund, Investigation of the effect of microstructure on CGI machining, in: Swedish Production Symposium, 2007.

[8] A. Sahm, Machining of Compacted Graphite Iron (CGI), Materialwissenschaft und Werkstofftechnik 33 (2002) 501–506.

[9] T. Schmitt, U. Reuter, Examination of the wear mechanisms of different cutting materials, in: Proceedings of CGI Design & Machining Workshop, Bad Homburg, Germany, 1997.

[10] H. Schulz, U. Reuter, Basic investigations in CGI machining, in Proceedings of CGI Design & Machining Workshop, Bad Nauheim, Germany, 1998.

[11] L. Özler, Theoretical and experimental determination of tool life in hot machining of austenitic manganese steel, International Journal of Machine Tools and Manufacture 41 (2001) 163–172.

[12] D. Ojha, An economic and reliable tool life estimation procedure for turning, Int. J. Adv. Manuf. Technol. 26 (2005) 726–732.