PREDICTION AND EXPERIMENTAL STUDY ON CUTTING FORCES OF STEPPED AUSTEMPERING GRAY CAST IRON USING ARTIFICIAL NEURAL NETWORK

[1]AHMET MAVI, [2]SEMIH OZDEN, [3]ISMAIL OVALI

[1]Gazi University, OSTIM Vocational College, Department of Mechatronics, Turkey
[2]Gazi University, OSTIM Vocational College, Department of Electrical and Energy, Turkey
[3]PamukkaleUniversity, Faculty of Technology, Department of Manufacturing Engineering, Turkey
E-mail: [1]amavi@gazi.edu.tr, [2]semihozden@gmail.com, [3]iovali@pau.edu.tr

Abstract- A novel stepped austempering process has been widely used for improving of mechanical properties of cast iron. Although most of the stepped austempering process focused on ductile iron, only minimal study has been carried out in gray cast iron. In this study, the effects of stepped austempering on the cutting force of gray cast iron. Mathematical model developed for prediction of cutting force with Artificial Neural Network (ANN). Experimental result showed that stepped austempering heat treatment significantly influences the cutting force of gray cast iron. In addition, artificial neural network model provide highly accurate and consistent prediction for all cutting forces.

Keywords- Neural Network, Cutting Force, Machining, Gray Cast Iron, Stepped Austempering

I. INTRODUCTION

Gray cast iron has been used for automotive parts such as crankshaft and pressure plate because of its anti-vibration, machinability and frictional properties [1]. Most of the gray cast iron automotive parts are subjected to wear in service conditions. Therefore, Investment in research of improving wear resistance has become important factor in production of gray cast iron. The machinability of gray cast iron can be controlled significantly by controlling of the matrix microstructure [2-4].

Austempering heat treatment process significantly affects and changes the gray cast iron microstructures [1]. The microstructures of austempered gray cast iron (AGI) are characterized by a matrix consisting of bainitic ferrite and high carbon austenite. This matrix is called ausferrite. In the literatures, some studies on the mechanical properties of austempered gray cast iron are reported [5-7]. Generally, the studies focused on improving toughness on gray iron and show that an ausferrite structure improves the mechanical properties of gray cast iron [8-11]. Austempering process is also successfully used for wear resistance applications of gray cast iron [12-15].

Stepped austempering process is a novel two-step austempering process. This process was developed by SusilPutatunda. In this process, the higher austenitic carbon in samples processed and ausferrite morphology can be controlled [16]. His studies focused on ductile iron and showed that stepped austempering improve the fracture toughness and yield strength of austempered ductile iron [16-18]. His studies also showed that stepped austempering improve the wear resistance of ductile iron because this process increase ausferrite volume fraction [16-18].

There has not been any studies so far been made to determine the cutting force of stepped austempering gray cast iron by controlling the ausferrite morphology and volume fractions. Therefore, in the present study, the effects of stepped austempering process on cutting force of gray cast iron were investigated.

II. DETAILS EXPERIMENTAL

2.1. Experimental setup and measurements

The material used in the present study is a gray cast iron. The chemical composition of the material is given in Table 1. As cast material had ferrite+perlite and flake graphite structure (Fig. 1).

Table 1: Chemical composition of experimental gray cast iron (wt %)

C	Si	Mn	P	S	Cr	Ni	Al	Cu
3,2	1,7	0,48	0,07	0,1	0,16	0,16	0,17	0,6

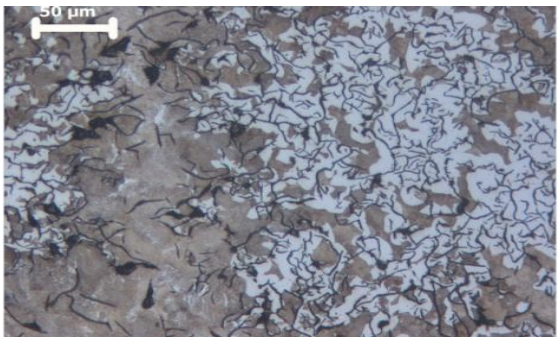

Fig.1. The microstructure of gray cast iron

2.2 Heat treatments

The work piece bars were 50 mm long and 26 mm in diameter. All specimens were austenitized at 900 °C for 90 minutes and then quenched into first salt bath held at 260 °C for 5 minutes than transferred into second salt bath at austempering temperature of 315 °C and 375 °C for various time. Some specimens

were also conventionally (one stepped) austempered for comparison (Fig. 2.).

The work piece bars were 240 mm long and 26 mm in diameter. Cutting force experiment was done on a Johnford TC-35 CNC lath at four cutting speed of 150,190,230,270 m/min, feed rates 0.20, 0.25, 0.30 mm/rev and cutting depths of 2 mm. 9 mμ TiCN - Al2O3 CVD coated tools were selected to machine the specimens. Mechanical properties of austempered ductile iron were taken consideration in selecting cutting tool. Inserts produced by Sandvik are grades GC 3125. The inserts' code is SCMT120408-KR according to ISO 3685. The insert was assembled mechanically on tool holder. Coolant was not used for the tests. In order to provide a fresh cutting surface, insert was replaced each time. Cutting force measured by dynamometer. Cutting forces standard deviation rate is ± 5N.

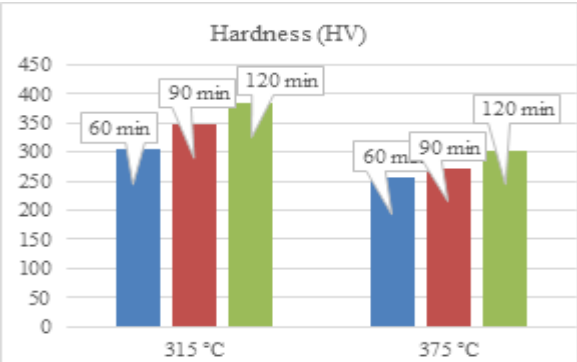

Fig.2. Hardness values of GCI under different austempering times and temperatures

2.2. ANN Modeling

Artificial neural network (ANN) system designed and developed with modeling of human brain theory. In the brain theory, the synapses collect signals (information) than transmit them to nuclei (neuron) by means of dendrites. Afterwards, the neuron encodes the signals than yield adaptive interactions with the environment [19]. ANNs are a logic programming technique developed with the purpose of automatically performing skills such as learning, remembering, deciding, and inference, which are features of the human brain, without receiving any aid [20].

The learning of ANN was accomplished by a back-propagation algorithm. Backpropagation is the most commonly used supervised training algorithm in multilayer feed-forward networks. In backpropagation networks, information is processed in the forward direction from the input layer to the hidden layer(s) and then to the output layer. An ANN with a backpropagation algorithm learns by changing the connection weights, and these changes are stored as knowledge [21, 22].

The ANN model is given in Fig. 3. The values were trained by ANN in two hidden layers in this study. Different network structures were performed and optimized. Best values were kept 3-12-12-1 network structures with three inputs, one output and twelve hidden neurons. Input parameters of ANN are hardness, feed rate and cutting speed. Cutting force values experimentally obtained from piezoelectric dynamometer constitute the output parameter of ANN.

The experimental design and setup have been demonstrated to develop an ANN model real-time cutting force prediction system. In this paper, cutting force is measured in turning of stepped austempering gray cast irons (GCI). The effect of cutting parameters such as hardness of GCI, speed and feed rate on f is evaluated. The model is formulated for all cutting parameters and machining variables using neural networks. Then the models are compared for their prediction capability with the actual values. The ANNs are used widely in decision making of complex manufacturing processes and have been used as prediction models.

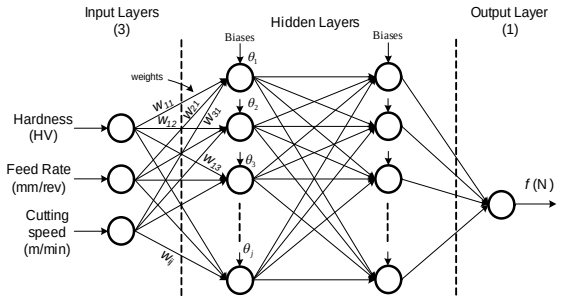

Fig.3. The ANN structure for application

In this study, 84 experimental data sets were prepared for the training and testing data for the ANN. The ratio for training and testing data was selected as 85%:15%, i.e. 12 and 72 sets of the experimental data were randomly selected for the testing data and training data, respectively. In the back propagation model, the scaling of inputs and outputs dramatically affects the performance of an ANN [20]. As mentioned above, the logistic hyperbolic tangent transfer function was used in this study. One of the characteristics of this function is that only a value between 0 and 1 can be produced. The input and output data sets were normalized before the training and testing process to obtain the optimal predictions. Hardness, feed rate, cutting speed and cutting force were normalized dividing by 383, 0.3, 270 and 990.99, respectively. Cutting force values predicted after ANN training were compared with values obtained from the experimental study. Predictive accuracy was evaluated using the root mean squared error (RMSE), coefficient determination (R^2), mean absolute error (MAE) and mean percentage error (MPE).

III. RESULTS AND DISCUSSION

Predictive accuracy of neural network model evaluated as the coefficient determination i.e. Root mean squared error (RMSE), coefficient

determination (R^2), mean absolute error (MAE) and mean percentage error (MPE). RMSE and R^2 provide baseline measures of predictive accuracy. All results reported are for the training set and test set. The predictive estimation results are summarized in Table 2.

Table 2: Accuracy of predictions of the neural network model

	Normalized		Real	
	Training	Test	Training	Test
RMSE	1.08E-06	0.0113	1.07E-03	10.6342
R^2	0.9999	0.9990	0.9999	0.9990
MAE	5.51E-07	0.0036	5.46E-04	3.2457
MPE	7.63E-05	0.4510	7.63E-05	0.4071

Depending on results of ANN, it shows that predictive test values are very close to real values. RMSE and R^2 normalized test results are 0.0113 and 0.9690, respectively.

The values of both training and test values are drawn Fig. 4. and 5. These values are normalized data.

Fig. 6 and 7 represent comparison between measured and predicted values. Fig.6. is for training 72 data, Fig.7. is for 12 test data.

Fig.4. The regression analysis of training values

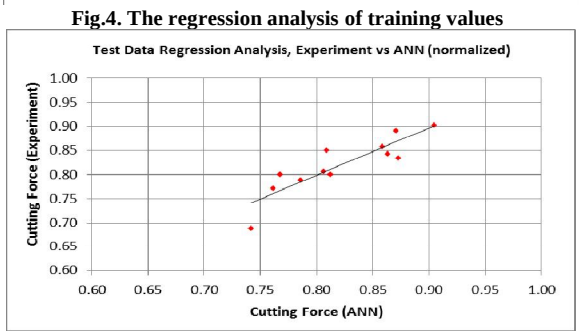

Fig.5. The regression analysis of test values

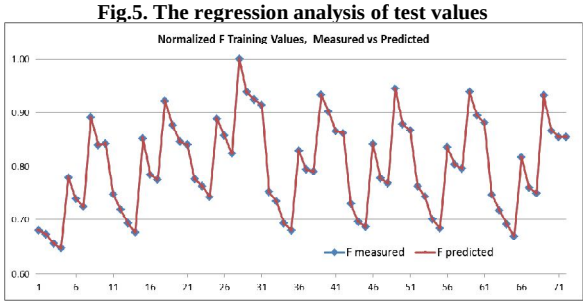

Fig.6. The comparison between measured and predicted training values

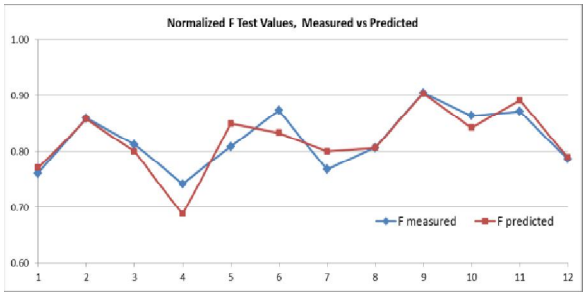

Fig.7. The comparison between measured and predicted test values

CONCLUSIONS

In the present study, experimental and modeling studies show that the cutting force of stepped austempering gray cast irons can be controlled with austempering heat treatment and machining parameters. Artificial neural network can be used for the prediction of the cutting force. The results can be summarized in the experimental section results and modeling section results. Feed possesses the most significant effect on cutting force followed by cutting speed. An increment of cutting speed and decrement of feed will result in better cutting forces.

In modeling design, hardness, feed rate and cutting speed were selected as input parameters of artificial neural network. The best network structure with minimum error rate was achieved 3-12-12-1. The ANN model, developed to predict the cutting force value, could provide predicted values of cutting force quietly close to the actual values found in the experiments. Predictive accuracy of neural network model evaluated as RMSE, R^2, MAE and MPE. The R^2 results of ANN are 99.99% and 96.90% for training and test values confidence level for the adequacy.

REFERENCES

[1] A. Vadiraj, G. Balachandran, M. Kamaraj, B. Gopalakrishna, and K. P. Rao, "Structure-property correlation in austempered alloyed hypereutectic gray cast irons", Materials Science and Engineering a-Structural Materials Properties Microstructure and Processing, vol. 527, no. 3, pp. 782-788, 2010.

[2] A. M. de Souza, W. F. Sales, S. C. Santos, and A. R. Machado, "Performance of single Si3N4 and mixed Si3N4+PCBN wiper cutting tools applied to high speed face milling of cast iron", International Journal of Machine Tools & Manufacture, vol. 45, no. 3, pp. 335-344, 2005.

[3] E. O. Ezugwu and S. H. Tang, "Surface abuse when machining cast iron (G-17) and nickel-base superalloy (Inconel 718) with ceramic tools", Journal of Materials Processing Technology, vol. 55, no. 2, pp. 63-69, 1995.

[4] K. Shintani, H. Kato, H. Sugita, and N. Suzuki, "Wear Mechanism of PcBN Tool in High Speed Machining of Gray Cast Iron", Journal of the Japan Society for Precision Engineering, vol. 64, no. 2, pp. 261-265, 1998.

[5] A. R. Riahi and A. T. Alpas, "Wear map for grey cast iron", Wear, vol. 255, no. pp. 401-409, 2003.

[6] A. Vadiraj, G. Balachandran, and M. Kamaraj, "Structure and Property Studies on Austempered and As-Cast Ausferritic Gray Cast Irons", Journal of Materials Engineering and Performance, vol. 19, no. 7, pp. 976-983, 2010.

[7] A. Vadiraj, G. Balachandran, M. Kamaraj, B. Gopalakrishna, and K. Prabhakara Rao, "Structure–property correlation in austempered alloyed hypereutectic gray cast irons", Materials Science and Engineering: A, vol. 527, no. 3, pp. 782-788, 2010.

[8] A. Vadiraj, G. Balachandran, M. Kamaraj, B. Gopalakrishna, and K. P. Rao, "Studies on mechanical and wear properties of alloyed hypereutectic gray cast irons in the as-cast pearlitic and austempered conditions", Materials & Design, vol. 31, no. 2, pp. 951-955, 2010.

[9] M. Terheci, R. R. Manory, and J. H. Hensler, "The Friction and Wear of Automotive Grey Cast-Iron under Dry Sliding Conditions .2. Friction and Wear Particle Generation Mechanisms and Their Progress with Time", Wear, vol. 185, no. 1-2, pp. 119-124, 1995.

[10] M. Terheci, R. R. Manory, and J. H. Hensler, "The Friction and Wear of Automotive Grey Cast-Iron under Dry Sliding Conditions .1. Relationships between Wear Loss and Testing Parameters", Wear, vol. 180, no. 1-2, pp. 73-78, 1995.

[11] E. P. Fordyce and C. Allen, "The dry sliding wear behaviour of an austempered spheroidal cast iron", Wear, vol. 135, no. 2, pp. 265-278, 1990.

[12] A. S. M. I. H. Committee, Properties and Selection: Irons, Steels, and High-Performance Alloys vol. 1: ASM International, 1990.

[13] M. Hatate, T. Shiota, N. Takahashi, and K. Shimizu, "Influences of graphite shapes on wear characteristics of austempered cast iron", Wear, vol. 251, no. 1–12, pp. 885-889, 2001.

[14] Y. Zhang, Y. Chen, R. He, and B. Shen, "Investigation of Tribological Properties of Brake Shoe Materials - Phosphorus Cast Irons with Different Graphite Morphologies", Wear, vol. 166, no. 2, pp. 179-186, 1993.

[15] Y. C. Liu, J. M. Schissler, and T. G. Mathia, "The influence of structure oxidation on the wear resistance of cast iron", Tribol. Int., vol. 28, no. 7, pp. 433–438, 1995.

[16] S. K. Putatunda and P. K. Gadicherla, "Influence of austenitizing temperature on fracture toughness of a low manganese austempered ductile iron (ADI) with ferritic as cast structure", Materials Science and Engineering a-Structural Materials Properties Microstructure and Processing, vol. 268, no. 1-2, pp. 15-31, 1999.

[17] S. K. Putatunda, "Development of austempered ductile cast iron (ADI) with simultaneous high yield strength and fracture toughness by a novel two-step austempering process", Materials Science and Engineering a-Structural Materials Properties Microstructure and Processing, vol. 315, no. 1-2, pp. 70-80, 2001.

[18] L. Bartosiewicz, A. R. Krause, B. Kovacs, and S. K. Putatunda, "Fatigue Crack Growth Behavior of Austempered Ductile Cast Iron", AFS Transactions, vol. 92 no. 135, pp. 135-143, 1992.

[19] M. A. Arbib, The Handbook of Brain Theory and Neural Networks. London: MIT Press, 2002.

[20] Y. Cay, I. Korkmaz, A. Cicek, and F. Kara, "Prediction of engine performance and exhaust emissions for gasoline and methanol using artificial neural network", Energy, vol. 50, no. pp. 177-186, 2013.

[21] H. Xie, F. Ma, and Q. Bai, "Prediction of Indoor Air Quality Using Artificial Neural Networks," presented at the Fifth International Conference on Natural Computation, China, 2009.

[22] M. Dursun and S. Ozden, "An efficient improved photovoltaic irrigation system with artificial neural network based modeling of soil moisture distribution - A case study in Turkey", Computers and Electronics in Agriculture, vol. 102, no. pp. 120-126, 2014.

★★★