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A study on cutting forces of austempered gray iron using artificial neural networks

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ABSTRACT

Austempering heat treatment has become more useful for improving the mechanical and machinability properties of gray iron. On the other hand, this heat treatment process has many variables having non-linear relationship and these variables affect directly the structure of the gray iron. Thus, the present study investigates the influence of austempering heat treatment on cutting forces of gray iron with using artificial neural network. Artificial network modelling has more ability than regression analysis to solve problems having non-linear relationship between their inputs and output parameters. In the experimental study, grey iron specimens were austenised at 900 °C than quenched to salt bath at austempering temperatures 315°C and 375 °C for various austempering times. All specimens were machined at various feed rates and cutting speeds after heat treatments at constant cutting depth. In the modelling study, SCG and LM feed-forward back-propagation algorithm was used in the networks. Log- Sigmoid transfer function has been used in both hidden layers and output layers. The new formulas have been created for cutting force Fc, Fr and Ff with ANN modeling. The experimental results showed that, the cutting forces of gray iron can be optimized via austempering process. In addition, artificial neural network model provide highly accurate and consistent prediction for all cutting forces.

1. Introduction

The gray cast iron is widely used materials for rotating parts in mechanical system. The parts are subjected to irregular force under working condition so some mechanical properties such as fatigue, wear resistance and tensile become more important. Controlling the cutting force properties is important to obtain optimum mechanical properties.

There are many important parameters influence the cutting forces of gray iron. The cutting forces can be optimized with austempering heat treatments. After austempering, the matrix of ferritic or perlitic gray iron changes to an acicular microstructure, consisting of 60–80% bainitic ferrite without carbide and 20–40% high carbon austenite. This structure has been called ausferrite structure [1-4]. Austempering heat treatments cost high and heat treatments require more time than most of heat treatment process. Consequently, it is not easy carrying out many experiments to define optimum austempering parameters for best cutting force values.

Some research in recent year have been focused on austempering of gray iron .Aravind and his coworkers studied that Structure–property correlation in austempered alloyed hypereutectic gray cast irons. They investigated the austempering behavior of a series of hypereutectic alloyed gray iron compositions with carbon equivalent from 4,37 to 5,14 to understand the influence of microstructure on its mechanical and wear properties. They found that the wear rate was found to increase with volume of austenite, austenite carbon content and austenite lattice parameter, which is attributed to increased stability of austenite against strain induced martensite formation and the increased formation of bainitic carbides in the second stage tempering [5]. Hasan and Thamizhmanii analyzed roughness, forces and wear of gray cast iron in turning. Their study results showed that the cutting tool has produced micro chipping and has not affected the surface finish. Micro cracks were obtained from the edge of micro chipping [6]. Ferry et al.studied the effect of ausferrite formation on the mechanical properties of gray iron. An increase in volume fraction of ausferrite resulted in a concomitant linear increase in key mechanical properties with the fully ausferritic gray iron producing the optimum combination of mechanical properties [7].

The cutting force measurement cost also limits the researcher and the optimum cutting condition cannot be defined precisely in many of the machining process. The cutting force parameters have complex interaction with each other so improving a mathematical model is

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not easy. Some theoretical models that have been used are not enough accurate and these models can be used only in limited range. An alternative approach is necessary to develop an effective and inexpensive process for defining optimum cutting forces parameters. Consequently, it seems that artificial neural network is a more suitable method for dealing with complex structure of machining process.

However the shortcomings of those studies that the authors have not been reported the using of artificial neural network model on the cutting forces of gray iron and austempered gray iron.

To clear mentioned shortcomings above, the present study trains an artificial neural network (ANN) to include the most important factors affecting machinability of gray cast iron to achieve accurate prediction cutting forces parameters for using new variables.

This study consists of two sections. In the first section, the experimental analysis carries out. Austempering heat treatments performed for various austempering temperatures and time. In the second section, cutting force parameters are modeled with artificial neural network.

2. Experimental And Modelling Study

2.1 Experimental studies

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 (Figure 1).

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

C	Si	Mn	P	S	Cu
3,65	2,48	0,440	0,223	0,078	0.110

The work piece bars were 240 mm long and 30 mm in diameter. These specimens were austenitized at the 900 °C for 90 minutes and then rapidly transformed to a salt bath containing 50 % KNO_3 + 50 % $NaNO_3$ held at the 315 and 375 °C for austempering for 30, 60 and 120 minutes to produce different ausferrite structure morphology. Heat treatments summary and heat treatments experimental set up are showed in the Figure 1.

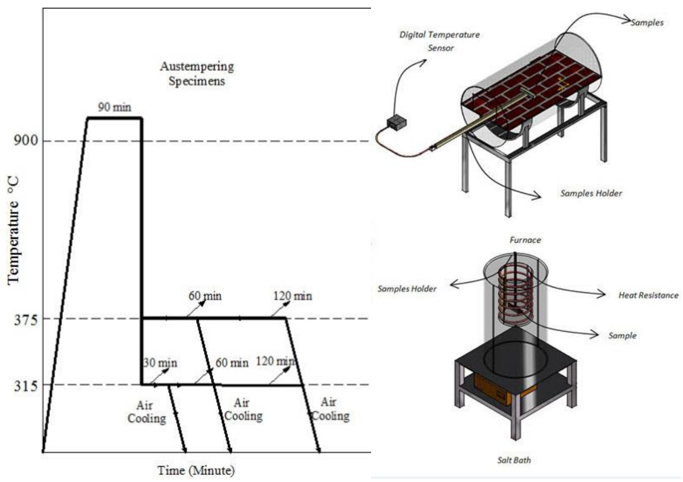


Figure 1. Heat treatments summary and heat treatments experimental set up.

Machining test were performed according with Standard ISO 3685 to evaluate cutting force of gray iron by cutting forces (F_c,F_r,F_f) . Cutting force measurement was done on a Johnford TC-35 CNC lathe. The tests were carried out at four cutting speeds of 200, 220, 240 and 260 m/min respectively, at three feed rate of 0.15, 0.25 and 0.30 mm/rev respectively 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 Co. 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. Primary (F_c), feed (F_f) and radial (F_r) cutting force components acting on the tool post were measured with a three-component dynamometer. The dynamometer is "TD 500KA model of Lathe Dynamometer TD-A.

2.1. Modeling Study

2.1.1. Artificial Neural Network

Artificial neural network 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 [8].The illustration of a simplified model of a biological neuron in the Figure 2, which simplifies understanding of neural network theory [9].

Haykin defined neural network: a neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the human brain in two respects. First, Knowledge is acquired by the network through a learning process. Second, Inter-neuron connection strengths known as synaptic weights are used to store the knowledge [10].

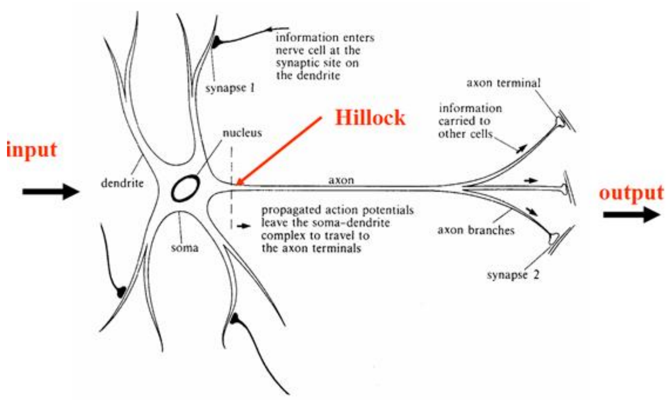


Figure 2. Illustration of a simplified model of a biological neuron.

Some learning algorithms are used for the learning process to create network. The most popular learning algorithms is Levenberg-Marquardt. The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix. Newton's method is faster and more accurate near an error minimum, so the aim is to shift toward Newton's method as quickly as possible. The performance function is always reduced at each iteration of the algorithm.

In the ANN approaches, transfer function is the important element of the model because the net input is passed through the transfer functions, which produces the output and determine result. Log-sigmoid transfer function (logsig), hyperbolic tangent sigmoid transfer function (tansig), and hard limit transfer function (hardlim) have been used ANN models. The selection of transfer function depends on the structure and complexity of the problem. Nonlinear transfer functions provide more capable network to solve problem which outputs and inputs have none-linear interactions.

The flexibility of ANN provides them to solve more complex relationships between data than conventional statistical models. Therefore, it is successfully used in the most of engineering field for forecasting, optimization, pattern recognition and classification [11-22].

Some studies were carried out on cutting force with using ANN. Al-Ahmari devoloped empirical models for tool life, surface roughness and cutting force in the turning operations. He used two important data mining techniques are used; they are response surface methodology and neural networks. The study results showed that the developed neural networks predict the tool life, cutting force, and surface roughness together [23].

Hamouda and Wong investigated Machinability data representation with artificial neural network. They focused on the the feasibility of using neural network in representing machinability data. The authors introduce a new type of artificial neuron in the design of neural network for turning process, namely the Product neuron, which has multiplication instead of summation. The authors showed the possibility of representing the machinability data with simple neural networks [24].

Aykut and friends used artificial neural networks (ANNs) for modeling the effects of machinability on chip removal cutting parameters for face milling of stellite 6 in asymmetric milling processes. Cutting forces with three axes (Fx, Fy and Fz) were predicted by changing cutting speed (Vc), feed rate (f) and depth of cut (a_p) under dry conditions. The cutting speed (Vc, m/min), feed rate (f, mm/min), depth of cut (a_p, mm) and cutting forces (Fx, Fy and Fz, N). V_c, f and a_p were used as the input dataset while Fx, Fy and Fz were used as the output dataset. The modeling and experiments results showed that ANN can be used for predicting the effects of machinability on chip removal cutting parameters for face milling of stellite 6 in asymmetric milling processes [25].

The literature study has showed that no attempts have been made to improve the artificial neural network model on the cutting force of gray cast iron. In the present study, an artificial neural network model was developed. The new formulas of cutting forces (F_c, F_r, F_f) were also developed for heat treatment and machinability parameters.

2.2 Application of ANN

A neuron in the neural network system can be defined as an information unit that fundamental to operation of neural network. The architecture of neural network is consisted of input, hidden layers and output, respectively.

The used ANN structures are shown in Figure 3. In put layer was consisted of four variables; austempering time, austempering temperatures, cutting force (m/min) and feed rate (mm/rev), respectively.

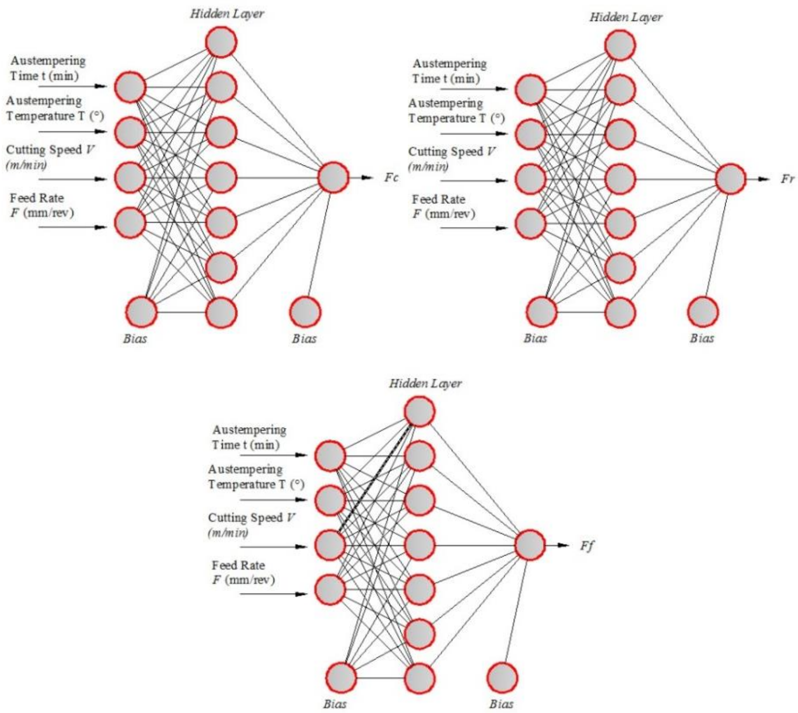


Figure 3. Artificial Neural Network Structure used in the ANN analysis.

In the austempering heat treatment process, austempering time and temperature affects the microstructures of gray iron. On the other hand, cutting speed and feed rate have significant effects on cutting properties of gray iron. Consequently, the parameters were selected as inputs for artificial neural network (Table 2). A selection of experimental result data are showed in Table 3 for illustration.

Table 2. The input variables used to neural network model

Input	Maximum	Minimum	Mean
Feed Rate (mm/rev)	0.45	0.15	0.3
Cutting Speed (m/min)	280	200	240
Austempering Time (Min)	120	30	75
Austempering Temperature	375	315	345
Hardness (HV)	255	220	237.5

Table 3. Illustration of some of experimental data were used in consisting of neural network model

Austempering Temperatures (C°)	**Austempering Time (Min)**	**Hardness (Hv)**	**Feed Rate (mm/rev)**	**Cutting Speed (m/min)**	***F_c(N)***	***F_r(N)***	***F_f(N)***
0	0	220	0.15	200	558.25	375.8	322.55
0	0	220	0.15	220	545.44	372.99	319.72
0	0	220	0.15	240	538.44	366.74	314.75
0	0	220	0.15	260	532.61	366.02	305.63
0	0	220	0.25	280	709.28	405.76	327.29
315	30	245	0.25	200	790.78	483.78	417.08
315	30	245	0.25	220	784.76	472.47	416.68
315	30	245	0.25	240	771.56	460.25	389.08
315	30	245	0.25	260	760.72	450.8	386.38
315	30	245	0.25	280	749.56	448.39	382.27
315	120	289	0.25	220	836.17	635.37	531.9
315	120	289	0.25	240	802.74	629.84	529.72
315	120	289	0.25	260	787.44	612.41	520.17
315	120	289	0.25	280	769.19	608.74	513.52

The input weight and bias of the network are determined with learning process to optimize of the network performance. The difference network output and target output are calculated in most of the learning process. An error function is used to decrease this error. Mean square error performance function, mean square error (MSE), is used in this study. It is showed in Eq. (1)

$$F = mse = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \quad (1)$$

The regression R^2 values are also used to analysis to show correlation between output and target output. R^2 is defined in Eq. (2).

$$R^2 = 1 - \left(\frac{\sum_j (t_l - o_j)^2}{\sum_j (o_j)^2}\right) \quad (2)$$

The back-propagation learning algorithm has been used in feed forward single hidden layer. In the training process, Levenberg-Marquardt and Scaled Conjugate Gradient, algorithms has been used for comparison and optimization. The network inputs and outputs are normalized in the specified range (0-1). This is also useful for avoiding different scales for different components. Eq. (8) is used for normalization.

$$X_n = 0.8.\left(\frac{X - X_{min}}{X_{max} - X_{min}}\right) + 0{,}1 \quad (3)$$

Where X_n is normalized value of X. X_{max} and X_{min} are the maximum and minimum values of X respectively.

Log- Sigmoid transfer function has been used in both hidden layer and output layer. The transfer function has not been used in the input neurons. The use of Log- Sigmoid transfer function (nonlinear transfer function) makes the network capable of a nonlinear relationship between the input and the output.

In the experimental study, 120 measurements were carried out to determine the effect of austempering temperatures and time, feed rate and cutting speed o the cutting force of gray cast iron. 600 experiment data were used in training and testing of neural network. The data were randomized than partitioned for training, testing and performance data set.

The numbers of hidden layer influence the complexity of hidden layer. Increasing of the neurons number requires more computation and cause the over fit of data. The numbers of hidden layer have to be optimized otherwise the model become meaningless .The number of hidden layer was defined by analyzing of test data. Seven hidden layers were found the reasonable complexity and error rate. It can be seen clearly form table 4 that more accurate results can be achieved by LM algorithm with seven hidden layers.

Table 4. Statistical values of training, testing and Validation data

Fc						
	Training Data		**Testing Data**		**Validation Data**	
	RMS	**R**	**RMS**	**R**	**RMS**	**R**
LM5	1.9187e-004	0.99763	3.57E-04	0.99712	4.7645e-004	0.99706
LM6	7.18E-04	0.99297	9.87E-04	0.99068	5.48E-04	0.99434
LM7	2.94E-05	0.99972	4.4671e-004	0.99427	3.65E-04	0.99533
SCG5	0.0021	0.97613	0.0027	0.97606	0.0019	0.98617
SCG6	0.0015	0.98395	9.11E-04	0.98455	0.0016	0.98801
SCG7	0.0031	0.94112	0.0029	0.9405	0.0038	0.9698
Fr						
	Training Data		**Testing Data**		**Validation Data**	
	RMS	**R**	**RMS**	**R**	**RMS**	**R**
LM5	1.79E-04	0.99784	4.71E-04	0.99467	3.54E-04	0.99372
LM6	1.76E-04	0.99801	5.85E-04	0.9869	5.0501e-004	0.99293
LM7	2.26E-04	0.99731	3.24E-04	0.99583	3.76E-04	0.9961
SCG5	0.0072	0.89871	0.0147	0.84444	0.0111	0.81603
SCG6	0.0132	0.80831	0.0138	0.81301	0.008	0.87796
SCG7	0.0025	0.96627	0.0025	0.96657	7.81E-04	0.99342
Ff						
	Training Data		**Testing Data**		**Validation Data**	
	RMS	**R**	**RMS**	**R**	**RMS**	**R**
LM5	7.33E-04	0.98993	5.5239e-004	0.9891	5.07E-04	0.9938
LM6	4.49E-04	0.99828	1.31E-04	0.98753	3.09E-04	0.99251
LM7	2.00E-04	0.99727	8.94E-04	0.98085	8.12E-04	0.98488
SCG5	0.0011	0.9814	0.0023	0.96968	0.0013	0.98736
SCG6	0.0079	0.86492	0.0077	0.89553	0.0056	0.88801
SCG7	6.12E-04	0.99004	0.0011	0.98314	5.58E-04	0.99246

The new formulas has been created for cutting force F_c, F_r and F_f with ANN modeling which the structures are showed in the Figure 3. These equations (Eq. 4-6) provide high accurate prediction of cutting force for new inputs which are austempering heat treatment and machinability variables. Sozen et all use the same formulization in the some of the their studies [26,27]. Computer program has been written in MATLAB programming language.

$$Cutting\ Force(F_c) = \frac{1}{1+e^{-(-0.0684\,F_1-0.7857\,F_2-0.6313\,F_3-0.7328\,F_4-0.1452\,F_5-0.2027\,F_6-0.1915F_7-0.3914)}} \quad (4)$$

$$Cutting\ Force\ (F_r) = \frac{1}{1+e^{-(0.0545\,F_1-0.5134\,F_2+0.0370F_3+1.0243\,F_4+0.7258\,F_5+0.6752\,F_6+0.0106\,F_7-0.8995)}} \quad (5)$$

$$Cutting\ Force\ (F_f) = \frac{1}{1+e^{-(1.1589\,F_1+0.8029\,F_2-0.2911\,F_3-0.0770\,F_4-0.1834\,F_5-0.1531\,F_6-0.0459\,F_7-0.7916)}} \quad (6)$$

$$Fi = \frac{1}{1+e^{-E_i}} \quad (7)$$

Where $\boldsymbol{E_i}$

$$E_i = A_1 w_1 + A_2 w_2 + C_1 w_3 + F_1 w_4 + b_0 \quad (8)$$

where, weights and bias between input and hidden neurons (w_i and b_0). The weights and bias are given Table 5. A_1 , A_2 , C_1 and F_1 are the inputs, austempering temperatures, austempering time, cutting speed and feed rate, respectively.

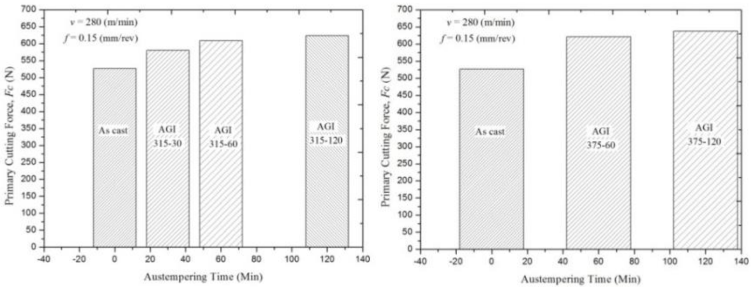
Table 5. The weights and bias between input and hidden neurons.

Neuron	***Fc***				***Bias Weight***	***Ff***				***Bias Weight***	***frwi***				***Bias Weight***
	w1	***w2***	***w3***	***w4***	***bo***	***w1***	***w2***	***w3***	***w4***	***bo***	***w1***	***w2***	***w3***	***w4***	***bo***
1	0.3481	-3.8258	3.0975	0.3913	-1.1412	-2.6032	0.4814	0.1941	-0.1289	2.0832	-2.6415	0.3216	-0.1477	-0.0214	2.6049
2	2.4055	-3.0466	-2.6774	-0.0242	-2.0082	2.0274	-1.3986	2.3735	0.4959	1.5166	1.4662	1.5609	-0.0284	-0.0184	-0.5790
3	-1.1716	0.7508	-0.6517	-0.1758	0.9300	0.2256	2.3683	-0.1937	1.9337	1.0051	-2.4092	1.4111	-1.2575	0.1148	1.8150
4	0.7789	0.0560	2.0253	-0.0320	-0.5723	0.5207	5.0956	-0.3296	0.6609	-2.9345	1.1423	-1.2910	0.4676	2.1971	-0.2941
5	-2.4918	3.4974	-2.4775	-0.1202	-0.7739	0.0539	0.7885	0.0795	-0.0112	-0.2053	-0.4846	1.2612	-2.2305	-0.1788	1.3441
6	-2.2636	-1.8063	-7.7198	0.1847	2.6279	2.2943	0.2960	1.0485	-2.1960	2.4706	-1.9447	1.9313	-2.6552	0.1647	-2.0424
7	-2.9611	-0.5039	0.9436	0.4859	-2.0351	4.0213	-1.1344	1.2140	-0.4046	3.3854	0.1469	3.0632	0.2098	-2.9636	-1.8208

3. Results And Discussion

3.1 Experimental Results

Austempering heat treatments have considerable effects on machinability of austempered gray iron (AGI) because it changes the microstructures. In the austempering process, austenite transformed to high carbon austenite and bainitic ferrite which is called ausferrite. Ausferrite structure is harder than perlite and austenite structures. For the sake of simplicity, only a primary cutting force (F_c) were evaluated. It can be seen from figure 4 that cutting force of austempered parts can be controlled with austempering time and temperatures. Various cutting speed and feed rate values were used in the machining test. The best cutting force was obtained at feed rate of 0.15 mm/rev and cutting speed of 280m/min. Therefore, these parameters used to evaluate the effects of austempering heat treatments on the primary cutting force of AGI (Figure 4).



a) b)

Figure 4 . The effects of austempering time and temperature on the cutting force of AGI. a)315 °C, b)375 °C

All cutting force increases with increasing austempering temperatures. Rises in cutting force is attributed the hardness increasing with austempering temperature. On the other hand, As cast samples showed the lowest cutting force value at. 297.82 N because of perlite in the structures. In addition, the more homogen microstructure was obtained in austempered structures because of transformation of perlite to ausferrite.

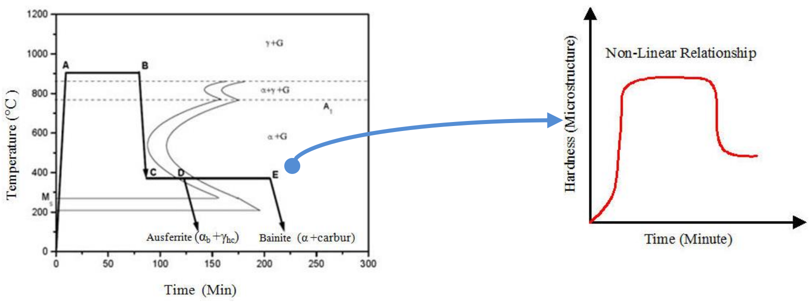


Figure 5. Austempering heat treatment process.

Austempering is a complex heat treatments process and austempering time has significant effects on austempered structure because it determines the phases in the microstructures. Austempering time and hardness (microstructure) do not have linear relationships. This relation can be seen Figure 5. It can be easily understood that the use of artificial neural network modelling on the inputs and output having non-linear relationships made the present experimental study more efficient.

3.2 Neural Network Results

The neural network has the significant ability for interaction caption between input and output because the neural networks use the nonlinear functions. This ability gives the opportunity to predict cutting force of gray cast iron for different heat treatments and cutting parameters.

Performing the regression analysis is an important step in the ANN approach for evaluating performance of the network. The regression of the network outputs with respect to targets for training, validation, and test sets are showed figure 6. In the all figures, near the perfect fit is obtained because all data fallen along 45° line where the outputs are equal to the target. R^2 data are also given in the Table 5. The regression figures exhibited that the performance of network is reasonably high and can be used in the predictions of cutting forces on the austempered gray iron.

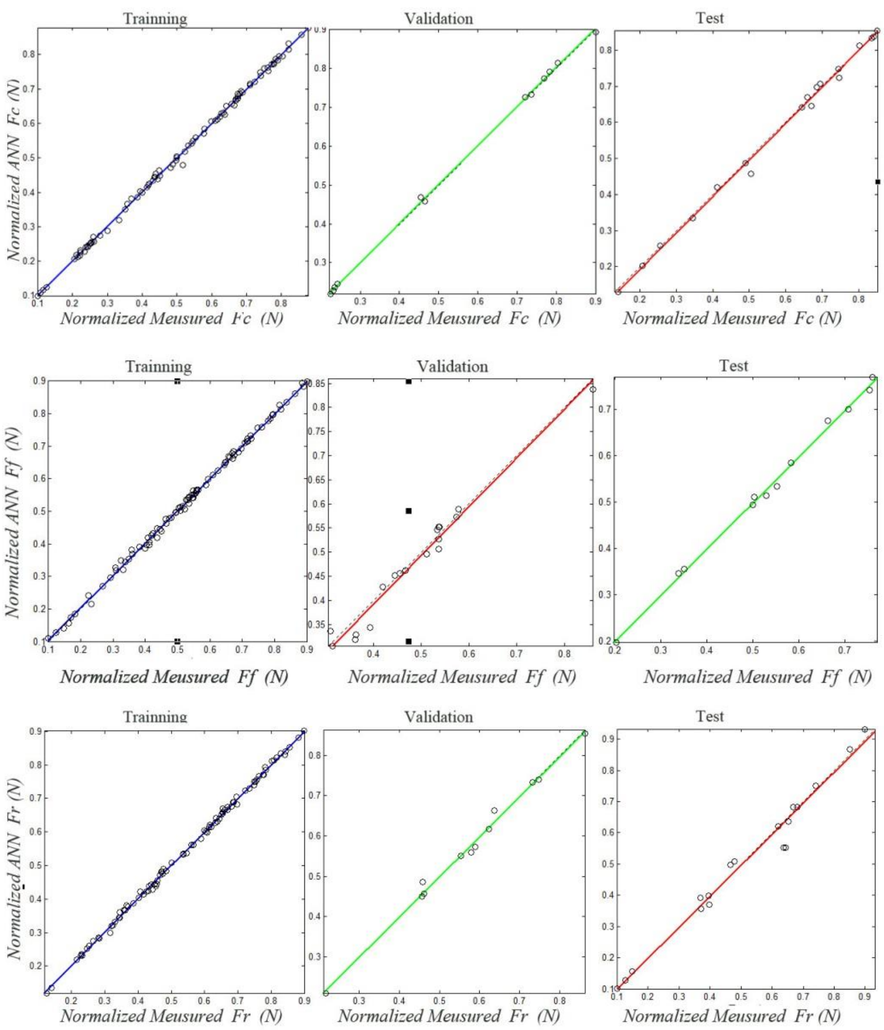


Figure 6. The comparison of normalized measured cutting force, f_c, f_f, f_r , with normalized ANN cutting force.

The experimental results and ANN results are compared in the Figure 7 to evaluate the accuracy of the ANN model. It can be clearly seen that ANN provide accurate predictions for f_c cutting force. Deviations are tolerably small and negligible in the all heat treatments conditions. Figure 7 proves that LM algorithm with seven hidden neurons in the single layer can be used for new inputs without new experimental studies.

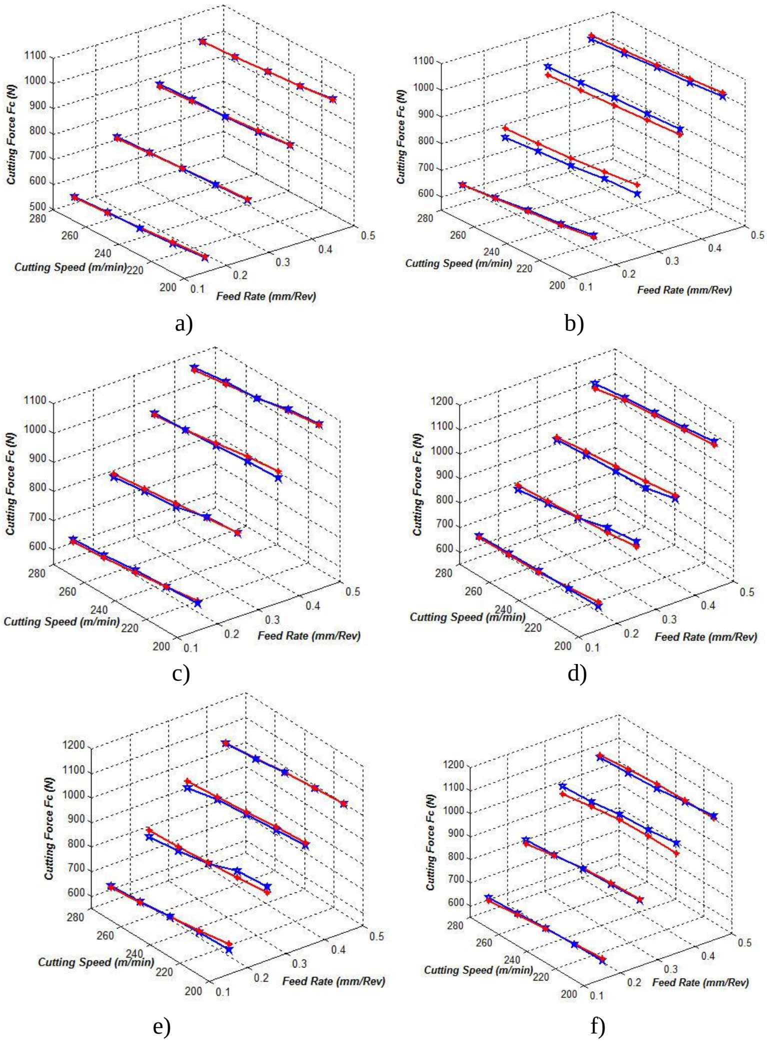


Figure 7. The comparison of normalized measured cutting force, $f_{c,}$,, with ANN cutting force; a) As cast, b) 315°C-30 Min , c) 315°C-60 Min, d) 315°C-120 Min, e) 375°C-60 Min, f) 315°C-120 Min

4. Conclusion

In the present study, experimental and modeling studies show that the cutting force of gray iron can be controlled with austempering heat treatment and machining parameters. Artificial neural network can be used for the prediction of the cutting forces. The results can be summarized in the experimental section results and modeling section results.

In the experimental section, austempering conditions have to be controlled to obtain desired microstructure changing the machinability properties of gray iron. Austempering heat treatment increases all cutting force of gray iron. The maximum cutting force was obtained from the samples austempered at 375 °C for 120 minutes. The cutting force can be optimized with austempering time and temperature. The gray iron having high toughness and machinability combination can be improved with austempering heat treatments.

In the modeling section, The minimum error rate was obtained with LM algorithm with seven hidden layers. The use of Log- Sigmoid transfer function (nonlinear transfer function) makes the network more efficient in the prediction of cutting forces. The new formulas have been developed to predict cutting forces (F_c) austempered gray iron, which can be used for new austempering heat treatments and cutting force parameters. It can be analysed the effects of inputs on the output with assessment of network weight.

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