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Full Length Article

Modeling and prediction of cutting forces during the turning of red brass (C23000) using ANN and regression analysis

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ABSTRACT

The life of a cutting tool is greatly influenced by the forces acting on it during a cutting operation. A machining operation is a complex process. It is very difficult to develop a comprehensive model involving all the parameters. The present study aims to develop a model to investigate the effects of cutting parameters (speed, depth of cut and feed rate) on the cutting forces during the turning operation of red brass (C23000) using high speed steel (HSS) tool. The experimental results are based on full factorial design methodology to increase the reliability and confidence limit of the data. Artificial neural network and multiple regression approaches were used to model the cutting forces on the basis of cutting parameters. In order to check the adequacy of the regression model, analysis of variance (ANOVA) was used. It was clear from the ANOVA that the regression model is capable to predict the cutting forces with high accuracy. However, ANN model was found to be more accurate than the regression model.

1. Introduction

The cutting forces are a result of extreme conditions at the tool-workpiece interface. The interaction can be directly related to the tool wear and in worst cases to the failure of the tool. Consequently, the tool wear and cutting forces are related to each other [1,2]. Thus, it is necessary to carry out the optimization of cutting process to evaluate the optimal values of cutting parameters to determine the performance and useful life of the cutting tool. Surinder et al. [3] investigated the cutting forces (tangential and feed force) in turning of unidirectional glass fiber reinforced plastics (UD-GFRP). The process parameters of cutting tool (nose radius, rake angle, cutting speed, feed rate, depth of cut and cutting environment) were investigated using Taguchi robust design methodology. The relative significance of parameters was studied using ANOVA. The tangential force was found to decrease with decrease in tool nose radius, feed rate and depth of cut and increase with the cutting speed. Cascona et al. [4] developed mechanistic model for prediction of cutting forces in turning of non-axis-symmetric parts. This study presents a mechanistic model for predicting the orthogonal turning forces (in 3 directions), torque and power consumption along the machining path of non-axis-symmetric parts. Dorlin et al. [5] studied the geometrical modeling of tool-workpiece interaction and its effects on the cutting forces during turning. The analysis focused on convex contact radius between the machined part and the tool. The experiments were based on cylindrical and face turning of Ti6Al4V titanium alloy. It was observed that the contact radius had significant effect on the cutting forces and the cutting forces increase with the increase in the radius. Xie et al. [6] studied cutting force and cutting temperature during the turning of titanium alloy using micro-grooved tool under dry conditions. The objective of the study was to estimate the influence of shape and size of micro groove on the temperature and force in dry turning. The micro-grooved tool decreases cutting temperature by 103 °C, while as the shear angle increases with decreasing micro-groove depth. Philip et al. [7] studied the effects of cutting speed and feed rate on tool wear, surface roughness and cutting force on nitrogen alloyed duplex stainless steel in a dry turning process, using Taguchi method**.** The results revealed that the feed had the most significant influence on the cutting forces. The cutting speed was found to be the most significant parameter affecting the tool wear. Shear force, ploughing force and particle fracture force were considered by Sikder et al. [8] to estimate the cutting force during the machining of metal matrix composites (MMCs). The chip formation force, ploughing force and fracture force were obtained by Johnson-Cook model, slip line filed theory and Griffith's theory respectively. The results showed good agreement between the predicted and experimental values of the cutting forces. Two body abrasion and three body rolling due to

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Nomenclature

fx	thrust force (N)	Df	degrees of freedom
fy	cutting force (N)	SS	sum of squares
fz	feed force (N)	MSE	mean square error
fR,	resultant force (N)	MAPE	mean absolute % error
v	cutting speed (m/min)	φ	transfer function
f	feed rate (mm/rev)	t_i	target values
d	depth of cut (mm)	o_i	observed values
k, c_1, c_2, c_3	Model parameters	R^2	coefficient of determination

reinforcements in composites was studied by Uday et al. [9] during the machining of Al/SiCp composite. Theory of oblique cutting was used for predicting the cutting forces during the machining of this composite. With the assumption that 40% of the finer reinforcement particles contribute to abrasion at tool-chip interface, the model was found to be accurate. Similarly for 60% of coarser reinforcement contributing to the abrasion, the model yielded good results. Pramanik et al. [10] proposed a model for predicting the cutting forces during the cutting of aluminum-based SiC/Al_2O_3 particle reinforced MMCs. Three factors, chip formation force, ploughing force and particle fracture force were considered to be the force generation mechanisms. Merchant's analysis was used to obtain the chip formation force, while as, slip line field theory of plasticity and the Griffith theory of fracture were used to formulated the matrix ploughing deformation and particle fracture. It was concluded that the force due to chip formation is much higher than those due to ploughing and particle fracture. Joardar et al. [11] studied the influence of cutting speed, depth of cut and weight percentage of SiCp on the cutting forces during the turning of aluminum MMC (aluminum alloy reinforced with silicon carbide particles) under dry conditions, using response surface methodology. Cutting speed was found to be the most significant factor influencing the cutting forces. Shoba et al. [12] investigated the influence of machining parameters (cutting speed, feed rate and depth of cut) on the cutting forces during the turning of hybrid composites. Different percentages of SiC (0, 2, 4, 6 and 8%) by weight and rice hush ash were used in reinforced composite specimens. The comparison of reinforced and unreinforced specimens revealed that cutting forces decrease with the increase in weight percentage of the reinforcement. This trend was attributed to the dislocation densities produced from the mismatch between the reinforcement and the matrix. Fountas et al. [13] investigated the influence of cutting speed and feed-rate on the cutting forces during the turning of *PA66 GF-30* Glass Fiber Reinforced Polyamide using carbide cutting tool. It was concluded that the soft computing techniques can be effectively used to predict the cutting force components. Vaxevenidis et al. [14] also concluded from their research that ANN can be effectively used to predict the cutting forces and surface roughness while investigating the turning of AISI D6 tool steel, Ti6Al4V ELI and CuZn39Pb3 brass under dry cutting environment with spindle speed, feed rate and depth of cut as input; and surface roughness and cutting forces as outputs. Fountas et al. [15] conducted a series of 5 axis machining experiments in CAM environment to simulate operations using an L_{27} orthogonal array. Four machining parameters namely tool type, stepover, lead angle and tilt angle as inputs and surface deviation and machining time were selected as the outputs. Similar investigation was conducted by Vaxevanidis et al. [16] while turning the Ti-6Al-4V alloy with input as spindle speed, the feed rate and the depth of cut; and outputs as cutting force and the centre line average surface roughness. The methodology was found to be robust enough to predict optimal values for quality objectives.

Although several materials such as steels, aluminum alloys, composites etc. have been investigated during the turning to develop the model for cutting forces. But very few models and investigations are devoted to brasses. The intention of the present work is to develop a cutting force predictive model and to investigate the influence of cutting parameters on the cutting forces during the turning of red brass (C23000) using regression analysis and ANN (see Fig. 1).

2. Experimentation

In this study, red brass (C23000) cylindrical bars of diameter 30 cm as work piece material and ***HSS*** tool were used. The experiments were performed under dry conditions on a (5HP and 45–2000 rpm range) ***Kiloshkar*** make lathe. The tool post was fitted with a dynamometer for measuring three components of the cutting force, namely feed force (f_z), radial thrust force (f_x) and tangential (main) cutting force (f_y) The forces were recorded in a digital computer which was interfaced with the dynamometer. A full factorial design methodology was adopted and in total 27 (3^3) experiments were performed. Feed rate, cutting speed and DOC were chosen for the study. The experimental details of machining process are given in Table 1. The resultant force was calculated by $f_{R=}\sqrt{f_x^2+f_y^2+f_z^2}$.

3. Results and discussion

3.1. Regression model

The model of predicted cutting force, F_R can be expressed as Eq. (1).

$$F_R = kv^{c_1}f^{c_2}d^{c_3} \tag{1}$$

where k, c_1, c_2 and c_3 are model parameters

By logarithmic transformation Eq. (1) can be written as

$$ln F_R = ln k + c_1 ln v + c_2 lnf + c_3 lnd \tag{2}$$

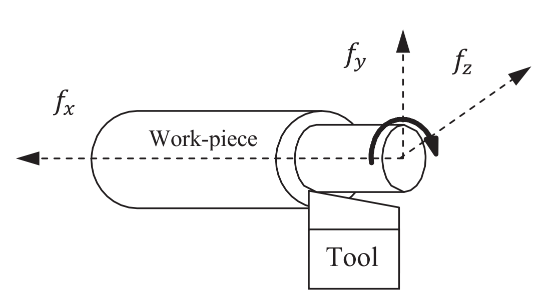

Fig. 1. Direction of forces in turning operation.

Table 1
Experimental data obtained from turning operation.

S. No	Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	$f_x(N)$	$f_y(N)$	$f_z(N)$	$f_R(N)$
1	840	0.40	0.10	1.8640	4.2310	2.2150	5.1266
2	840	0.40	0.13	1.9946	4.1226	3.6500	5.8563
3	840	0.40	0.16	3.1940	5.3203	3.9776	7.3708
4	1280	0.40	0.10	2.3749	4.7795	3.2778	6.2632
5	1280	0.40	0.13	4.0120	5.0208	4.5283	7.8619
6	1280	0.40	0.16	3.9443	6.4434	5.0099	9.0650
7	1000	0.40	0.10	3.4921	4.2817	3.7600	6.6832
8	1000	0.40	0.13	3.6121	5.0568	3.1600	6.9717
9	1000	0.40	0.16	4.0353	5.8314	3.1893	7.7756
10	840	0.80	0.10	3.8638	6.3423	3.1522	8.0678
11	840	0.80	0.13	2.5223	7.7341	2.1280	8.4087
12	840	0.80	0.16	2.8110	9.1173	3.0937	10.0298
13	1280	0.80	0.10	2.4642	7.6636	2.9444	8.5716
14	1280	0.80	0.13	3.1269	7.4498	2.6920	8.5161
15	1280	0.80	0.16	2.7561	8.8065	3.7529	9.9617
16	1000	0.80	0.10	4.3497	6.7663	3.8258	8.9073
17	1000	0.80	0.13	4.3497	6.7663	3.8258	8.9073
18	1000	0.80	0.16	1.7883	7.6812	2.5603	8.2918
19	840	0.12	0.10	2.8105	1.6157	2.4624	4.0710
20	840	0.12	0.13	1.8123	1.6314	2.2874	3.3434
21	840	0.12	0.16	1.2031	2.7263	2.7559	4.0590
22	1280	0.12	0.10	2.1616	2.5057	4.2470	5.3841
23	1280	0.12	0.13	1.3419	1.2452	1.5682	2.4105
24	1280	0.12	0.16	1.9665	2.8219	3.4265	4.8550
25	1000	0.12	0.10	1.7347	2.0911	2.8472	3.9355
26	1000	0.12	0.13	1.3625	2.3763	2.8540	3.9558
27	1000	0.12	0.16	1.7977	2.8515	4.1100	5.3155

Table 2
ANOVA analysis.

Source of variation	Df	SS	MS	F
Regression	3	108.254	36.080	52.59
Residual	23	15.789	00.686	
Total	26	124.000		

or

$$Y_r = K + c_1V + c_2F + c_3D \tag{3}$$

where $\ln F_R = Yr$, $\ln k = K$, $\ln v = V$, $\ln f = F$, $\ln d = D$.

The model parameters in Eq. (3) were evaluated by using least square method.

The data presented in Table 1 was used for developing the regression model. Accordingly Eq. (4) was obtained for estimating the cutting force.

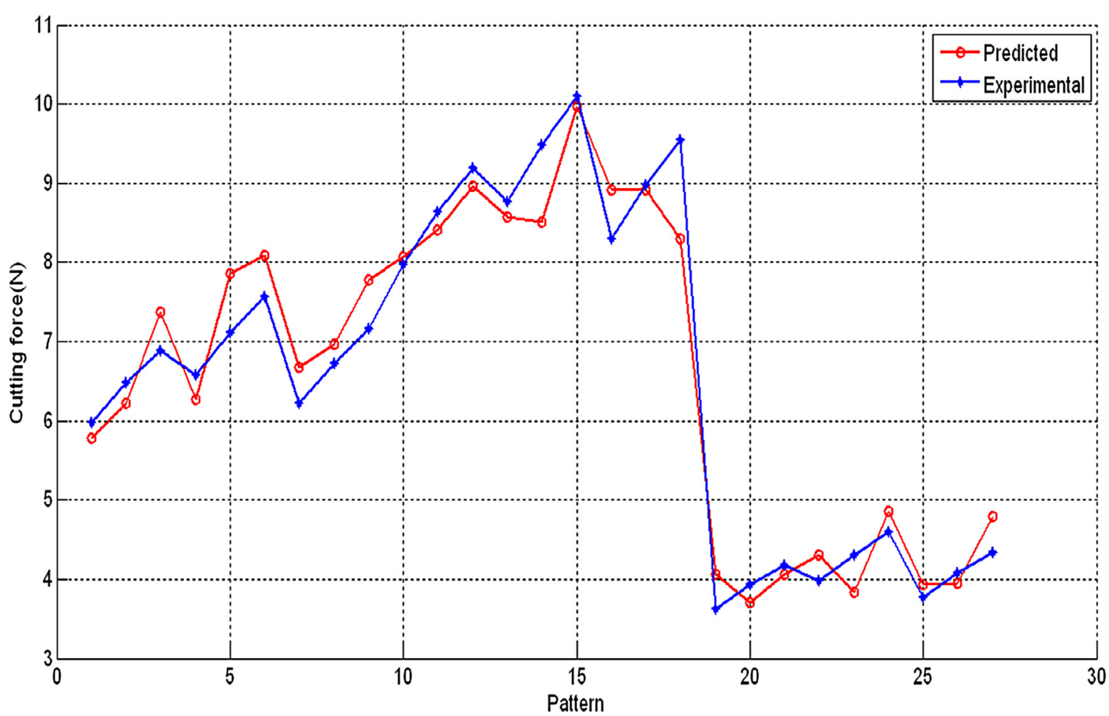

Fig. 2. Comparison of experimental and predicted values of cutting force by regression model.

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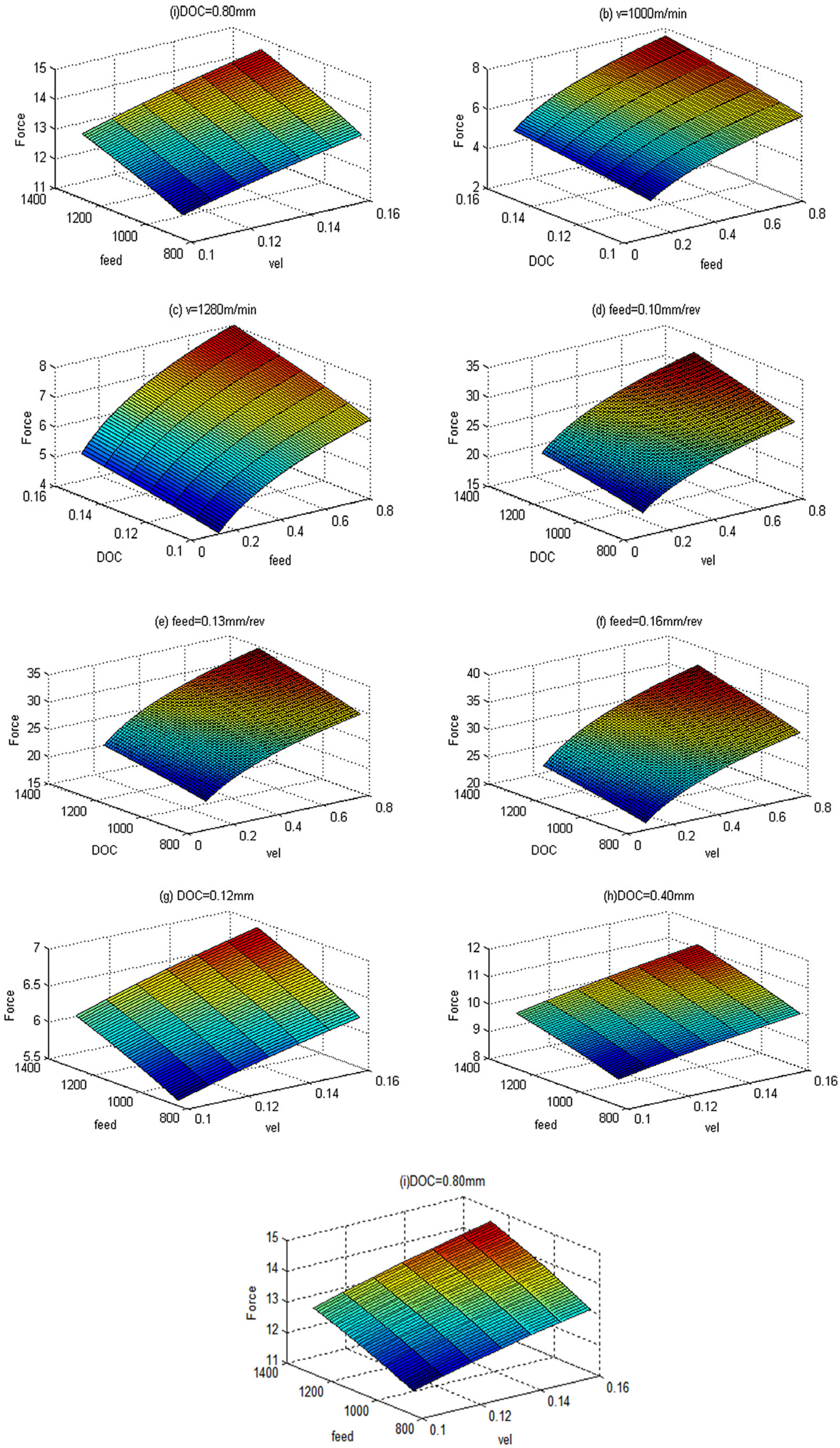

Fig. 3. (a–i) Cutting force versus cutting parameters.

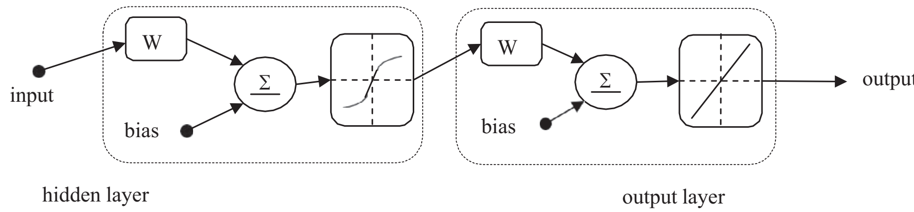

Fig. 4. ANN structure used for modeling.

Table 3
Training parameters of ANN model.

No. of neurons on the layer	i/p;1, hidden:2 and o/p:1
Initial weight and biases	−1 to 1
Activation function	Tansig
Learning rate	0.05
Momentum constant	0.95

$$F_R = 3.9093\,v^{0.2226} f^{0.4145} d^{0.3008} \quad (4)$$

In order to determine the influence of each parameter on the cutting force ANOVA was employed. The results of the ANOVA are presented in Table 2. Based on the F-ratio of the predictive model and that of the experimental results, the model was found to be adequate. The experimental and predicted values of regression model are depicted in Fig. 2. It is obvious from Fig. 2 that there is a close agreement between the experimental values and that of the predicted values.

From Fig. 3(a–i) it is clear that the cutting force strongly depends on the feed rate. At (a) $v = 840$ m/min and (b) 1000 m/min, the effect of feed rate on force is almost same but at (c) $v = 1280$ m/min the effect of feed rate on force is prominent as the velocity is also high. Similarly at constant feed rate the effect of depth of

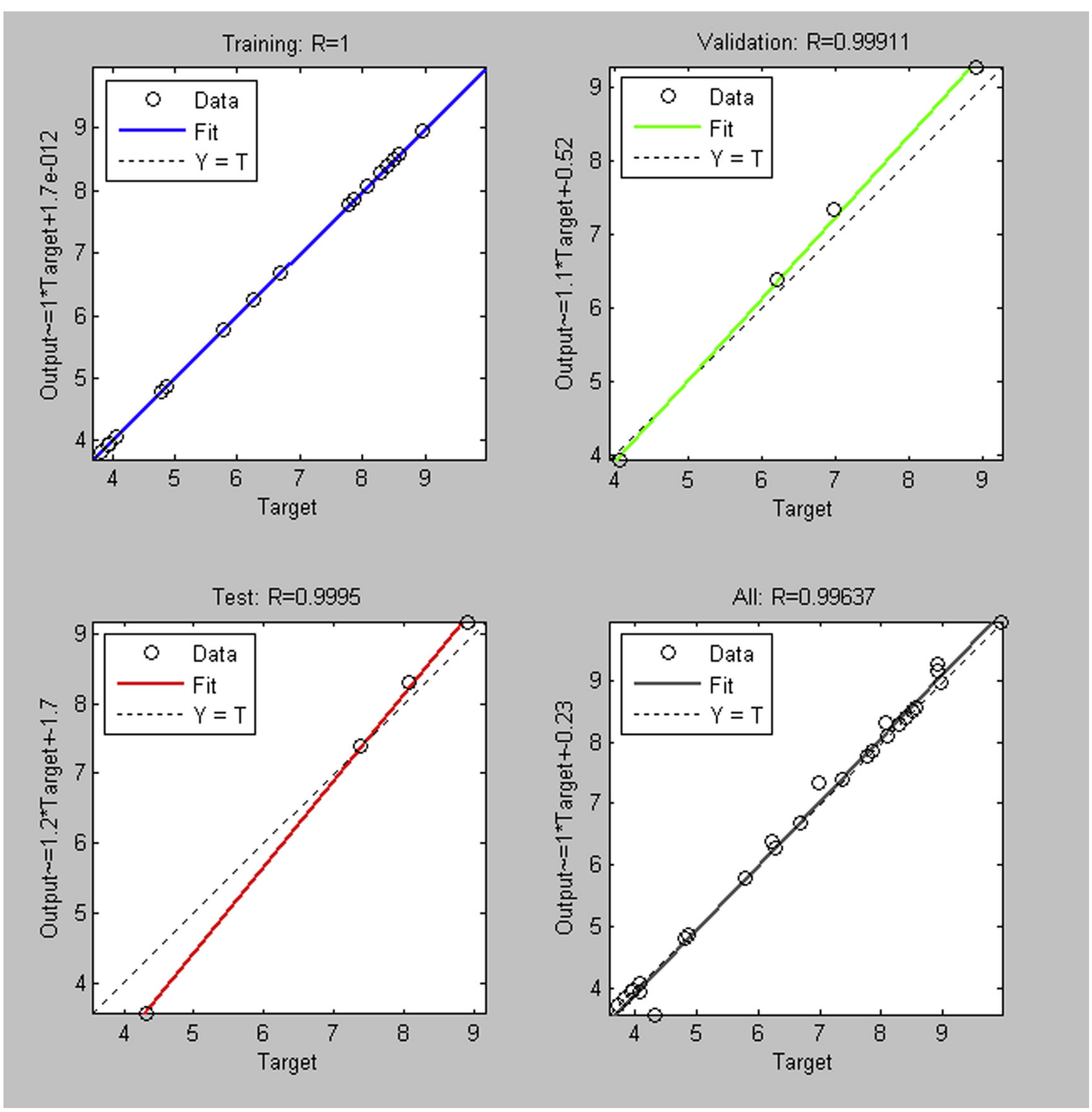

Fig. 5. ANN output.

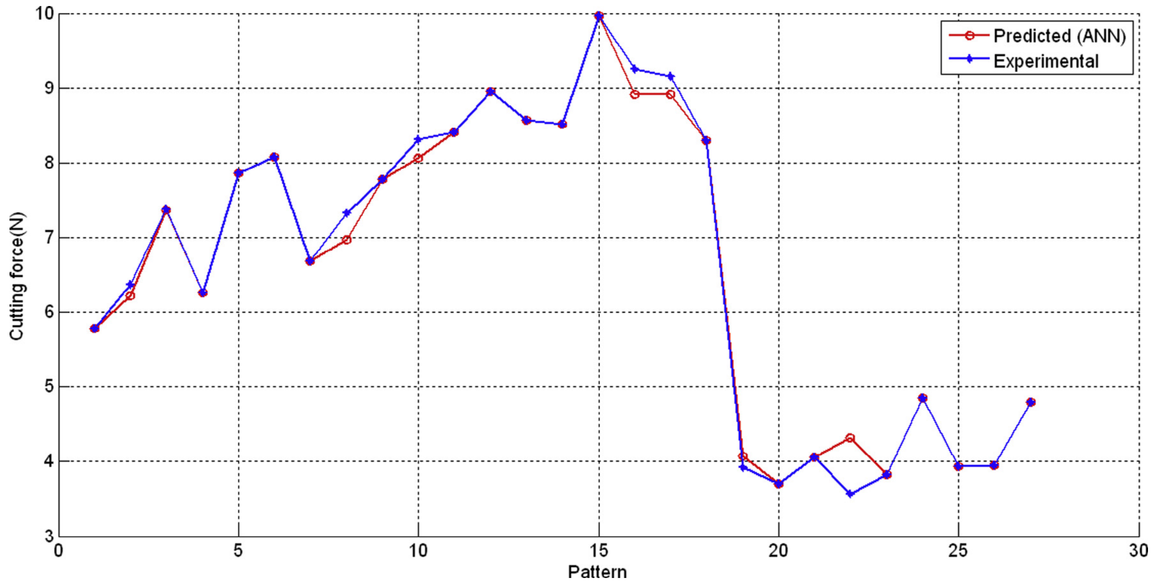

Fig. 6. Comparison of experimental and predicted values of cutting force by ANN model.

Table 4
Statistical parameters of output of ANN.

Sample	Size	MSE	R^2
Training	19	3.77217×10^{-24}	1.00
Validation	4	7.39120×10^{-2}	0.999
Testing	4	1.70073×10^{-1}	0.999
All values	27	3.6146×10^{-2}	0.996

cut is prominent which is clear from (d) $f = 0.10$ mm, (e) $f = 0.13$ mm and (f) = 0.16 mm. As stated earlier the velocity has least effect on the force, which is evident from (g) $d = 0.12$ mm, (h) $d = 0.40$ mm and (i) $d = 0.80$ mm.

3.2. ANN model

Due to the fact that the ANN has a capacity to solve non-linear problems, it has been widely used by the researchers. Thus, in present work ANN was also employed to model and predict the cutting forces during turning of red brass. Depending upon the complexity and nature of the problem, an ANN model has several layers. In general, ANN has an input layer, hidden layers and output layer. The input and output layers constitute the first and last layers respectively. The hidden layers process the data received from the input layer. Similarly, the next hidden layer computes the output and the last layer processes this output to produce the final result. The final results are computed by hidden and output layer using transfer functions.

In this paper a transfer function – *tansig* was used, as is given in Eq. (5).

$$\varphi = \frac{e^n - e^{-n}}{e^n + e^{-n}} \tag{5}$$

The structure of the ANN model is shown in the Fig. 4.

The first step in the ANN is training. An input is fed to the ANN along with the target outputs and the weights are set randomly, initially. The satisfactory level of performance is achieved by minimizing the global error using back propagation algorithm. Back propagation algorithm is a learning technique that adjusts weights in ANN by propagating weight changes from the output to input neurons in backward direction. The training of the network is stopped when the desired level of performance is achieved. The weights computed during this stage are used to make decisions for the evaluation of output. The MATLAB toolbox was used for ANN training, validation and testing in this investigation. The parameters used for ANN are presented in Table. 3. Several independent runs were performed to achieve a satisfactory solution, with different initial random weights. The error during the learning process was calculated by

$$MSE = \frac{\sum_{i=1}^{N} |t_i - o_i|^2}{N} \tag{6}$$

The weights between hidden layer and output are adjusted and are again calculated using

$$\Delta w_{ji}(n) = \alpha \Delta w_{ji}(n-1) + \eta \delta_j(n) y_i(n) \tag{7}$$

where $\Delta w_{ji}(n)$ is the change in weights, α is the momentum coefficient, δ_j is the error-scaled by the signal slope, η is learning rate parameter and $y_i(n)$ is the output. After satisfactory training the experimental data, not presented in the previous stage was used for testing the network. The statistical methods (R^2 and MAPE) were used for comparing the results obtained from the models.

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N} (t_i - o_i)^2}{\sum_{i=1}^{N} o_i^2} \right) \tag{8}$$

The mean absolute percentage deviation (MAPD), also known as mean absolute percentage error (MAPE) was estimated to measure of accuracy of the model and is defined as

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \left(\left| \frac{t_i - o_i}{o_i} \right| \right) \tag{9}$$

where N is the number of experiments

In order to develop ANN model, the network was trained by using a set of experimental values. After successful training the network was used to predict the cutting force for validation and testing. The ANN results are presented in Fig. 5. It is clear from the Fig. 5 that all the experimental and predicted values during training coincide perfectly on the regression line which make the $R^2 = 1$ in training. The R^2 was found to be equal to 0.99690 and 0.99962 for validation and testing, respectively. At this stage the training was stopped and all the 27 experimental values were used to predict cutting forces from the ANN model. The comparison of the experimental values with that of the predicted values of the model are shown in Fig. 6. It is obvious from the Fig. 6 that the error between the experimental and the predicted values has been reduced considerably. The mean square error in ANN model was found to be 0.0059 (see Table 4).

4. Conclusions

In this paper a predictive model for determining the cutting forces was developed in turning operation of red brass and the following conclusions were drawn from this investigation.

(i) The cutting force increases with increase in all the three parameters (feed, cutting speed and depth of cutting).
(ii) Out of three cutting parameters resultant cutting force was found to be largely influenced by feed rate and least by depth of cut.
(iii) ANOVA results confirm that the regression model is adequate and is capable to predict the cutting forces.
(iv) On the basis of statistical parameters, it was concluded that the ANN model can predict the cutting forces more accurately that the regression model.

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