841. ANN prediction and RSM optimization of cutting process parameters in boring operations using impact dampers

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Abstract. The cantilever shape of the boring bar induces chatter vibrations in boring operations. Chatter vibrations consequently lead to increase in tool wear. Present work focuses on the prediction and optimization of cutting process parameters using ANN and RSM methods for phosphor bronze damping material attached to the boring tool. All-geared head lathe with temperature measurement setup was used to conduct experiments for various levels of cutting speed, depth of cut and position of damper from the cutting edge. Tool wear was measured using profilometer, while the temperature and tool wear were accurately predicted using the developed ANN model. The minimum value of temperature of 280^0 C and tool wear of 0.13 mm were obtained by using Response Surface Methodology for the following input conditions: cutting speed of 300 rpm, depth of cut of 0.25 mm and damper position of 65 mm from the cutting edge.

Keywords: chatter, tool wear, natural frequency, impact dampers.

1. Introduction

Chatter vibrations in machining operations are of two types: forced and self-excited. Self-excited vibrations are of two types: primary (non-regenerative) and regenerative. The non-regenerative self-excited vibrations are induced when there is no interaction between the vibratory motion of the system and the undulatory surface produced in the revolution of the workpiece. So it is related to the dynamics of the cutting process. But the regenerative self-excited vibrations occur due to the interaction of the cutting force and the workpiece surface undulations produced by previous tool passes. The regenerative self-excited vibrations constitute the most detrimental phenomena in most machining processes and are of particular importance.

Literature review reveals that a number of research works were carried out with the aim of reducing tool wear and increasing dynamic stability of the tool [1]. The optimal design of an impact damper for a nonlinear friction-driven oscillator and its effects were given effectively [2]. The vibration absorber design which was used to suppress vibrations was investigated thoroughly [3]. Model development and the experimental verification of tool chatter stability in turning and boring operation were also considered [4]. The investigation of an impact vibration absorber with hysteresis damping was carried out with the various impacts occurring due to the vibration absorber [5] and the studies on boring/drilling with vibration cutting conditions were also discussed [6].

The investigations on the granular damping in transient vibrations using Helbert transform techniques discuss the various conversion techniques [7]. The studies [7] also focus on granular damping and not on impact damping due to less energy distribution. The performance of a harmonically excited vertical impact damper and its functions are limited in predicting dynamics and damping characteristics [8]. The problems in chatter during turning operation for uniform and stepped workpieces were studied and the developed theoretical models were also discussed but not the respective soft computing methods [9].

Recent advances in nonlinear passive vibration isolation were discussed in [10] and stability of plunge milling operations were studied in [11]. These research works on performance of a new particle fine damper [12] and an improved tool path model for chatter prediction [13] and active control of regenerative chatter [14] provided the platform for effective control and prediction of chatter vibrations in manufacturing [15] modeled progression of flank wear in hard turning and in Artificial Neural Network (ANN) training [16]. The application of computational techniques for the prediction of tool wear in the drilling of polymeric composites and the suggestion for the systematic procedure were discussed elaborately in the statistical analysis [17]. The optimization techniques to determine the thrust force, torque and tool wear in the drilling of coir fiber reinforced composites using Nelder-Mead and genetic algorithm methods were considered in [18]. The regression and neuro fuzzy models for prediction of thrust force and torque in drilling of glass fiber reinforced composites were also studied [19]. The analytical modeling of chatter stability in turning and boring operations were verified experimentally and spindle speed, depth of cut and feed rate for boring operations were proposed to minimize the chatter stability [20].

Damping material is selected based on the criteria referred in the material selection. It is then machined and fabricated with the boring tool holder. The natural frequency of the assembly is determined by hammer test. Experiments are carried out in a all geared head lathe, by employing the selected dampers at various positions from the cutting edge and the temperature and tool wear are measured.

After obtaining the experimental data, the feed-forward back-propagation network was chosen for the current application as the degree of accuracy needed is one of the primary constraints. The network is trained using the experimental data and the responses for the input parameter combinations which lie beyond the scope of experimental observations.

2. Material selection

The material should serve the desired purpose at minimum cost. Such factors as ease of availability, cost, mechanical properties and manufacturing difficulties were considered while selecting the suitable material for machine tool and damper. The properties of boring tool and damper are described in Table 1. The boring tool of EN8 material with density of 7.84×10^{-6} kg/mm^3 and the damper material of phosphor bronze with density of 8.85×10^{-6} kg/mm^3 were used.

Table 1. Material properties

S. No	Material property	Density (kg/mm^3)	Young's modulus (N/mm^2)	Poisson's ratio	Thermal conductivity (W/m K)
1	Boring tool	7.84×10^{-6}	2.84×10^{5}	0.3	46.6
Damping material					
2	Phosphor bronze damper	8.85×10^{-6}	1.234×10^{5}	0.3	63

2. 1. Tool geometry

The boring tool geometry and the position of dampers in the boring tool holder are shown in Figures 1 and 2 respectively. The impact dampers were fabricated in the opposite surface of the cutting edge. This is done to ensure that the damper does not maintain any contact with the workpiece. The length and width of the boring bar is 234 mm and 18 mm respectively. The height of the damper protruded from boring tool surface is 9 mm and cross-section diameter of the damper is 18 mm.

Damper positions were arranged at 44 mm, 54 mm and 64 mm from the cutting edge in order to reduce induced vibrations partly.

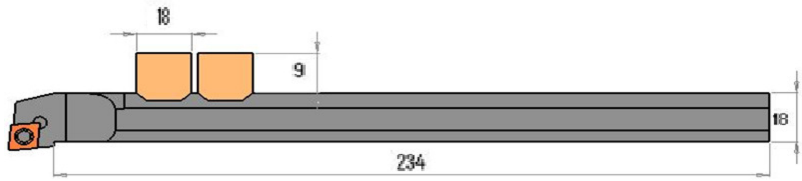

Fig. 1. Boring Tool Geometry

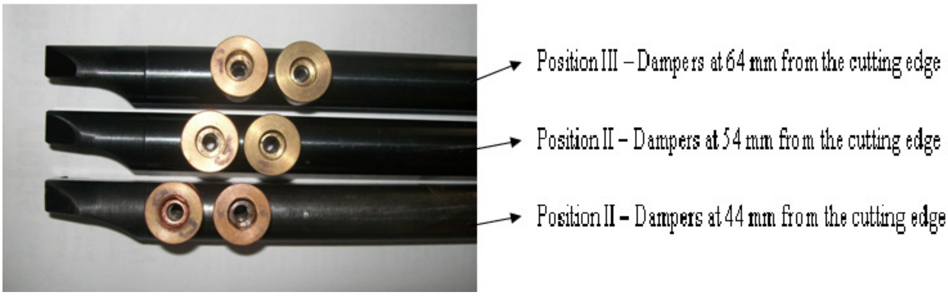

Fig. 2. Position of dampers on boring tool

3. Experimental analysis

3. 1. Impact Hammer test

The impact hammer test setup is shown in Figure 3. In order to determine the natural frequency of boring tool with and without impact dampers the impact hammer test was conducted with the help of LMS Pimento system using PimentoV.5.2 software. From the hammer test, it was clear that the natural frequency of the boring tool with phosphor bronze damper is 1515 Hz, which is more than that of the boring tool without damper which is around 1310 Hz. Whenever a damper is added to the tool, the natural frequency of the tool increases which in turn increases the stability of the tool thereby the tool withstands against the tool chatter and suppresses the chatter produced during boring operations. The natural frequency of the boring bar when employed with the damping material of phosphor bronze was found and is plotted in Figure 4.

Fig. 3. Photographic image of Impact Hammer test

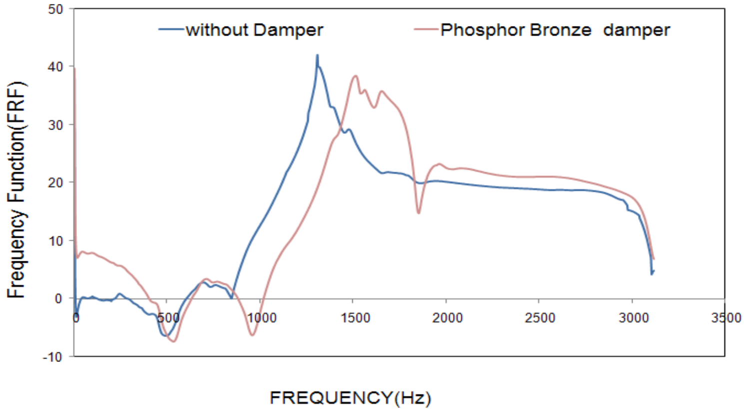

Fig. 4. Natural frequency plot for the phosphor bronze material

3. 2. Experimentation

An all-geared head lathe with chromel-alumel thermocouple setup was used to measure tool wear and temperature in boring operations. The block diagram of the experimental setup and its image are presented in Figures 5 and 6 respectively. The recommended spindle speed, depth of cut, and feed rate were followed for boring operations in the mild steel cylindrical workpiece based on literature [20]. Tool wear was measured using a profilometer by calculating tool profile dimensional difference before and after boring operations. Temperature was measured using chromel-alumel thermocouple setup and the graphs were obtained from YOKOGAWA software.

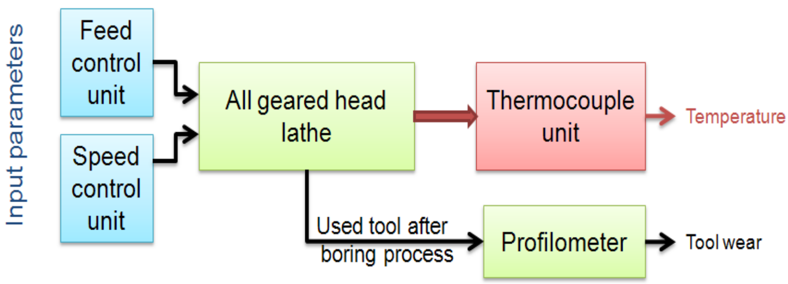

Fig. 5. Block diagram of the experimental setup

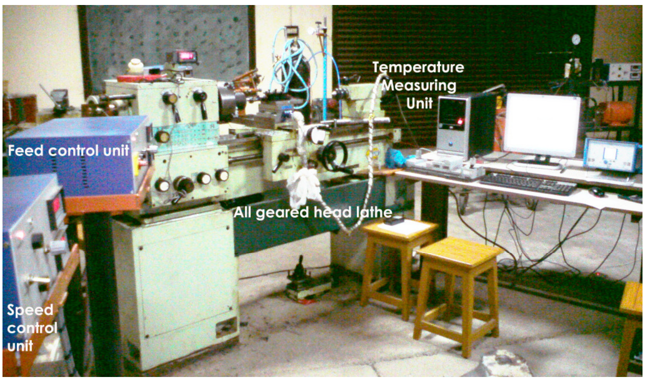

Fig. 6. Image of the experimental setup

3. 2. 1. Parameter selection

The boring operation is influenced by various cutting parameters such as speed, depth of cut, feed rate, over hanging length, etc. Since the present investigation focuses on the reduction of boring tool chatter, prominent parameters such as speed, depth of cut, damping materials, position of dampers from the cutting edge are selected at various levels. The parameter levels are listed in Table 2. Experiments were carried out with various combinations of these parameters in full factorial method. Finally 9 observations without damper and 27 observations with the damper were obtained. The temperature values were obtained digitally by chromel-alumel thermocouple being incorporated with a digital display.

Table 2. Levels of the parameters

Parameters Used	Values
Speed in rpm	300, 400, 500
Depth of cut in mm	0.25, 0.5, 0.75
Damper	Phospor bronze
Position of dampers from cutting edge in mm	44, 54, 64

4. Neural network training

An artificial neural network consists of an interconnected group of artificial neurons and it processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Using a large amount of data out of which they build knowledge bases, ANN establishes analytical model to solve the problem in the estimation, prediction, decision making and diagnosis. Each neuron has inputs and generates an output that can be seen as the reflection of local information that is stored in connections. The output signal of a neuron is fed into other neurons as input signals via interconnections. Since the capability of a single neuron is limited, complex functions can be realized by connecting many neurons. It is widely reported that structure of a neural network, representation of data, normalization of inputs, outputs and appropriate selection of activation functions have strong influence on the effectiveness and performance of the trained neural network.

A neural network consists of at least three layers i.e., input layer, hidden layer and output layer, where inputs are applied to the input layer and outputs are obtained from the output layer and learning is achieved with the associations between a specified set of input and output pairs. The following steps were followed in ANN modeling:

1. Feeding of normalized experimental data.
2. Creating the Feed Forward Back Propagation Network.
3. Configuring the network.
4. Initializing the weights and biases.
5. Training the network.
6. Validating the network.
7. Using the network.

Among the supervised, unsupervised and reinforced learning methods, supervised learning was selected to train the network for improving performance. The feed-forward back-propagation algorithm was used in layered feed-forward ANN in this work. This means that the artificial neurons are organized in layers, and send their signals “forward”, and then the errors are propagated backwards. The network receives inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer. The back-propagation algorithm uses supervised learning to compute error (difference between actual and expected results). The idea of the back-propagation algorithm is to reduce this error, until the ANN learns the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal.

Feed-forward back-propagation (FFBP) algorithm was used for the prediction of tool wear and temperature of the damper used in boring operations. Multi-layer networks use a variety of learning techniques, the most popular being back-propagation. Here, the output values are compared with the correct answer to compute the value of some predefined error-function. By various techniques, the error is then fed back through the network. Using this information, the algorithm adjusts the weights of each connection in order to reduce the value of the error function to a little extent. After repeating this process for a sufficiently large number of training cycles, the network will usually converge to some state where the error of the calculations is small. In this case, one would say that the network has learned its target function.

4. 1. ANN training

The neural network has to be first trained and then tested to apply for the required application. The training was done with MATLAB R2010a software. In this work ANN module (nn tool) was utilized for predicting the cutting process parameters of boring operations like tool wear and temperature. Such parameters as speed, depth of cut, position of damper from the cutting edge and natural frequency are the inputs, while the tool wear and temperature are the output for ANN training. Weights between input layer and hidden layer as well as between hidden layer and output layer are generated randomly for the selected topology of the network. The number of parameter set used for ANN training using FFBP algorithm is 27. Training of the ANN was performed without any allowable error. The parameter sets are selected for training and testing of the ANN. The selected parameter sets were normalized. 27 parameter sets were selected for training the ANN.

The inputs and outputs are normalized by:

$$X_i = \frac{X_i}{X_{\max}}$$

where X_i is the value of a feature and X_{max} is the maximum value of the feature.

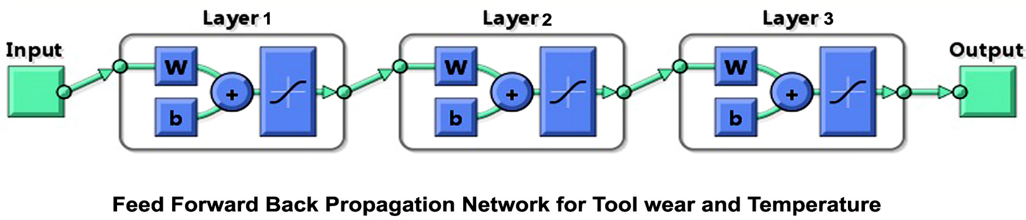

Fig. 7. Structure of network for output model

FFBP ANN was selected for the training of responses and the network is shown in Figure 7. The learning process with 1000 Epochs and goal of 0 were set for the training of tool wear values and the obtained graph is provided in Figure 8. The performance curve for temperature model is shown in Figure 9. The following parameters were set in the training of ANN models:

Training Function	-	TRAINLM
Adaption Learning Function	-	LEARNGDM
Performance Function	-	MSE
Transfer Function	-	TRANSIG

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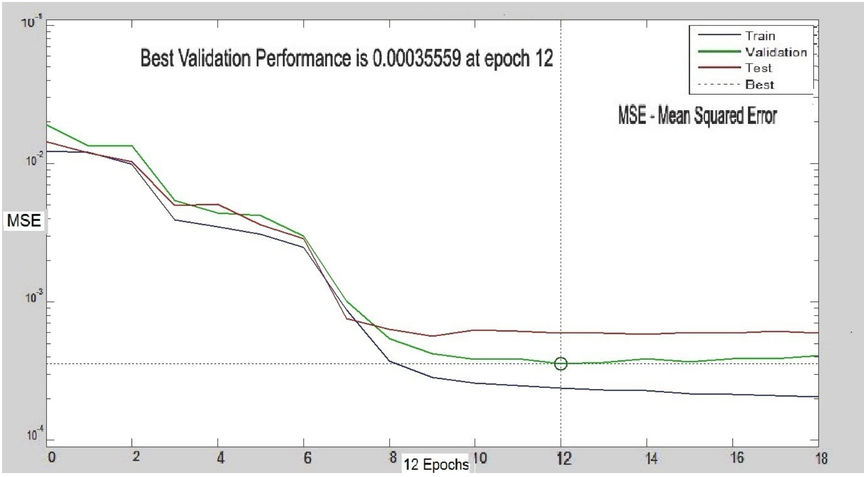

Fig. 8. Performance curve for tool wear

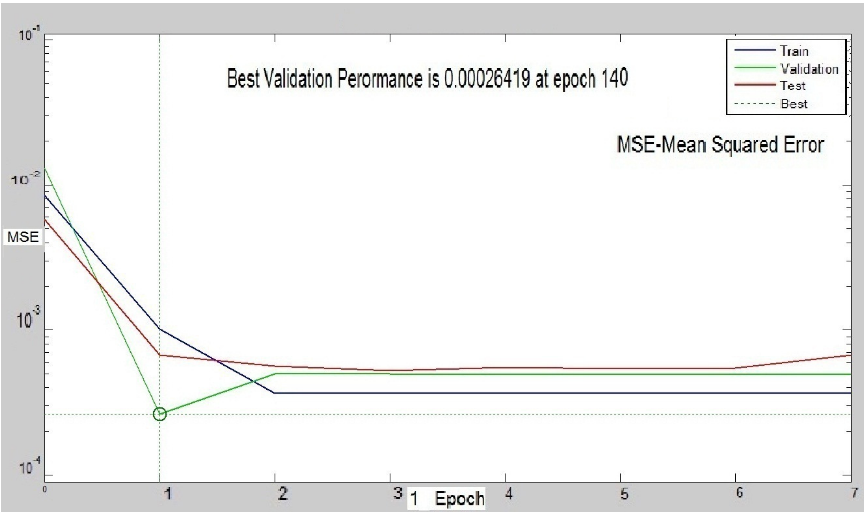

Fig. 9. Performance curve for temperature

5. Result and discussion

Experimental results (Table 3) indicate that there was a considerable reduction of tool wear and temperature when the tool is installed with impact dampers. The experimental values and the ANN predicted values were compared. The percentage of error was calculated using the following formula for the validation of ANN model:

$$\%\text{ of error} = \frac{\text{experimental value - predicted value}}{\text{experimental value}} \times 100$$

5. 1 Comparison charts

Figures 10 and 11 present the relationship between input parameters and responses with the help of 3-D response and contour plots. For a clear view of the surface the model was displayed in 3-dimensional surface plots. The distribution of response surface with respect to two different factors was illustrated using 3-D surface plot. Contour line displayed the connection of all points that had the same responses to produce constant lines.

Table 3. Comparison of the measured and predicted values

Natural frequency	Position of damper from cutting edge	Speed	Depth of Cut	Tool wear		
				Experimental values	Predicted values	% of error
Hz	mm	rpm	mm	mm	mm	%
1	0.69	0.6	0.33	0.36	0.51	-41.67
1	0.69	0.6	0.67	0.38	0.49	-28.95
1	0.69	0.6	1	0.41	0.54	-31.71
1	0.69	0.8	0.33	0.44	0.49	-11.36
1	0.69	0.8	0.67	0.46	0.54	-17.39
1	0.69	0.8	1	0.59	0.62	-5.08
1	0.69	1	0.33	0.62	0.59	4.84
1	0.69	1	0.67	0.64	0.7	-9.37
1	0.69	1	1	0.69	0.84	-21.74
1	0.84	0.6	0.33	0.38	0.46	-21.05
1	0.84	0.6	0.67	0.44	0.49	-11.36
1	0.84	0.6	1	0.46	0.51	-10.87
1	0.84	0.8	0.33	0.46	0.46	0.00
1	0.84	0.8	0.67	0.51	0.49	3.92
1	0.84	0.8	1	0.54	0.54	0.00
1	0.84	1	0.33	0.54	0.54	0.00
1	0.84	1	0.67	0.59	0.62	-5.08
1	0.84	1	1	0.64	0.7	-9.37
1	1	0.6	0.33	0.36	0.46	-27.78
1	1	0.6	0.67	0.38	0.43	-13.16
1	1	0.6	1	0.41	0.49	-19.51
1	1	0.8	0.33	0.41	0.41	0.00
1	1	0.8	0.67	0.44	0.46	-4.55
1	1	0.8	1	0.49	0.54	-10.20
1	1	1	0.33	0.46	0.46	0.00
1	1	1	0.67	0.51	0.54	-5.88
1	1	1	1	0.54	0.62	-14.81
0.86	-	0.6	0.33	0.46	0.65	-41.30
0.86	-	0.6	0.67	0.56	0.57	-1.79
0.86	-	0.6	1	0.69	0.57	17.39
0.86	-	0.8	0.33	0.54	0.57	-5.56
0.86	-	0.8	0.67	0.59	0.57	3.39
0.86	-	0.8	1	0.74	0.78	-5.41
0.86	-	1	0.33	0.69	0.76	-10.14
0.86	-	1	0.67	0.9	1	-11.11
0.86	-	1	1	1	1	0.00
Average Absolute Error Percentage				11.83		

Figure 10 provides the relationship between speed, depth of cut, position of damper from the cutting edge and tool wear. Figure 10 clearly demonstrates that the position of damper closer to the cutting edge and optimum cutting speed reduces the tool wear to an optimum level. At a speed of 300 rpm for the depth of cut of 0.25 mm and for the damper position of 64 mm from the cutting edge the tool wear is minimum. The same is compared for various positions of dampers from 44 mm to 64 mm, speeds of 300 to 500 rpm and depth of cut of 0.25 to 0.75 mm. Among all the combinations from the Figures 10(a-e) the speed of 300 rpm, depth of cut 0.25 mm and the position of damper of 64 mm from the cutting edge the tool wear reduces to a minimum.

Table 4. Comparison of the measured and predicted values for temperature

Natural Frequency	Position of damper from cutting edge	Speed	Depth of Cut	Temperature		
				Experimental values	Predicted values	% of error
Hz	mm	rpm	mm	^{0}C	^{0}C	%
1	0.69	0.6	0.33	0.92	0.92	0.00
1	0.69	0.6	0.67	0.94	0.93	1.06
1	0.69	0.6	1	0.95	0.95	0.00
1	0.69	0.8	0.33	0.93	0.94	-1.08
1	0.69	0.8	0.67	0.95	0.95	0.00
1	0.69	0.8	1	0.96	0.97	-1.04
1	0.69	1	0.33	0.95	0.96	-1.05
1	0.69	1	0.67	0.98	0.98	0.00
1	0.69	1	1	0.99	0.99	0.00
1	0.84	0.6	0.33	0.9	0.91	-1.11
1	0.84	0.6	0.67	0.93	0.93	0.00
1	0.84	0.6	1	0.94	0.95	-1.06
1	0.84	0.8	0.33	0.93	0.94	-1.08
1	0.84	0.8	0.67	0.95	0.95	0.00
1	0.84	0.8	1	0.96	0.97	-1.04
1	0.84	1	0.33	0.95	0.95	0.00
1	0.84	1	0.67	0.97	0.98	-1.03
1	0.84	1	1	0.98	0.99	-1.02
1	1	0.6	0.33	0.9	0.91	-1.11
1	1	0.6	0.67	0.92	0.92	0.00
1	1	0.6	1	0.94	0.95	-1.06
1	1	0.8	0.33	0.93	0.93	0.00
1	1	0.8	0.67	0.94	0.95	-1.06
1	1	0.8	1	0.95	0.96	-1.05
1	1	1	0.33	0.94	0.95	-1.06
1	1	1	0.67	0.97	0.98	-1.03
1	1	1	1	0.98	0.99	-1.02
0.86	-	0.6	0.33	0.92	0.92	0.00
0.86	-	0.6	0.67	0.94	0.95	-1.06
0.86	-	0.6	1	0.96	0.96	0.00
0.86	-	0.8	0.33	0.95	0.95	0.00
0.86	-	0.8	0.67	0.97	0.97	0.00
0.86	-	0.8	1	0.96	0.95	1.04
0.86	-	1	0.33	0.96	0.98	-2.08
0.86	-	1	0.67	0.98	0.99	-1.02
0.86	-	1	1	1	1	0.00
Average Absolute Error Percentage				0.64		

Figure 11 provides the relationships between speed, position of damper, depth of cut and temperature. Among all the possible combinations, the 3D plot clearly reveals that for a speed of

300 rpm, depth of cut of 0.25 mm and the position of damper of 64 mm from the cutting edge, the temperature of the carbide tool insert is minimum.

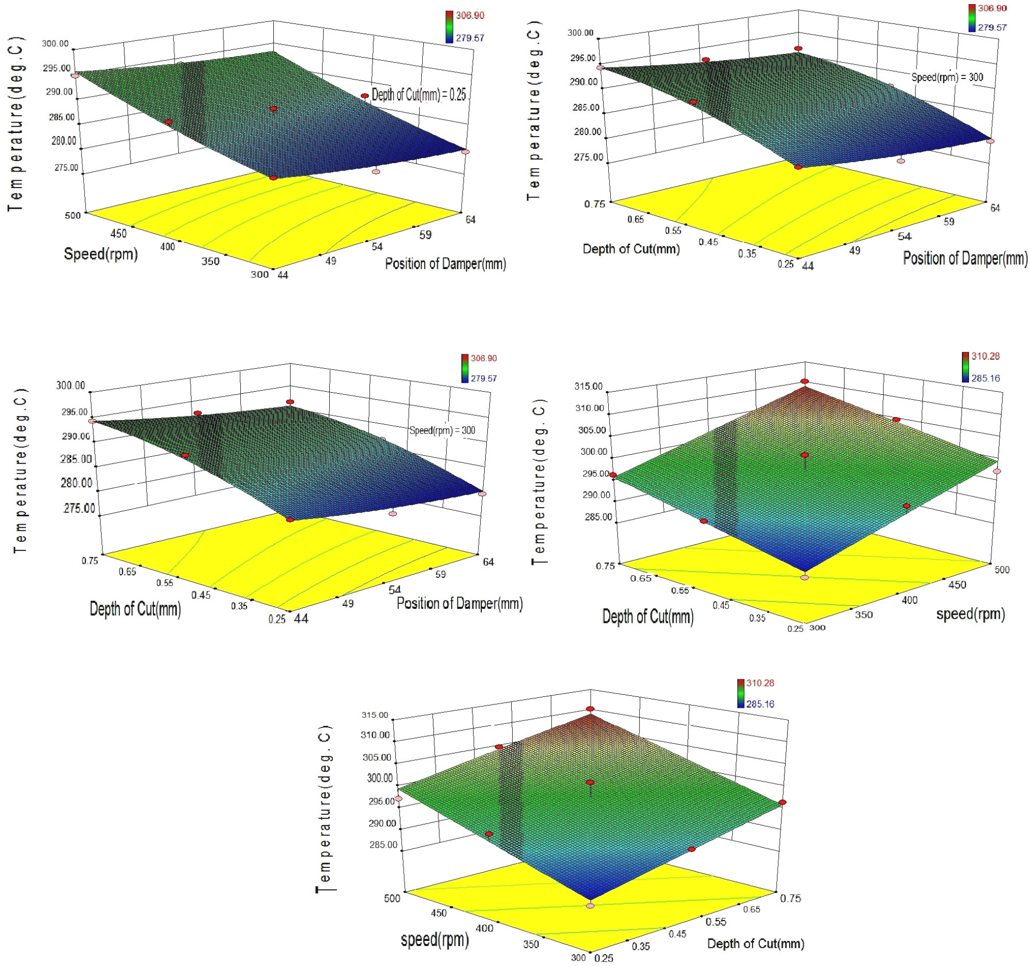

Fig. 10. 3D plots for tool wear

Figures 12 and 13 represent the tool wear and temperature characteristics of the boring bar fabricated with phosphor bronze impact damper at position I (44 mm from the cutting edge), position II (54 mm from the cutting edge) and position III (64 mm from the cutting edge). Among the positions I, II and III, it is clear from Figure 12 at the position III i.e. at 64 mm from the cutting edge that the tool wear reduces to a maximum and from the Figure 13, at the position III the temperature reduces further when compared to all other positions. This is because when the dampers are placed nearer to the tool post in the lathe the dynamic stability of the boring bar formed is higher for a given overall length. This inherently reduces the tool chatter produced in the boring operations.

5. 2. ANN Results and ANOVA for responses

By training the networks separately for tool wear and temperature, good regression values are obtained in the regression curves.

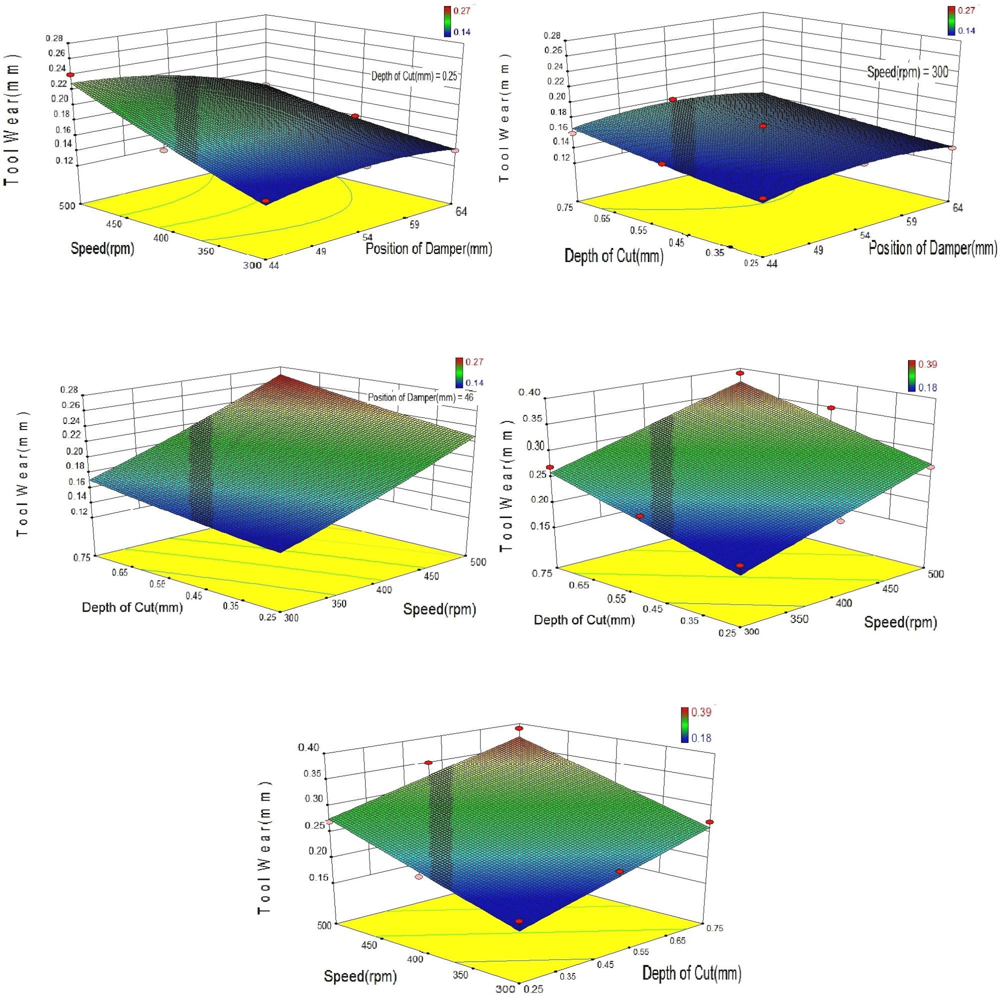

Fig. 11. 3D plots for temperature

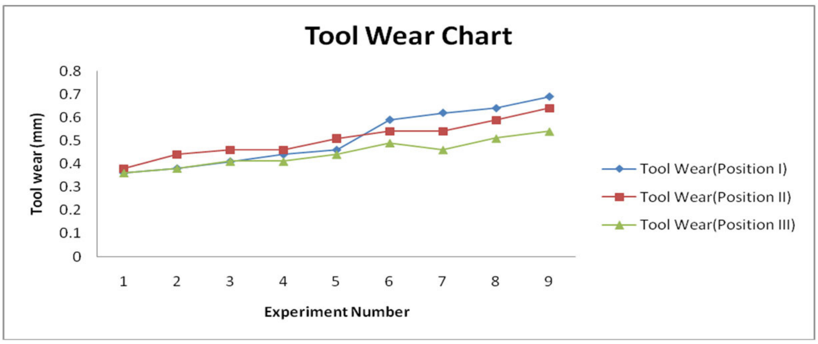

Fig. 12. Tool wear chart

The regression values estimate how the predicted values are likely to occur. Coefficient of correlation ranges from 0 to 1 and its values for response models indicate the closeness of predicted values with the experimental values.

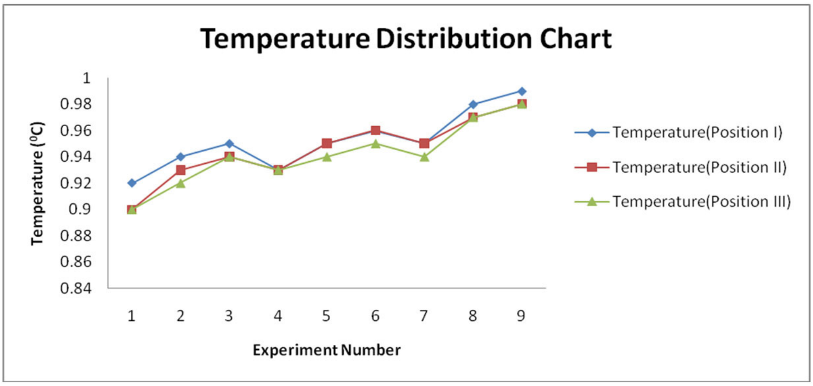

Fig. 13. Temperature distribution chart

Figure 14 illustrates the regression curve for tool wear with a regression value of 0.92343 and Figure 15 illustrates the regression curve for temperature distribution with a regression value of 0.99279.

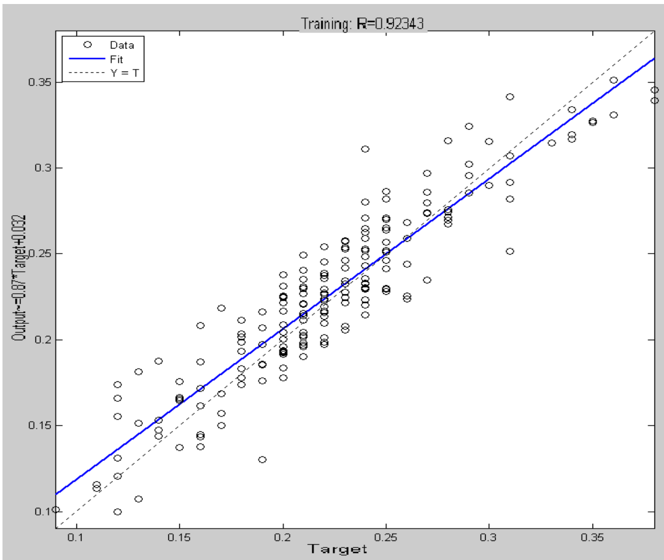

Fig. 14. Regression chart for tool wear model

The comparison of experimental values with the predicted values obtained by using developed ANN model are shown in Figures 16 and 17 for tool wear and temperature respectively. It is observed that the ANN model accurately predicts the responses over a wide range of conditions. A close curve was obtained between the experimental and predicted values for tool wear as well as temperature. This indicates that the experimental values were so good and the well-trained ANN network predicted the tool wear and temperature values accurately.

Figure 16 shows that the experimental tool wear without damper was maximum and when the experimental and predicted values were compared it lies more or less on the same curve. The figure also indicates the experimental and predicted tool wear when phosphor bronze impact damper is used. The ANN prediction is very close to the experimental tool wear and the same has happened for temperature when the experimental and predicted values were compared (Figure 17). This clearly depicts that the impact dampers play a major role in the reduction of tool wear and temperature. It also demonstrates that ANN is one of the best tools for making predicting in agreement with experimental values.

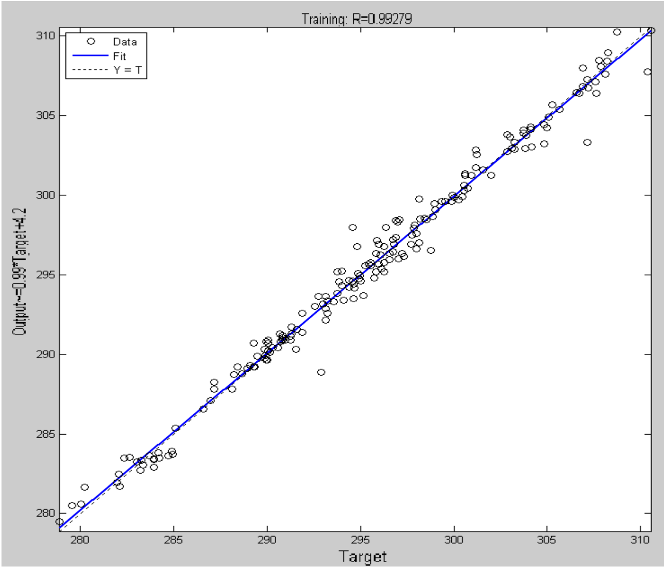

Fig. 15. Regression chart for temperature distribution

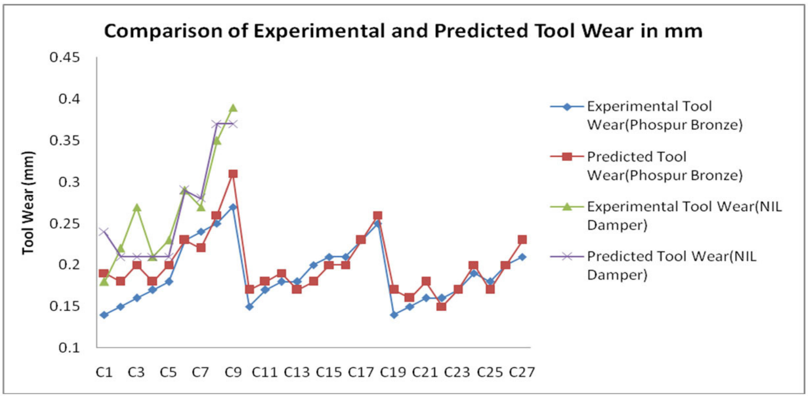

Fig. 16. Tool wear comparison plot

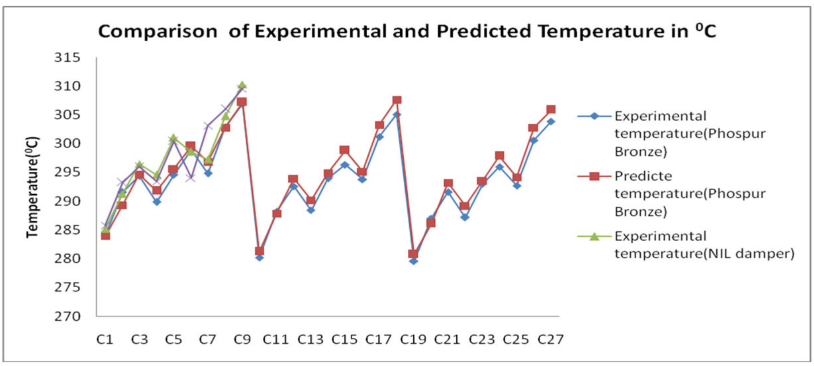

Fig. 17. Temperature comparison plot

Tables 5 and 6 present ANOVA results for tool wear and temperature models respectively. Degrees of freedom are used to describe the number of values in the final calculation of a statistics that are free to vary. Estimates of statistical parameters were based on different amounts of information or data. In general, the degrees of freedom of an estimate is equal to the number of independent scores that go into the estimate minus the number of parameters estimated as intermediate steps in the estimation of the parameter itself. The Mean Squared Error (MSE) of an estimator is one of many ways to quantify the amount by which an estimator differs from the true value of the quantity being estimated. MSE measures the average of the square of the 'error'. The error is the amount by which the estimator differs from the quantity to be estimated. The difference occurs because of randomness that could produce a more accurate estimate. Mathematically, the degrees of freedom are the dimensions of the domain of a random vector, or essentially the number of free components where the number of components needs to be known before the vector is fully determined. The present design consists of three factors, each at three levels.

Table 5. ANOVA for tool wear model

Source	Sum of Squares	df	Mean Square	F-Value	p-value Prob > F	Remarks
Model	0.033825	9	0.003758	65.52991	< 0.0001	Significant
p_d-position of damper (mm)	0.002939	1	0.002939	51.24217	< 0.0001	-
c_s-speed (rpm)	0.022756	1	0.022756	396.7635	< 0.0001	-
d_c-depth of cut (mm)	0.004672	1	0.004672	81.46439	< 0.0001	-
p_d -c_s	0.002408	1	0.002408	41.99145	< 0.0001	-
p_d-d_c	$7.5\cdot10^{-05}$	1	$7.5\cdot10^{-05}$	1.307692	0.2687	-
c_s -d_c	$7.5\cdot10^{-05}$	1	$7.5\cdot10^{-05}$	1.307692	0.2687	-
p_d^2	0.000817	1	0.000817	14.23932	0.0015	-
c_s^2	$6.67\cdot10^{-05}$	1	$6.67\cdot10^{-05}$	1.162393	0.2960	-
d_c^2	$1.67\cdot10^{-05}$	1	$1.67\cdot10^{-05}$	0.290598	0.5968	-
Residual	0.000975	17	$5.74\cdot10^{-05}$	-	-	-
Corrected Total	0.0348	26	-	-	-	-

Table 6. ANOVA for temperature model

Source	Sum of Squares	df	Mean Square	F-Value	p-value Prob > F	Remarks
Model	1271.623	9	141.2914	171.9151	< 0.0001	Significant
p_d-position of damper (mm)	38.48569	1	38.48569	46.82713	< 0.0001	-
c_s-speed (rpm)	706.88	1	706.8800	860.0901	< 0.0001	-
d_c-depth of cut (mm)	502.445	1	502.4450	611.3456	< 0.0001	-
p_d -c_s	1.576875	1	1.576875	1.918649	0.1839	-
p_d-d_c	0.016875	1	0.016875	0.020533	0.8877	-
c_s -d_c	0.0048	1	0.004800	0.00584	0.9400	-
p_d^2	1.699563	1	1.699563	2.067928	0.1686	-
c_s^2	3.95823	1	3.958230	4.816141	0.0424	-
d_c^2	16.55574	1	16.55574	20.14405	0.0003	-
Residual	13.97175	17	0.821867	-	-	-
Corrected Total	1285.595	26	-	-	-	-

Model F-Value of 65.52991 implies that the tool wear model was significant. The p-value probability of < 0.0001 was obtained in Fisher's ANOVA test for tool wear model. In the tool wear ANOVA table, all the input parameters p_s, c_s, d_c were significant because of the low *p*-value of probability (< 0.001). The interaction effects of position of damper (p_s) and cutting speed (c_s) were better and the second order effects of the position of damper were also better.

Model *F*-value of 171.9151 implies that the temperature model was significant. The *p*-value probability of < 0.0001 was obtained in Fisher's ANOVA test for temperature model. In the temperature ANOVA table, all the input parameters were significant because of the low *p*-value of probability (< 0.0001). The interaction effect of position of damper and cutting speed seem to be better compared to the other interaction effects p_d-d_c, c_s-d_c respectively. The second order effect of the depth of cut was better when compared the same width p_d with c_s.

5. 3. RSM optimization

RSM is a technique for determining and representing the cause and effect relationship between true mean responses and input control variables influencing the responses as a two or three-dimensional hyper surface. The accuracy and effectiveness of an experimental program depends on careful planning and execution. The results obtained for the minimum value of tool wear and the temperature individually and in combined condition are given in Table 7.

Table 7. Optimum parameters and their response values

No	Position of damper (mm)	Speed (rpm)	Depth of cut (mm)	Temperature (ºC)	Tool wear (mm)
1	64	300	0.25	280.13	-
2	44	306	0.30	-	0.14
3	64	300	0.25	280.13	0.14

At each iteration the internally constructed response surface model for the objective is being optimized within the current search region. After the iteration process, the actual mathematical model of the system for optimal point is obtained from optimized internal response surface model. During operation, the information about the system behavior is stored for the points in the neighborhood of the extreme, so that the response surface model becomes more accurate for this search area.

6. Conclusion

This investigation reveals that the tool wear and temperature of the boring tool are reduced when the boring bar is equipped with impact dampers. Out of the three phosphor bronze damper positions, the position III (64 mm from the cutting edge) generates minimum value of tool wear and temperature distribution. The effect of individual parameters and their interactions on tool wear and temperature distribution were studied using 3D plots and are verified with ANOVA. Boring responses were accurately predicted for various sets of input conditions using the developed ANN and Average Absolute Error Percentages of 11.83 % and 0.64 % were obtained for tool wear and temperature respectively. The boring tool fabricated with the phosphor bronze material located at a distance of 64 mm from the cutting edge running at a speed of 300 rpm and depth of cut of 0.25 mm constitutes the best case of cutting parameters for achieving the minimum tool wear and temperature distribution. This also leads to reduction of machining cost and machining time. The passive impact damper proposed in the present study plays a major role in suppressing tool wear and reducing temperature distribution along the length of the boring bar which results in tool life improvement.

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