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EXPERIMENTAL INVESTIGATION OF THE EFFECT OF CUTTING PARAMETERS ON CUTTING TEMPERATURE USING RSM AND ANN IN TURNING AISI 1040

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KEYWORDS

AISI 1040, Turning, Cutting Temperature, Response Surface Methodology (RSM), Main Effects Plot, Artificial Neural Network (ANN)

ABSTRACT

In the present research, experimental investigation is done to identify the impact of cutting parameters (feed rate, cutting speed and depth of cut) on the cutting temperature in turning of AISI 1040 by using Response Surface Methodology (RSM) and Artificial Neural Network (ANN). Response surface methodology (RSM) is used to design the experimental layout consisting of 16 datasets using Central Composite Design (CCD). Significance of the cutting parameters is determined utilizing statistical analysis of variance (ANOVA) which indicates that all the three cutting parameters have noteworthy impact on the cutting temperature. The 3D response graphs present cutting temperature is increased with the increase of feed rate, cutting speed and depth of cut. Desirability Function Analysis (DFA) is employed to decide optimal values of cutting parameters. It is suggested from DFA that minimum temperature is obtained at lower feed rate (0.100 mm/rev), lower cutting speed (62.172 m/min) and lower depth of cut (0.200 mm). Afterward, main effects plot is analyzed to show the variation of response with the three input variables and the result found from main effects plot is almost coherent to the results found from 3D plots and Desirability Function Analysis (DFA). The predicted results using ANN indicate good agreement between the predicted values and experimental values. The R^2 value for model θ is noticed to be 0.99081. The deviation between experimental values, RSM predicted values and ANN predicted values is very minimum which presents the efficacy of the proposed RSM and ANN model. But MAPE for RSM is 0.001336 and ANN is 0.006245 which evidently indicates that the prediction capabilities of RSM model are better as compared to the ANN models for this experiment.

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1. Introduction

In manufacturing, it is necessary to have certain knowledge about heat generation and temperature rise (including average and maximum temperature) during machining process. The temperature that develops in the cutting process has a significant effect on the performance of a cutting tool and the quality of the machined component. Quality of machined surface, a metallurgical structural alteration in tool and workpiece material also depends on the maximum temperature, temperature gradient and cooling rate of both tool and workpiece.

Choudhury and Bartarya [1] proposed an empirical relation between the cutting zone temperature and input variables such as cutting speed, feed and depth of cut in turning process by employing design of experiment and artificial neural networks. They compared the predicted values with the experimental values and determined their closeness with the experimental values. Aouici et al. [2] studied the influence of cutting parameters on the cutting temperature during dry hard turning of AISI H11 steel using CBN insert. They used RSM technique to determine the relationship between the cutting parameters with the desired response i.e. cutting temperature. They found that the temperature increases with increase in the cutting speed, feed rate and depth of cut. Lin et al. [3] investigated the effect of cutting speed on cutting temperature in turning of high hardness alloy steels (AISI 4340) by CBN tools. It was observed from their investigation that the cutting temperature increases with increase in the cutting speed. Venkataramaih P. [4] have conducted turning experiments on Aluminum Alloy 6061 work material for different values of cutting parameters and experimental responses such as cutting temperature and surface finish are measured and recorded. Bouchelaghem et al. [5] investigated the effect of cutting parameters on hard turning of AISI D3 (60 HRC) using CBN tool. Their results showed that increase in the value of cutting parameters results in an increase in the cutting temperature. They also observed that longer cutting time leads to larger wear which in turn increases the temperature in the cutting zone. Fnides et al. [6] studied the influence of the cutting parameters (cutting speed, feed rate and depth of cut) on temperature in the cutting zone during dry hard turning of AISI H11 steel treated at 50 HRC using a mixed ceramic tool (insert CC650) . They noticed from their study that the effect of cutting speed on the temperature in the cutting zone is more significant than the feed rate and depth of cut.

The measurement of cutting temperatures is more difficult because the temperature is a scalar field which varies throughout the system and cannot be uniquely described by values at a point. The most widely used method to measure cutting temperatures is tool-work thermocouple, which measures average interfacial temperature at tool work piece interface [7] . The tool-chip thermocouple technique is the most effective method for measuring the average tool -chip interface temperature during metal cutting. The implementation of tool-chip thermocouple is easy and economical as compared to other temperature measurement techniques [8]. Gosai and Bhavsar [9] investigated the cutting tool's average temperature by placing analog K-type thermocouple sensor in cutting tool. Smart and Trent [10] measured the cutting temperature by inserting thermocouple in the hole drilled in the work piece. O'Sullivan and Cotterell [11] had done experiment on cutting tool's temperature while machining of aluminum AI 6082-T6 with help of k-type thermocouple and analyzed with LabVIEW but they have not used any methodology and taking just small amount of readings

Ren et al. [12] utilized the combination of FE modeling and the use of a thermocouple on tool/shim interface in order to model temperature field in a PCBN tool and thus increase resolution of the data. The model, however, assumed a fixed and constant tool-chip temperature on the tool rake. Abdil and Yashya [13] has recently examined with comparative study of different to two cutting temperature measurement technique used simultaneously (i.e. Thermocouple and Infrared based technique) and concluded that the cutting speed was the parameter most affecting the tool-chip interface temperature whereas feed rate was not significant.

Response Surface Method is a group of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response [14]. Bhushan [15] investigated the influence of cutting parameters during turning of 7075 Al alloy SiC composite using the Response Surface Method and desirability analysis in order to reduce the power consumed by the machine and increase the tool life. Rudrapati et al. [16] studied the effect of process parameters of cylindrical grinding process on the responses like workpiece vibration and surface roughness using RSM methodology. Process parameters were optimized for the desired responses using multi-objective genetic algorithm and predicted model was verified using confirmatory test. Palanikumar [17] carried out statistical modeling using RSM to investigate the effect of process parameters on surface roughness and delamination factor in turning operation of glass fiber reinforced composite. RSM central composite design matrix was employed for the experiment. The adequacy of the model was verified at 95% confidence level within limit of input parameters being considered. Artificial neural networks (ANNs) are comparatively new modeling techniques, which can be used to solve problems that are difficult for conventional computers or human beings. The ANNs have been applied to model complicated processes in many engineering fields, such as aerospace, automotive, electronics, manufacturing, robotics, telecommunications, etc. Over recent years the interest in the ANN modeling in the fields of physical metallurgy and materials science has increased rapidly [18]. Risbood et al. [19] developed a prediction equation using ANN taking radial vibration of tool holder as a feedback signal. Neural networks provide significant advantages in solving process problems that require real-time encoding and interpretation of relationships among the variables of high-dimensional space [20]. Nouioua et al. [21] introduced RSM and ANN methods to find out optimal prediction of uncontrollable parameters. The ANN method gives more precise results and suggested for usefulness in relating to correlation coefficients, Mean prediction errors and root mean square errors correlate towards those acquired by RSM method.

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2. EXPERIMENTAL CONDITION AND PLANNING OF EXPERIMENT

Experiment has been done on Lathe Machine (China). AISI 1040 is used as work-piece material. The details about the workpiece and chemical composition of AISI 1040 are given in Table 2.1 and Table 2.2 respectively. PSBNR2525M12 cutting tool holder is used which cutting edge angle is 60°. An uncoated carbide cutting Tool (SNMG) has been inserted into the tool holder. The experiment is conducted on dry condition with three controllable input variables (feed rate, cutting speed, depth of cut) and one output variable (temperature) which are showed in Table 2.3.

Table 2.1: Workpiece Details

Material	Medium Carbon Steel
Carbon content	Approx. 30%
Type	Solid
Diameter	150 mm
Length	2.5 feet (762 mm)

Table 2.2: Chemical Composition of AISI 1040

Iron, Fe	Manganese, Mn	Carbon, C	Sulfur, S	Phosphorous, P
98.6-99%	0.60-0.90%	0.370-0.440%	≤ 0.050%	≤ 0.040%

Table 2.3: Experimental Factors

Factor	Name	Units	Minimum	Maximum
A	Feed Rate	mm/rev	0.1000	0.1600
B	Cutting Speed	m/min	41.62	122.46
C	Depth of Cut	mm	0.2000	0.8000

2.1. Experimental Layout

The experimental layout plan (Table 2.4) is established using Response Surface Methodology (RSM) in Design Expert 11.0 Software. The experiments have been done with the values of these three inputs. Full factorial design with 16 runs is used. RSM can be conducted by two methods- Box-Behnken and Central Composite Design (CCD). In this investigation, CCD method is utilized, since it offers more advantages over other design methods.

Table 2.4: Experimental Layout of Input Parameters and their Resultant Output

Run No.	Feed Rate S_o mm/rev	Cutting Speed V_c m/min	Depth of Cut d mm	Temperature θ °C
1	0.1	62.172	0.2	522
2	0.16	62.172	0.2	568
3	0.1	122.46	0.2	389
4	0.16	122.46	0.2	420
5	0.1	62.172	0.8	826
6	0.16	62.172	0.8	865
7	0.1	122.46	0.8	695
8	0.16	122.46	0.8	726
9	0.1	92.316	0.5	605

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10	0.16	92.316	0.5	641
11	0.13	41.62	0.5	740
12	0.13	122.46	0.5	554
13	0.13	92.316	0.2	475
14	0.13	92.316	0.8	783
15	0.13	92.316	0.5	629
16	0.13	92.316	0.5	636

2.2. Experimental Setup

The experimental setup of our turning operation has been presented in Figure 1. Initially, the cutting tool holder with uncoated carbide insert has been fixed on the tool post of lathe and AISI 1040 workpiece has been mounted on the headstock. The experiment is conducted by changing the feed rate, cutting speed and depth of cut according to the values given in Table 3. The average chip-tool interface cutting temperature has been measured under dry condition undertaken by simple but reliable tool-work thermocouple technique with proper calibration. This method is very useful to specify the effects of the cutting speed, feed rate, depth of cut and cutting parameters on the temperature. Thermocouples are conductive, rugged and inexpensive and can operate over a wide temperature range. To record emf as millivolt a digital multi-meter has been used where one end of multimeter has been connected to the workpiece and other end to the tool.

Figure 1. Experimental Setup for the Experiment

2.3. Experimental Investigation

2.3.1. Millivolt to Temperature Conversion

After measuring the millivolt reading using thermocouple, the cutting temperatures are calculated using the following equation:

$$\text{Cutting Temperature}, \theta = 75.28 + 63.05\ \text{mV} - 0.57\ \text{mV}^2\ (°\text{C})\ (1)$$

2.3.2. Response Surface Methodology (RSM)

Response surface methodology (RSM) is employed to develop the model equations for the response i.e. cutting temperature as a function of input variables.

Response Surface Methodology (RSM) is a collection of mathematical and experimental techniques that requires sufficient number of experimental data to analyze the problems and to develop mathematical models for several input variables and output performance characteristics.

After completing the machining work, all the experimental data for the output were inserted into the experimental layout found from response surface methodology. Then Analysis of variance (ANOVA) is conducted to determine the result (P-Value) that independent variables (feed rate, cutting speed, depth of cut) have on the dependent variables through a regression study and check the model is significant or not. In the experimenters based mathematical model of temperature (θ) was developed in terms of three pro-

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cess parameters, namely Feed Rate (f), Cutting Speed (V_c) and Depth of Cut (d).

$$Y_n = F(f, Vc, d) + e_{ij} \quad (2)$$

Here, Y_n is desired response (temperature) and F is the response function of feed rate, cutting speed and depth of cut.

The output response are proposed using the fitted second-order polynomial regression model which is called quadratic model. The quadratic model of Y can be written as follows:

$$Y = a_0 + \sum_{i=1}^{k} a_i x_i + \sum_{i=1}^{k} a_{ii} x_i^2 + \sum_{i=1}^{k} a_{ij} x_i x_j \quad (3)$$

Here, Y represents the response and x_i,x_j are the independent variables.

The influence of cutting parameters and their interaction effects have been analyzed by using 3-D response graph. Desirability Function Analysis (DFA) shows the optimized results in terms of the response.

After that, the main effects plot have been drawn to examine differences between level means for three factors. There is a main effect when different levels of a factor affect the response differently.

2.3.3. Artificial Neural Network (ANN)

An artificial neural network (ANN) is a computational model in view of the structure and elements of organic neural systems. As the "neural" some portion of their name recommends, they are mind motivated frameworks which are proposed to imitate the way that we people learn. Neural systems comprise of input and output layers, and in addition (much of the time) a hidden layer comprising of units that change the input to something that the output layer can utilize. They are great tools for discovering designs which are very intricate or numerous for a human software engineer to concentrate and instruct the machine to perceive. Data that courses through the system influence the structure of the ANN in light of the fact that a neural system changes - or learns, it could be said - in view of that input and output. ANNs are viewed as nonlinear statistical information demonstrating tools where the complex relationships amongst inputs and outputs are displayed or designs are found. ANNs have three layers that are interconnected. The primary layer comprises of input neurons. Those neurons send data on to the second layer, which in turn sends the output neurons to the third layer. Learning ability and use of different learning algorithms are the key features of artificial neural network.

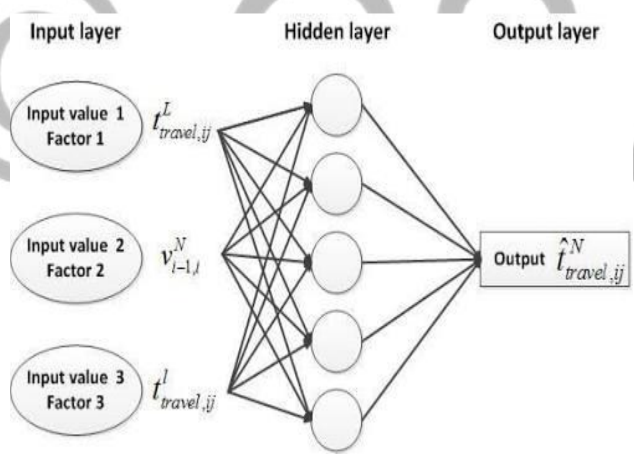

Figure 2. ANN Structure

3. Analysis of Result

3.1. Analysis of Variance (ANOVA) of Cutting Temperature

The results of analysis of variance (ANOVA) are appeared in Table 3.1 which reveals the model to be significant as its F value is 1860.02. It might be noticed that the model terms with P values (Prob> F) less than 0.1000 are significant. What's more, it can likewise be seen from Table 5 that cutting rate (A), feed rate (B), depth of cut (C), have huge impact on the cutting temperature; while the interaction between feed rate and cutting speed (AC), cutting speed and depth of cut (BC) have no huge impact. The “Lack of Fit F-value” of 0.6507 implies that the Lack of Fit is not significant relative to the pure error. There is a 72.99% chance that a “Lack of Fit F-value” this large could occur due to noise. Non-significant lack of fit is good because it is desired that the model should fit to the data.

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Table 3.1: ANOVA Results of Cutting Temperature for Quadratic Model

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	**2.908E+05**	**9**	**32306.39**	**1860.02**	**< 0.0001**	**significant**
A-Feed Rate	3348.90	1	3348.90	192.81	< 0.0001	
B-Cutting Speed	49692.58	1	49692.58	2861.02	< 0.0001	
C-Depth of Cut	2.313E+05	1	2.313E+05	13319.48	< 0.0001	
AB	66.13	1	66.13	3.81	0.0989	
AC	6.13	1	6.13	0.3526	0.5743	
BC	15.13	1	15.13	0.8708	0.3867	
A^2	35.39	1	35.39	2.04	0.2034	
B^2	21.17	1	21.17	1.22	0.3119	
C^2	18.35	1	18.35	1.06	0.3437	
Residual	104.21	6	17.37			
Lack of Fit	79.71	5	15.94	0.6507	0.7299	not significant
Pure Error	24.50	1	24.50			
Cor Total	2.909E+05	15				

It is clear from Table 3.2 that the "Predicted R^2" of 0.9983 is in reasonable agreement with the "Adjusted R^2" of 0.9991. "Adeq Precision" measures the signal to noise ratio. A ratio greater than 4 is desirable and the resulted ratio is 145.4893 which indicates an adequate signal. This model can be used to navigate the design space.

Table 3.2: Regression Co-efficient

R^2	0.9996
Adjusted R^2	0.9991
Predicted R^2	0.9983
Adeq Precision	145.4893

Quadratic Model Equation

The relationship between the factors (A-feed rate, B-cutting speed, C-depth of cut) and response (cutting temperature) were modeled by linear regression. The following quadratic equation is the final regression model in terms of actual parameters.

$$\mathbf{Temperature} = +\mathbf{395.81432} + \mathbf{1959.84660} * \mathbf{A} - \mathbf{1.61171} * \mathbf{B} + \mathbf{477.69522} * \mathbf{C} - \mathbf{3.17918} * \mathbf{A} * \mathbf{B} - \mathbf{97.22222} * \mathbf{A} * \mathbf{C} + \mathbf{0.152048} * \mathbf{B} * \mathbf{C} - \mathbf{3875.94581} * \mathbf{A}^2 - \mathbf{0.001891} * \mathbf{B}^2 + \mathbf{27.90721} * \mathbf{C}^2 \quad (4)$$

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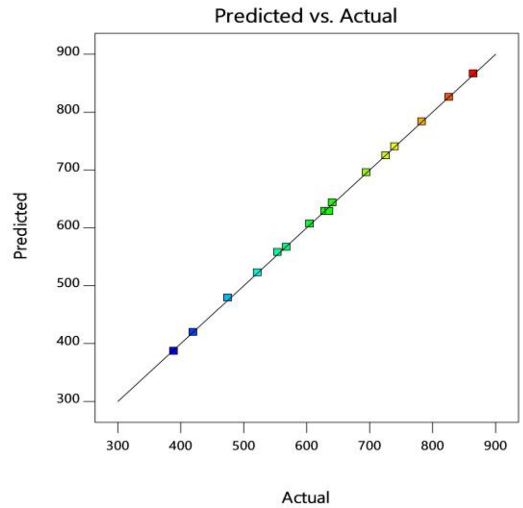

Figure 3. Predicted vs Actual Temperature

Predicted Cutting Temperatures and Actual Cutting Temperatures are represented in Figure 3. This graph for cutting temperature ensures the fairly close distribution to a straight line which revealed that the actual values and predicted values are very close to each other, confirming that the terms related with the models are significant. It also ensures perfect correlations between experimental and predicted values.

The influence of Cutting parameters and their interaction effects can be analyzed by using 2-D contour graph and 3-D response graph. Figure 4 show the 2-D contour graphs and 3-D response graphs for cutting temperature. The response surface graphs are drawn by varying two parameters and keeping the other parameter at constant middle level. At minimal of all interaction parameters, we can observe that the cutting temperature is minimum. Figure 4(a) shows the response graph for two varying parameters feed rate and cutting speed ($f*V_c$) by keeping the third parameter depth of cut (d) at constant middle level which indicates that the increase of feed rate and cutting speed increases the cutting temperature. Figure 4(b) shows the surface plot for two varying parameters feed rate and depth of cut (f*d). The results show that the increases of the both parameters increase the cutting temperature. The relation between cutting speed with respect to depth of cut (v*d) is presented in figure 4(c). The increases of depth of cut increase the cutting temperature. At maximal of cutting speed and minimal depth of cut, minimum temperature is observed.

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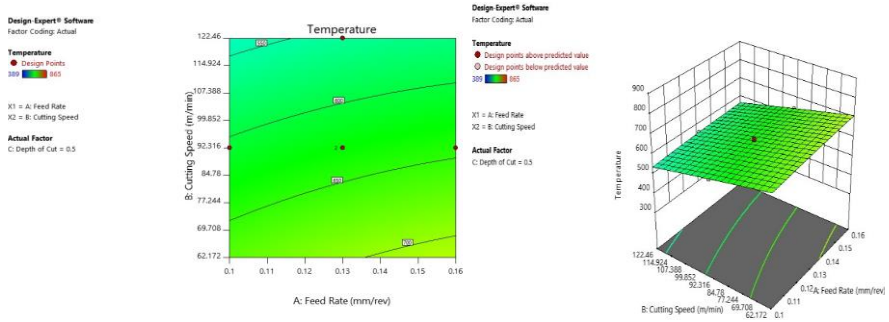
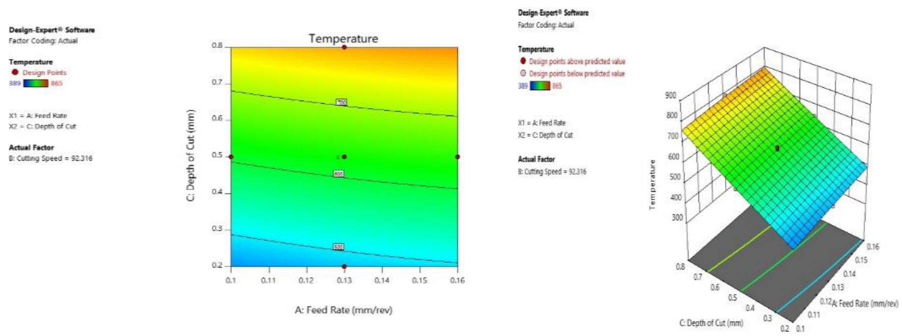


(a)



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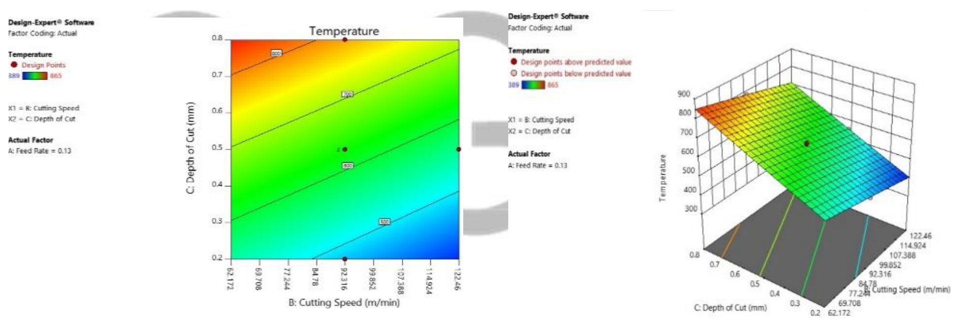

(c)

Figure 4. (a) Effect of feed rate and cutting speed on cutting temperature at constant depth of cut (b) Effect of feed rate and depth of cut on cutting temperature at constant cutting speed (c) Effect of cutting speed and depth of cut on cutting temperature at constant feed rate

The Desirability Function Analysis (DFA) takes values in range $0 < d < 1$. When the response variable is at its goal or target, d becomes 1, and if the response variable is outside the acceptable range, d becomes zero. In this study, the target for the response is minimum value (smaller-the-better).

Desirability function optimization of the RSM has been employed for single response optimization. The use of response surface optimization helps to find the optimal values of cutting parameters in order to minimize the cutting temperature during the turning process. Table 3.3 shows the constraints and parameter ranges used during the optimization process. Table 3.4 shows the RSM optimization results for the input process parameters and the response i.e. cutting temperature. It can be seen from Table 3.4 that the optimized value of cutting temperature is 522.361°C at optimized values of feed rate, cutting speed and depth of cut 0.100 mm/rev, 62.172 m/min and 0.200 mm respectively. So, it is suggested from DFA that minimum temperature is obtained at lower feed rate, lower cutting speed and lower depth of cut. Desirability of individual factor and response are portrayed in Figure 5.

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Table 3.3: Constraints for Optimization of Machining Parameters

Name	Goal	Lower Limit	Upper Lim-it	Lower Weight	Upper Weight	Importance
A:Feed Rate	is in range	0.1	0.16	1	1	3
B:Cutting Speed	minimize	62.172	122.46	1	1	3
C:Depth of Cut	is in range	0.2	0.8	1	1	3
Temperature	minimize	389	865	1	1	3

Table 3.4: Results for Optimization of the machining parameters

Number	Feed Rate	Cutting Speed	Depth of Cut	Temperature	Desirability	
1	**0.100**	**62.172**	**0.200**	**522.361**	**0.848**	**Selected**
2	0.100	62.172	0.200	522.584	0.848	
3	0.101	62.172	0.200	522.893	0.848	
4	0.100	62.420	0.200	521.832	0.847	
5	0.101	62.172	0.200	523.433	0.847	
6	0.100	62.172	0.202	523.476	0.847	
7	0.102	62.172	0.200	524.100	0.846	
8	0.103	62.172	0.200	524.761	0.845	
9	0.103	62.172	0.200	525.137	0.845	
10	0.100	62.173	0.206	525.461	0.845	

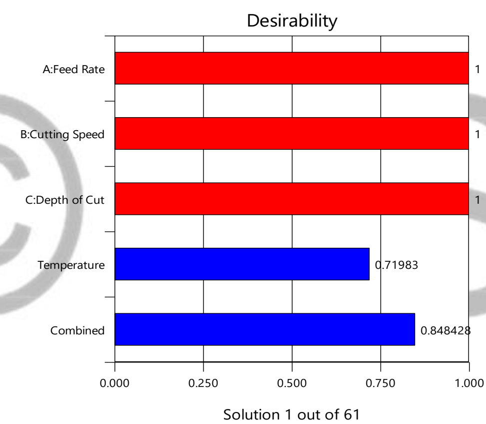

Figure 5. Bar Chart for Individual Desirability

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3.1. Main Effects Plot

Here, the main effects plot for temperature was analyzed with the help of software MINITAB and shown in Figure 6. The plot shows the variation of response with the three input variables; feed rate, cutting speed and depth of cut respectively. In case of temperature minimum value is better. From the main effects plot, it is clearly seen that lower feed rate (0.10 mm/rev) gives the best result for temperature along with the higher cutting speed (122.460 m/min) and higher depth of cut (0.20 mm) which is coherent to the results found from 3D plots and Desirability Function Analysis (DFA).

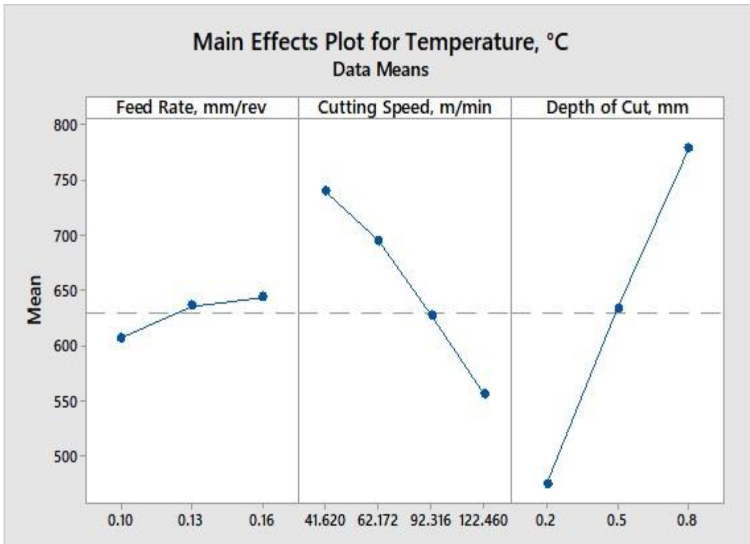

Figure 6. Main Effects Plot for Temperature

3.3. Results using Artificial Neural Network (ANN)

In this study, TRAINLM was used as training function and TANSIG was used as Transfer function. 12 hidden layer was selected with three input variables (feed rate, cutting speed, depth of cut) and one output variable (temperature) and so, the network structure is 3-12-1.

The performance of the developed network was examined for training data in terms of temperature using Artificial Neural Network (ANN) on the basis of correlation coefficient (R^2). Interrelationship between actual and predicted values for training is shown in Figure 7. The R^2 value for model θ is noticed to be 0.99081. However R^2 for response model are near to unity which indicates the successful prediction of dataset under considered neural parameters. After training the data has been simulated and compared with input data and the mean absolute percentage error (MAPE) was calculated.

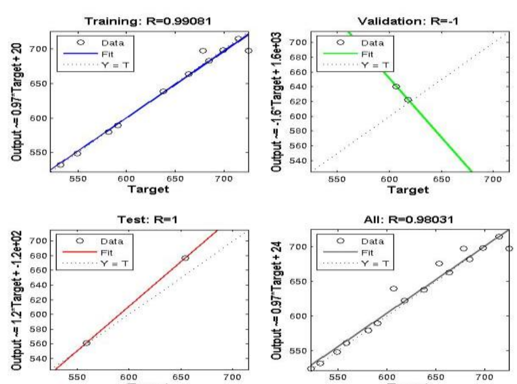

Figure 7. Linear Regression Plot for Cutting Temperature

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3.4. Comparison of RSM, ANN Predicted Temperatures and Experimental Temperatures

Absolute percentage error (APE) and mean absolute percentage error (MAPE) are calculated to measure the error of the processes which are defined as follows:

$$\mathrm{APE} = \frac{\mathrm{tj-oj}}{\mathrm{tj}} * 100 \qquad (5)$$

$$\mathrm{MAPE} = \frac{\mathrm{APE}}{\mathrm{Pj}} \qquad (6)$$

MAPE calculation for predicted values are shown in Table 3.5. Meanwhile, from Figure 8, it is shown that, the deviation between experimental values, RSM predicted values and ANN predicted values is very minimum as the lines are very close to each other which presents the efficacy of the proposed RSM and ANN model. But MAPE for RSM is 0.001336 and ANN is 0.006245 which evidently indicates that the prediction capabilities of RSM model are better as compared to the ANN models for this experiment.

Table 3.5: Comparison of predicted values and experimental values

Run No	Experimental Temperature	RSM Predicted Temperature	APE for RSM	ANN Predicted Temperature	APE for ANN
1	522	522	0.001914	519	0.005747
2	568	566	0.001765	573	0.008803
3	389	387	0.002585	391	0.005141
4	420	419	0.002384	424	0.009524
5	826	826	0.001211	827	0.001211
6	865	866	0.001155	861	0.004624
7	695	696	0.001438	699	0.005755
8	726	725	0.00138	729	0.004132
9	605	607	0.001648	607	0.003306
10	641	643	0.001554	652	0.017161
11	740	740	0.001351	749	0.012162
12	554	558	0.001793	553	0.001805
13	475	479	0.002088	465	0.021053
14	783	783	0.001277	796	0.016603
15	629	629	0.001591	630	0.00159
16	636	629	0.001591	632	0.006289
			0.026726		0.124906
		MAPE	**0.001336**		**0.006245**

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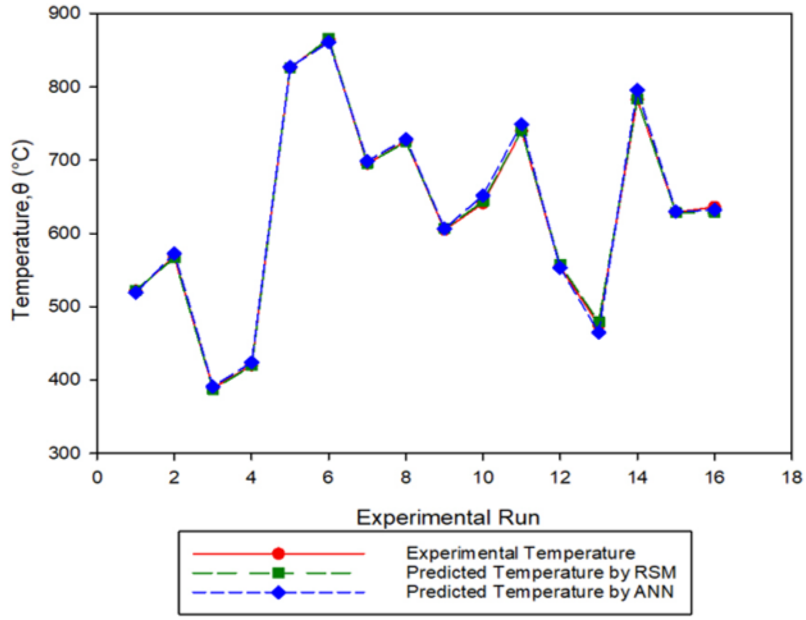

Figure 8. Comparison of RSM, ANN Predicted Temperatures and Experimental Temperatures

4. CONCLUSIONS

The present study focused on using tool-chip thermocouple technique to measure the cutting temperature during turning of AISI 1040 using Response Surface Methodology (RSM) and Artificial Neural Network (ANN). Based on the results of the present study, following conclusions are drawn:

- R^2 (correlation coefficients) for the quadratic model has been found from Analysis of Variance (ANOVA) which is quite satisfactorily as 0.9996 for cutting temperature and the P values of the models are less than 0.05 which indicate that the models are significant to 95% level of confidence.
- From 3-D Response Graphs, it has been clearly observed that cutting temperature increases significantly with the increase of feed rate, cutting temperature and depth of cut.
- An optimized result has been found from desirability function analysis (DFA) which indicates that minimum temperature is obtained at lower feed rate, lower cutting speed and lower depth of cut. The desired cutting condition has been attained at lower feed rate (0.100 mm/rev), lower cutting speed (62.172 m/min) and depth of cut (0.200 mm) which gives the minimum cutting temperature (522.361°C).
- From the main effects plot, it is clearly seen that lower feed rate gives the best result for temperature along with the lower cutting speed and lower depth of cut which is coherent to the results found from 3D plots and Desirability Function Analysis (DFA).
- ANN based modelling has been carried out where 3-12-1 was the proposed structure, TRAINLM was the training function and TANSIG was the transfer function. The developed correlations which is 0.99081 shows a strong agreement with actual results.
- The deviation between experimental values, RSM predicted values and ANN predicted values is very minimum which indicates the efficacy of the proposed RSM and ANN model. But MAPE for RSM is 0.001336 and ANN is 0.006245 which evidently indicates that the prediction capabilities of RSM model are better as compared to the ANN models for this experiment.

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