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Response surface and neural network based predictive models of cutting temperature in hard turning

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ABSTRACT

The present study aimed to develop the predictive models of average tool-workpiece interface temperature in hard turning of AISI 1060 steels by coated carbide insert. The Response Surface Methodology (RSM) and Artificial Neural Network (ANN) were employed to predict the temperature in respect of cutting speed, feed rate and material hardness. The number and orientation of the experimental trials, conducted in both dry and high pressure coolant (HPC)
High pressure coolant
Tool-workpiece interface temperature
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improved 3D model of chip-tool interface temperature in turn-
ture. Karpat and Özal [1] analytically modeled the cutting tem-
perature in turning AISI 1045 steel by considering inverse heat con-
duction method. Pervaiz et al. [3] modeled cutting temperature of
turning tool by considering the effect of flowing air sur-
rounding the insert and the result helped to better understand
the temperature scheme.
Sharma et al. [4] developed the optimization model of cut-
ting temperature in turning AISI D2 steel under the application
of different fluids using Taguchi method. The result revealed
that the carbon nanotubes, when used with fluid, reduced cutting
temperature effectively owing to the increase in heat transfer
rate. Davoodi and Tazekkand [5] investigated experimentally
and optimized, using RSM, the cutting temperature in turning
with an objective to eliminate cutting fluid. Yang and
Natarajan [6] optimized the turning process parameters for
the minimum tool wear and maximum material removal rate
but without upsetting the cutting temperature limit. In other
study, Umer et al. [7] optimized the turning temperature using
genetic algorithm but without compromising the power to cut
and material removal rate. Moura et al. [8] investigated the
capability of solid lubricant in reduction of chip-tool interface
temperature during turning and concluded that the better lubri-
cation is achieved with solid lubricant in suspension with oil.

The study on the application of cutting fluid, to reduce the
cutting temperature, and consequently, lessen the adverse
effects on the performances such as reduced tool wear, cutting
force, and surface roughness, has been carried out by many
researchers. Different fluid application methods such as mini-
umity lubricant [9,10], high pressure coolant [11,12],
and cryogenic [13,14] establish themselves as viable alternative
to dry cutting. Very few models [15,16] of chip-tool interface
temperature have been developed by considering the machin-
ing environments/parameters. Hence, to better control the
machining process, the prediction of cutting temperature is
inevitable. To meet this objective, in this work, the response
surface method and artificial neural network have been
employed to model the cutting temperature in respect of cut-
ting speed, feed rate and material hardness. It is also mention-
able, using these methods, very few has incorporated material
hardness as the input variable.

Methodology

Machine, method and equipment

In this work, three shafts of AISI 1060 steel (L = 200 mm, O.
D. = 120 mm, I.D. = 45 mm) have been heat treated to
achieve three hardness (H) values i.e. 40 HRC, 48 HRC and
56 HRC. The thermal treatment is performed in an induction
furnace with appropriate heating element: firstly – by raising
the temperature to 900 °C and holding at that temperature for
90 min, then suddenly reducing the temperature by oil quench-
ing to attain a very high hardness, lastly – by raising the tem-
perature to 375 °C, 235 °C and 150 °C for respective
workpieces to remove excess hardness and brittleness. The
results of hardness test are plotted in Fig. 1.
A powered center lathe (7.5 kW) was used to carry out the
experimental runs on dry and high pressure coolant (HPC)
applied turning. A sophisticated high pressure coolant supply
system [12] has been employed to impinge the cutting oil to the
tool-workpiece contact point. The cutting oil was supplied
at 80 bar pressure, at a flow rate of 61/min, through external
nozzle of 0.5 mm diameter. For better penetration and lubrica-
tion, the oil jet was aimed along the auxiliary cutting edge so
that oil can reach under the flowing chips [11]. The coated
(with TiCN, WC, Co) carbide insert (ISO specification-
SNMM 120408) placed on PSBNR 2525 M12 holder has been
used. The cutting speed (Vc) and feed rate (So) were chosen,
keeping in mind the recent industrial practice, as 58, 81,
115 m/min and 0.10, 0.12, 0.14 mm/rev respectively. The depth
of cut was maintained constant at 1.0 mm. These variables are
oriented into 54 experimental runs (27 for dry cutting and 27
for HPC cutting) generated by the full factorial design plan. Table 1 shows the experimental plan along with the measured cutting temperature. The photographic view of the experimental setup is shown in Fig. 2.

The average tool-workpiece interface temperature was measured by using a sophisticated tool-work thermocouple [17]. The calibration setup and equipments of the thermocouple are shown in Fig. 3(a) [18]. The chip of AISI 1060 steel (work material) and tungsten carbide (tool material) was joined to create the junctions of the thermocouple. Since there is possibility of parasitic electromotive force (EMF) initiation, an extension of the tool insert was produced by the carbide rod. A graphite block has been used as the heat sink. This block was surrounded by a heated porcelain tube. The temperature of a junction was measured by using a k-type thermocouple which was considered as the reference temperature. At the same time, the EMF (of the developed thermocouple) was measured by using a digital multi-meter. Then, a relation of the measured temperature and the generated EMF was plotted, as shown in Fig. 3(b), wherein the correlation coefficient was found to be 0.999. Therefore, this tool-work thermocouple is proved to be usable. Finally, the temperature of the cutting edge of the tool was measured by following the previously mentioned facts. The machining runs were conducted for a certain amount of time so that the generated EMF reaches at a stable value and only then that EMF was recorded. The schematic diagram of the temperature measurement circuit is displayed in Fig. 4.

Response surface model

The response surface methodology is a statistical tool that formulates a defined relation between two sets of data, wherein one set is dependent variable and the other sets are independent variables, along with mathematical correlation [19]. This model can determine the interaction effects of variables on the output quality. Among the versatileities of RSM, the prediction and optimization capabilities are highly appreciated. Furthermore, RSM is capable of generating both linear and quadratic models as shown in Eq. (1) and (2):

\[ X = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \epsilon \]  

Table 1 Experimental design plan and cutting temperature.

| SL no | Cutting speed, \( V_c \) m/min | Feed rate, \( S_o \) mm/rev | Hardness, H HRC | Temperature, °C | Status |
|-------|-------------------------------|-----------------------------|----------------|----------------|--------|
| 1     | 58                            | 0.1                         | 40             | 700            | 595    | Training |
| 2     | 58                            | 0.1                         | 48             | 735            | 635    | Testing  |
| 3     | 58                            | 0.1                         | 56             | 920            | 792    | Training |
| 4     | 58                            | 0.12                        | 40             | 726            | 632    | Training |
| 5     | 58                            | 0.12                        | 48             | 761            | 672    | Training |
| 6     | 58                            | 0.12                        | 56             | 958            | 835    | Training |
| 7     | 58                            | 0.14                        | 40             | 764            | 670    | Training |
| 8     | 58                            | 0.14                        | 48             | 799            | 710    | Training |
| 9     | 58                            | 0.14                        | 56             | 996            | 920    | Training |
| 10    | 81                            | 0.1                         | 40             | 750            | 645    | Training |
| 11    | 81                            | 0.1                         | 48             | 785            | 685    | Training |
| 12    | 81                            | 0.12                        | 48             | 976            | 875    | Training |
| 13    | 81                            | 0.12                        | 56             | 750            | 660    | Training |
| 14    | 81                            | 0.12                        | 40             | 785            | 700    | Training |
| 15    | 81                            | 0.12                        | 48             | 998            | 892    | Training |
| 16    | 81                            | 0.14                        | 40             | 805            | 708    | Training |
| 17    | 81                            | 0.14                        | 48             | 840            | 748    | Training |
| 18    | 81                            | 0.14                        | 56             | 1035           | 942    | Training |
| 19    | 115                           | 0.1                         | 40             | 809            | 725    | Training |
| 20    | 115                           | 0.1                         | 48             | 844            | 765    | Training |
| 21    | 115                           | 0.12                        | 56             | 1064           | 932    | Training |
| 22    | 115                           | 0.12                        | 40             | 833            | 746    | Training |
| 23    | 115                           | 0.12                        | 48             | 868            | 786    | Training |
| 24    | 115                           | 0.12                        | 56             | 1098           | 972    | Training |
| 25    | 115                           | 0.14                        | 40             | 854            | 770    | Testing  |
| 26    | 115                           | 0.14                        | 48             | 889            | 810    | Training |
| 27    | 115                           | 0.14                        | 56             | 1150           | 1045   | Training |
\[ X = \beta_0 + \sum_{i=1}^{k} \beta_{i1} x_i + \sum_{i=1}^{k} \beta_{i2} x_i^2 + \sum_{i,j=1}^{k} \beta_{ij} x_i x_j + \varepsilon \quad (2) \]

where \( X \) is the quality response – cutting temperature for dry or HPC; \( \beta_0 \) is the fixed term; \( \beta_{i1}, \beta_{i2}, \ldots, \beta_{ij} \) in Eq. (1) are the coefficients of the linear terms; \( \beta_{i1}, \beta_{i2}, \beta_{ij} \) in Eq. (2) are the coefficient of linear, quadratic and cross-product terms, respectively; \( x_i \) is the input variables (i.e. cutting speed, feed rate and material hardness).

Artificial neural network model

Artificial neural network is formed as a non-linear mapping system that works like human brain wherein a total of three layers are interconnected and each layer has one or more neurons. First layer, named input layer, receives numerical values as input to the model. Herein, one neuron is defined by one variable. Second layer, i.e. hidden layer, receives the information from the input layer and processes further. Output layer, connected with hidden layer by synaptic weights, provides the output(s). The type of configuration, training algorithm, different functions, and weights and biases influence the accuracy of the ANN model.

In this work, a feed forward multi-layer neural network, for both dry and HPC cutting, having ‘3-n-1’ architecture has been adopted. A major problem in designing a neural network is establishing the optimal number of layers and number of neurons to achieve the most accurate results. The number of hidden layers can be increased up to three layers and this might help to achieve high accuracy but complexity of the neural network and training time will eventually increase along with waste of computer memory; again, unnecessary increment in the neurons or layer will lead to over-fitting problem [20]. As by using only one hidden layer in this study, high prediction accuracy has been observed, so no further hidden layer was added to check the performance. The ANN architecture is shown in Fig. 5. The ‘3-n-1’ symbolizes that the input layer is comprised of three neurons; hidden layer has \( n \) (unknown) neurons; and output layer has only neuron. The three input neurons are for cutting speed, feed rate and material hardness, whereas the single output neuron represents the tool-workpiece interface temperature. Among 27 experimental data sets, 22 sets have been used for training and 5 sets for testing the model.

MATLAB R2015a ‘nnstart’ wizard has been used to develop, train and test the cutting temperature prediction model. The network has been trained by using Bayesian regularisation (trainbr). Bayesian regularization (BR) was developed by MacKay [21] to deal with the imprecise noisy data and it possesses the ability to prevail over the under/over fitting issue. In BR, the weights and biases are random variables [21] and the optimum weights are used [22]. Moreover,
The effects of different variables on the dependent variable (cutting temperature) are evaluated by the analysis of variance (ANOVA). The ANOVA for dry and HPC regression models is listed in Table 3. The ANOVA table consists of sequential sum of square from which the percentage contribution of factors is determined, $F$-value and $P$-value. The $P$-value indicates the significance of a factor to a confidence level of 95%. The higher $F$-value indicates a relatively greater importance of that factor.

For RSM quadratic dry model, the cutting speed, feed rate and material hardness, all are statistically significant as $P$-value less than 0.05. The square terms of hardness and feed rate are also significant. In addition, the only significant interaction is the cutting speed-material hardness. The $F$-value analysis reveals the material hardness as the most important factor followed by the cutting speed and then the feed rate. The highest percentage contribution is exerted by material hardness. In HPC quadratic model, the cutting speed, feed rate and material hardness are statistically significant. Like dry model, a similar significance is observable for the quadratic terms. Unlike dry model, only the feed rate-material hardness interaction is statistically significant. The percentage contribution shows that the highest (64.23%) contribution is created by material hardness, followed by cutting speed (18.51%) and lastly by the feed rate. $F$-value also revealed similar effect.

The regression plot of actual and predicted cutting temperature for RSM model is shown in Fig. 6. The values of the regression coefficient, for dry and HPC models respectively, are 0.99988 and 0.99966 and these values reflect that the model is adequate to predict the tool-workpiece interface temperature for both the machining environments. RSM is showing a better accuracy in dry cutting than the HPC assisted cutting temperature prediction. Yet, RSM is applicable to develop model in both dry and HPC cutting.

Fig. 7 shows the perturbation plots of cutting temperature for dry and high pressure coolant cutting. For both these figures the reference point is feed rate 0.12 mm/rev, cutting speed 85.66 m/min, and material hardness of 48 HRC. Herein, the material hardness and feed rate have been appeared as the most important factors.

Fig. 8 shows the three dimensional response surface plots of cutting temperature. Fig. 8(a) shows the relation of the cutting temperature with the feed rate and cutting speed while Fig. 8(b) illustrates the temperature with cutting speed and material hardness. In dry and HPC cutting, the low feed rate and cutting speed are found to be attached with the low cutting temperature and high cutting temperature is generated at the high feed rate and cutting speed. Similarly, low hardness value produces low cutting temperature. For all the cases, the high pressure coolant reduces the cutting temperature.

The regression plot of the actual and ANN predicted cutting temperature is shown in Fig. 9. From this plot, the value of the regression coefficient is found more than 99.9% which strongly justifies the acceptability in the prediction capability of the models. In case of dry ANN model, the regression coefficient has a higher value; hence, it is conclusive that this model is more accurate than the HPC model. However, both the models can be employed in the cutting temperature prediction.

The results of the prediction of cutting temperature by RSM and ANN are shown in Table 4. In addition, the associated absolute percentage errors (APE) are calculated. Finally, the mean absolute percentage errors (MAPE) for all the mod-
els are computed and shown. It can be seen that actual and predicted value of temperature are closely matched. The corresponding APE is, in most of the cases, less than one percent. Consequently, the MAPE are less than 1 too. Hence these models are effective to predict the response within very short range of error. The dry model has a lower error rate for RSM model than the ANN model. Hence, for dry cutting the RSM model can be adopted to predict the tool-workpiece temperature. On the contrary, the HPC model reveals the superiority of the ANN model (0.69%) as the MAPE, in this case, is lower than the RSM model (0.93%). However, owing to the very low value of the MAPE, both these models are appropriate in predicting the cutting temperature.

Fig. 10 shows the comparison of the response surface model and artificial neural network model with actual cutting temperature for the testing data sets. The actual and predicted results show a good agreement between themselves. The associated mean absolute percentage error for the ANN model is also calculated. For HPC cutting, the ANN model shows higher accuracy than dry cutting.

It is noticeable from the analysis of variance shown in Table 3, carried out in RSM modeling, that the hardness is putting a dominant effect in determining the temperature at the tool-workpiece-chip interface. This is attributable to the fact that, in this work, hardened steel of very high hardness (up to 56 HRC) is machined with coated carbide insert.

### Table 2: Regression coefficients of RSM regression models.

| Models | Eqn. | $R^2$ (%) | $R^2$ (adjusted) (%) | $R^2$ (predicted) (%) |
|--------|------|-----------|---------------------|----------------------|
| $\theta_{dry}$ | 5 | 99.56 | 99.33 | 98.83 |
| $\theta_{HPC}$ | 6 | 99.43 | 99.13 | 98.32 |

### Table 3: Analysis of variance for tool-workpiece interface temperature.

| Source | DF | Dry quadratic model | HPC quadratic model |
|--------|----|---------------------|---------------------|
| Seq SS | % Cont. | F-value | P-value | Remark | Seq SS | % Cont. | F-value | P-value | Remark |
| Model | 9 | 398,007 | 99.56 | 427.35 | 0.000 | Significant | 362,834 | 99.43 | 329.52 | 0.000 | Significant |
| $V_C$ | 1 | 62,894 | 15.73 | 591.89 | 0.000 | Significant | 67,541 | 18.51 | 539.51 | 0.000 | Significant |
| $S_o$ | 1 | 16,744 | 4.19 | 159.42 | 0.000 | Significant | 25,238 | 6.92 | 201.05 | 0.000 | Significant |
| $H$ | 1 | 269,868 | 67.51 | 2623.0 | 0.000 | Significant | 234,384 | 64.23 | 1913.98 | 0.000 | Significant |
| $V_C^2$ | 1 | 252 | 0.06 | 2.43 | 0.137 | Not significant | 154 | 0.04 | 1.26 | 0.278 | Not significant |
| $S_o^2$ | 1 | 480 | 0.12 | 4.64 | 0.046 | Significant | 613 | 0.17 | 5.01 | 0.039 | Significant |
| $H^2$ | 1 | 45,879 | 11.48 | 443.36 | 0.000 | Significant | 32,955 | 9.03 | 269.36 | 0.000 | Significant |
| $V_C \times S_o$ | 1 | 53 | 0.01 | 0.51 | 0.485 | Not significant | 391 | 0.1 | 3.19 | 0.092 | Not significant |
| $V_C \times H$ | 1 | 1566 | 0.39 | 15.13 | 0.001 | Significant | 256 | 0.07 | 2.10 | 0.166 | Not significant |
| $S_o \times H$ | 1 | 271 | 0.07 | 2.62 | 0.124 | Not significant | 1302 | 0.36 | 10.64 | 0.005 | Significant |
| Error | 24 | 1759 | 0.44 | | | | 2080 | 0.57 | |
| Total | 33 | 399,766 | 100 | | | | 364,913 | 100 | |

![Fig. 6](image-url)  
(a) Dry machining condition ($R^2$:0.99988)  
![Fig. 6](image-url)  
(b) HPC machining condition ($R^2$:0.99966)
Although, coating over the tool provides some solid lubrication, yet it is not sufficient in providing perfect lubrication to reduce the effect of high friction and as there is no/minimum cooling (for dry cutting) by ambient air, a significant amount of temperature is risen in the contact point of tool-workpiece [25]. The rise of cutting temperature is due to the transfer of mechanical energy into heat energy [26] caused by the cutting tool given in the form of cutting force to deform the material plastically [8] and cut into chips. The restricting force is created by and within the material before breaking of the bonds of metals/alloy molecules against the cutting force imparted by the tool insert. The increased hardness of material gives rise to the restraining force [27] and supposedly rises the cutting temperature. Even though the application of coolant at high pressure reduces the cutting temperature and provides the lubrication [18], the change of hardness from 40 HRC to 48 HRC and then finally to 56 HRC originates different amounts of restraining force within the material and exerts severe effect on determining the cutting temperature.

Followed by material hardness, the cutting speed creates significant effect on the cutting temperature. This is because the increased cutting speed means increased amount of material removing per unit time; hence, higher friction is endured by the cutting tool which contributes to the generation of cutting temperature [28]. Furthermore, the higher cutting speed provides very short period of time to machine and within this time the cutting tool gets insufficient time to cool and consequently increases the cutting temperature [29]. When the cutting tool is hot, it becomes soft and loses its sharpness [8] and the blunt tool edge opens the higher tool contact surface (increased nose radius) and thus faces increased friction and engenders higher cutting temperature. The feed rate has little effect on the cutting temperature as the higher feed rate means a higher distance per revolution of the workpiece and this

Fig. 7  Perturbation plots of cutting temperature: (a) dry cutting and (b) HPC cutting.

Fig. 8  3D response plots.
hardly causes any change in the cutting mechanism and thus produces low impact on the temperature.

In modeling of dry cutting temperature by RSM and ANN, the mean absolute percentage error was found to be 0.78% and 0.86% respectively. Based on the lower MAPE, the RSM model is suitable; yet, due to the fact that all 27 sets of data were used for the development of the quadratic model and that model has predicted the cutting temperature of the same 27 sets of data, the error accordingly showed lower value of MAPE. Similar insight is also application for the cutting temperature model of the high pressure coolant applied hard turning. Despite the fact that different data were used for training and testing the ANN model, the neural network based predictive model revealed fairly reasonable accuracy (MAPE < 1%).

Among different tested network structures, the 3–15–1 structure showed the highest accuracy in predicting the temperature.

Table 4 Performance comparison of tool-workpiece interface temperature models.

| SL no | Predicted dry cutting temperature (°C) | Predicted HPC cutting temperature (°C) |
|-------|----------------------------------------|----------------------------------------|
|       | RSM         | ANN         | RSM-APE (%) | ANN-APE (%) | RSM         | ANN         | RSM-SE (%) | ANN-SE (%) |
| 1     | 710.28      | 706.57      | 1.47        | 0.94        | 603.82      | 597.17      | 1.48        | 0.36        |
| 2     | 729.90      | 734.86      | 0.69        | 0.02        | 629.10      | 629.02      | 0.93        | 0.94        |
| 3     | 924.42      | 926.51      | 0.48        | 0.71        | 802.61      | 790.67      | 1.34        | 0.17        |
| 4     | 729.03      | 729.71      | 0.42        | 0.51        | 626.04      | 613.15      | 0.94        | 0.13        |
| 5     | 753.41      | 759.97      | 1.00        | 0.14        | 661.74      | 662.21      | 1.53        | 1.46        |
| 6     | 952.67      | 958.81      | 0.56        | 0.08        | 845.66      | 839.74      | 1.28        | 0.57        |
| 7     | 765.67      | 754.30      | 0.22        | 1.27        | 668.48      | 675.42      | 0.23        | 0.81        |
| 8     | 794.80      | 786.99      | 0.53        | 1.50        | 714.60      | 717.39      | 0.65        | 1.04        |
| 9     | 998.82      | 992.66      | 0.28        | 0.34        | 908.94      | 915.61      | 1.20        | 0.48        |
| 10    | 743.35      | 743.03      | 0.89        | 0.93        | 648.46      | 643.74      | 0.54        | 0.20        |
| 11    | 772.14      | 773.52      | 1.64        | 1.46        | 677.46      | 683.00      | 1.10        | 0.29        |
| 12    | 975.82      | 974.99      | 0.02        | 0.10        | 854.67      | 851.92      | 2.32        | 2.64        |
| 13    | 760.42      | 769.01      | 1.39        | 2.53        | 666.11      | 665.04      | 0.93        | 0.76        |
| 14    | 793.96      | 802.70      | 1.14        | 2.25        | 705.52      | 704.60      | 0.79        | 0.66        |
| 15    | 1002.39     | 1011.05     | 0.44        | 1.31        | 893.15      | 891.65      | 0.13        | 0.04        |
| 16    | 795.39      | 795.26      | 1.19        | 1.21        | 703.98      | 701.89      | 0.57        | 0.86        |
| 17    | 833.68      | 833.05      | 0.75        | 0.83        | 753.80      | 751.33      | 0.78        | 0.45        |
| 18    | 1046.85     | 1048.2      | 1.14        | 1.28        | 951.85      | 958.28      | 1.05        | 1.73        |
| 19    | 808.40      | 803.18      | 0.07        | 0.72        | 727.08      | 727.04      | 0.29        | 0.28        |
| 20    | 850.73      | 843.43      | 0.60        | 0.97        | 761.55      | 763.33      | 0.45        | 0.22        |
| 21    | 1067.96     | 1060.91     | 0.37        | 0.29        | 944.25      | 928.94      | 1.31        | 0.33        |
| 22    | 822.99      | 827.40      | 1.20        | 0.67        | 737.96      | 744.00      | 1.08        | 0.27        |
| 23    | 870.07      | 873.66      | 0.24        | 0.65        | 782.85      | 785.99      | 0.40        | 0.00        |
| 24    | 1092.05     | 1098.66     | 0.54        | 0.06        | 975.96      | 973.85      | 0.41        | 0.19        |
| 25    | 855.47      | 850.13      | 0.17        | 0.45        | 769.07      | 776.32      | 0.12        | 0.82        |
| 26    | 907.30      | 903.03      | 2.06        | 1.58        | 824.37      | 832.16      | 1.77        | 2.74        |
| 27    | 1134.02     | 1135.28     | 1.39        | 1.28        | 1027.90     | 1043.02     | 1.64        | 0.19        |
| MAPE  | 0.78        | 0.86        |              |              | 0.93        | 0.69        |              |              |

Fig. 9 Linear regressions for actual and ANN predicted temperature.

(a) Dry machining condition (R²:0.99957) (b) HPC machining condition (R²:0.99918)
temperature during dry machining and the 3–12–1 structure revealed the minimum error in the HPC assisted hard turning. This is because of the fact that the 15 and 12 numbers of hidden neurons in the hidden layer understandably constructed the best relationship between the input and output for dry and HPC conditions respectively. The superiority of the ANN model over RSM model gets justified by the insight that the ANN forms a complex relation between the input and output corresponding to the necessity of the minimum prediction error [30], which is not attainable by the RSM as this can only form the quadratic relation between the input and the output. Hence any relation out of quadratic is non-comprehensive to RSM while ANN develops a logical relation there.

Conclusions

Based on the experiment and result analysis of the response surface and neural network based models of average cutting temperature in turning of hardened steel in respect of cutting speed, feed rate and material hardness under dry and high pressure coolant jet, the following conclusions can be drawn:

- The material hardness played an influential role on cutting temperature; yet, it was hardly considered as the quality input for the temperature prediction model. In this work, the material hardness was considered for temperature modeling along with the investigation of the effect of hardness on the cutting temperature.
- The material hardness exerted a contribution of 67% and 64% on cutting temperature for dry cutting and coolant cutting, respectively, due to an increased restraining force caused by the increased material hardness against the tool applied cutting force.
- The regression coefficients are found to be greater than 99.9% for both the RSM and ANN models and hence justify the acceptability of their prediction capability.
- The analysis of the mean absolute percentage error recommended the acceptance of the neural network based prediction model over response surface model owing to the better capability of ANN model to build an appropriate relation between the input and output.

Fig. 10  Graphical comparison of actual and predicted temperature values.

Conflict of interest

There is no conflict of interest with the concerned persons or organizations.

Compliance with Ethics Requirements

This article does not contain any studies with human or animal subjects.

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