

## **Modeling of Chip Tool Interface Temperature in Machining Steel- An Artificial Intelligence (AI) Approach**

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### **Abstract**

Chip tool interface temperature control is one of the critical factors during machining because it influences substantially the chip formation mode, cutting forces, tool life, surface finish and product quality. In this paper an artificial neural network (ANN) model has been developed as a function of cutting parameters in turning steel for predicting chip tool interface temperature. The cutting parameters used include cutting speed, feed rate and depth of cut. A feed-forward back propagation network with ten hidden neurons has been selected as the optimum network by trial and error method. The co-efficient of determination ( $R^2$ ) between model prediction and experimental value is found 0.9965. The result implies that, the model can be successfully used to forecast chip tool interface temperature in response to the cutting parameters for which the model has been constructed.

### **Keywords**

Chip tool interface temperature, ANN, cutting speed, feed rate, depth of cut

### **1. Introduction**

Machining process associated with high velocity and feed rate inherently generate large amount of heat as well as high cutting zone temperature. The magnitude of this cutting temperature increases, though in different degree, with the increase of cutting velocity, feed and depth of cut [1]. As a result, high production machining is constrained by rise in temperature. The cutting temperature if not controlled properly, cutting tools undergo severe flank wear and notch wear, loose sharpness of the cutting edge either wearing or become blunt by welded built-up edge and weaken the product quality. In normal cutting condition all such heat sources produce maximum temperature at the chip-tool interface, which substantially influence the chip formation mode; cutting forces, tool life and product quality. High production machining needs to increase the process parameters further for meeting up the growing demand and cost competitiveness. Cutting temperature thus increases with the increase in process parameter as well as with the increase in hardness and strength of the work material. Such high cutting temperature then influences the growth of tool wear and premature tool failure by plastic deformation and thermal fracturing. The surface quality of the products also deteriorates with the increase in cutting temperature due to built-up-edge formation, oxidation, rapid corrosion and induction of tensile residual stress and surface micro-cracks [2]. Such problems become more severe if the work materials are very hard, strong and heat resistive and the machined part is under dynamic or shock loading during functional operations. So, to control cutting temperature is of great importance in machining industries and attempts are to be made to reduce this detrimental effect of cutting temperature.

During machining, shearing of work material, friction between the flowing chips and rake face of the tool and friction of auxiliary flank with finished surface are the principal sources of heat generation. Cutting temperature increases with the increase in specific energy consumption and material removal rate i.e. with the increase of cutting velocity, feed and depth of cut. The high temperature generated adversely affects, directly or indirectly, chip formation, cutting forces, tool life, dimensional accuracy and surface integrity of the machined components. Thus generation of heat at the cutting zone is of prime concern in any machining process and this heat needs to be controlled to an optimum level in order to achieve better machining performance [2].

In this paper an artificial neural network (ANN) model has been developed for the analysis and prediction of the relationship between cutting and process parameters during turning of medium carbon steel. The input parameters of the Artificial Neural Networks (ANN) model are the machining parameters: speed, feed and depth of cut. The output parameter of the model is the chip tool interface temperature. Experimental studies have been conducted to establish and validate the proposed model. ANN can capture and model complex input-output relationships without the help of a mathematical model and behaves like model free estimators [3]. ANNs have been widely used for modeling complex process due to their learning and generalization capabilities, accommodation of non-linear variables, adaptability to changing environments and resistance to missing data. Adaptability in response to changing environment means ANN can be applied for solving machining problems with different changing input parameters such as cutting speed, depth of cut, feed rate, tool angles and machining time. ANNs have been successfully used in modeling many metal cutting processes, such as milling, turning and drilling [4]. Extensive research has been conducted on the application of ANNs in modeling and monitoring of machining operations [5]. In computer-integrated production processes ANNs have been used in adaptive control of cutting process, prediction of surface roughness, cutting forces, vibrations, prediction of tool wear and tool failure, solving of optimization problems [6].

A review of the literature on prediction of chip tool interface temperature reveals that no ANN model has been still developed to predict the cutting temperature while machining medium carbon steel with uncoated carbide insert designated as SNMG 120408 and considering the three cutting parameters -cutting speed, feed rate and depth of cut as input to neural network. This paper deals with developing an ANN model that can be used successfully to predict chip tool interface temperature for optimization of machining parameters while performing turning operations.

## 2. Experimental Procedure and Conditions

In this study, the machining tests have been considered for straight turning of medium carbon steel on a lathe (7.5 kW) by a standard uncoated carbide insert with ISO designation-SNMG 120408 at different speed-feed combinations [2]. A cylindrical bar of medium carbon steel of 167 mm diameter has been considered for straight turning. The conditions under which the machining tests have been carried out are briefly given in Table 1.

Table 1: Experimental conditions

<b>Machine tool</b>	: Lathe Machine(China), 7.5 kW
<b>Work materials</b>	: Medium Carbon Steel
<b>Cutting tool</b>	: Uncoated Carbide, (p-30 grade), Sandvik
Geometry	: -6°, -6°, 6°, 15°, 75°, 0.8 mm
<b>Tool holder</b>	: PSB NR 2525 M12 (ISO specification), Widia
<b>Cutting parameters</b>	
Cutting velocity, V	: 66 to 266 m/min
Feed rate, f	: 0.10 to 0.20 mm/rev
Depth of cut, d	: 1.0 and 1.5 mm

All these parameters have been selected as per tool manufacturer's recommendation as well as industrial practices for machining medium carbon steel with uncoated carbide insert tool configuration namely SNMG-120408 has been undertaken for this work. The insert was clamped in a PSB NR-2525 M12 type tool holder. The photographic view of the experimental set-up is shown in Figure 1.



Figure 1: Photographic view of the experimental set-up

### 3. ANN Model Formulation

To develop an ANN model to predict chip tool interface temperature, it is very much important to identify the input and output parameters of the network. The forecasting capability or interpolation capability of an artificial neural network (ANN) model strongly depends on the appropriate selection of input-output parameters. In our proposed model, the input parameters that have been considered are cutting speed ( $V$ ), feed rate ( $f$ ) and depth of cut ( $d$ ). These parameters can be set up in advance. It means that these parameters are controllable and can be selected prior to perform machining operation. The optimization of machining process can be achieved by proper selection of these parameters. The output parameter of the model is chip tool interface temperature. The input/output datasets of the ANN model that we are to going to be formulated to predict chip tool interface temperature are illustrated schematically in Figure 2.

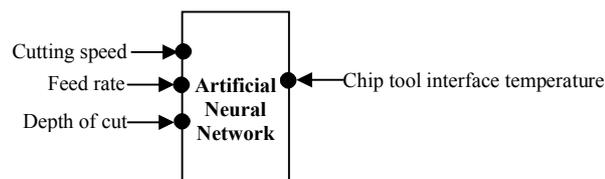


Figure 2: Schematic diagram of ANN for tool wear and surface roughness

Experimental studies have been conducted to establish and validate the proposed ANN model. In this work, four basic steps have been adopted in the development of the model: collection of input-output dataset; pre-processing of the input-output dataset; designing and training of the neural network and finally performance evaluation of the designed neural network. The optimal network architecture was determined after several simulation trials by MATLAB 7.1 software.

#### 3.1 Collection of Input-Output Dataset

In this paper, the machining tests have been carried out on a lathe by straight turning of medium carbon steel by a standard uncoated carbide insert with ISO designation-SNMG 120408 at different cutting speeds ( $V$ ), feed rates ( $f$ ) and depth of cuts ( $d$ ). During machining trials, the cutting insert was withdrawn at regular intervals to examine the pattern and extent of wear under a metallurgical microscope. After each trial, chip tool interface temperature has been measured. Thus the output variables in response to the different combinations of machining/input parameters have been obtained.

#### 3.2 Pre-processing of Input-Output Dataset

Capability of an artificial neural network (ANN) model to generalize regarding unseen data depends on several factors such as appropriate selection of input-output parameters of the system, the distribution of the input-output dataset, the format of the presentation of the input-output dataset to the neural network. For our ANN model, the input parameters used are the three main machining parameters (cutting speed, feed rate, depth of cut), while the output dataset is chip tool interface temperature.

In this study, several machining tests were carried out and thus 50 pairs of input-output dataset were obtained during the machining trials. Before training the ANN by feeding the dataset to the network and the input-output mapping, one significant task is to process the experimental data into patterns. Training and testing pattern vectors are formed before input-output dataset are fed to network. Each pattern is formed with an input condition vector ( $P_i$ ) and the corresponding target vector ( $T_i$ ), which is shown in the matrix. Before training the network, the input-output dataset were normalized within the range of -1 to +1 using the Matlab command 'premnmx'.

#### 3.3 Neural Network Design and Training

In this study, standard multilayer feed-forward back-propagation hierarchical neural network has been considered. The neural network has been designed with MATLAB 7.1 software. The back propagation algorithm is a gradient decent error-correcting algorithm which updates the weights in such a way that network output error is minimized [7]. The feed forward back propagation network usually consists of an input layer one hidden layer and an output layer which emits the outputs of the network. The number of hidden layer may vary depending on the nature, complexity and non-linearity of the data at hand, but single hidden layer is sufficient to deal with most of the practical case.

In this work, the input layer has three neurons corresponding to each of the three cutting parameters and one neuron in the output layer corresponding to cutting temperature (Figure1). The issue of determining the optimum number of hidden nodes is a crucial and complicated one in neuronal model. In general, network with smaller number of hidden neurons are preferable as they usually have better generalizations ability and less over fitting problems. But network with too few hidden neurons may not have enough power to model, store and learn the data. The most common approach in determining the number of hidden neurons (nodes) is via trial and error. The ANN configuration is represented as 3-10-1 that is input layer consists of three input neurons; the hidden layer consists of ten neurons and the output layer consisting of one neuron. The number of neurons in the hidden layer is determined by trial and error method after designing and investigating many networks which vary in their structure, transfer function, training algorithm etc.

A computer program was performed under this MATLAB version. The input-output dataset consisting of 50 patterns was divided randomly into two categories: training dataset consist of 80% of the data and test dataset which consist 20% the data. There are 40 training patterns considered for ANN modeling. After the training, the weights are frozen and the model is tested for validation. The input parameters to the network are sets of values (in this case 10 pairs of dataset which have been shown in Table 2) that have not been used for training the network (raw untrained data) but are in the same range as those used for training. This enables to test the network with regard to its capability for interpolation regarding unseen data.

Table 2: Test cutting conditions

Test cutting conditions	[V (m/min), f (mm/rev), d (mm)]
1	[68, 0.10, 1.00]
2	[133, 0.14, 1.00]
3	[95, 0.12, 1.50]
4	[266, 0.20, 1.50]
5	[190, 0.18, 1.50]
6	[95, 0.12, 1.00]
7	[266, 0.20, 1.00]
8	[190, 0.18, 1.00]
9	[68, 0.10, 1.50]
10	[133, 0.14, 1.50]

The momentum constant and learning rate used in this model is 0.5 and 0.1 respectively. The maximum number of training epochs that was set is 10,000 and the training error goal was 0.00001 shown in Figure 3. The optimum ANN architecture is shown in Figure 4. After the training is completed, the actual weight values are stored in a separate file. The value of  $R^2$  and MAPE values between the network predictions and the experimental values using training and test dataset for different network architecture have been shown in Table 3.

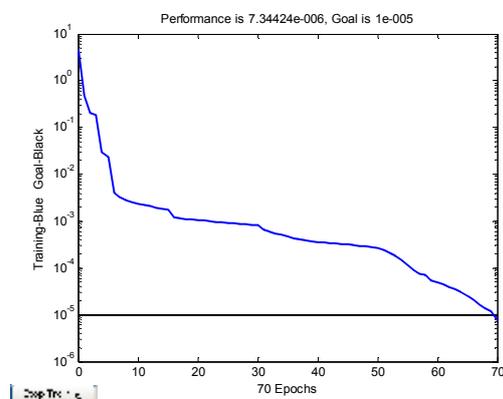


Figure 3: ANN training performance

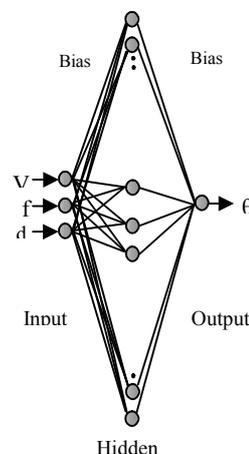


Figure 4: Proposed ANN architecture

Table 3: R<sup>2</sup> And MAPE values between the network predictions and the experimental values

Hidden layer	Training performance			Testing performance		
	1	1	1	1	1	1
Hidden neurons	8	10	12	8	10	12
R <sup>2</sup>	1.0000	1.0000	1.0000	0.9884	0.9965	.9845
MAPE	0.0001	0.0001	0.0093	.0296	0.5204	0.6194

### 3.4 Performance Evaluation of the Model

Training and testing performance of the optimum network architecture has been evaluated by the following measures:

$$RMSE = \left( \frac{1}{p} \sum_j |t_j - o_j|^2 \right)^{1/2} \quad (1)$$

$$MEP = \frac{\sum_j ((t_j - o_j) / t_j) \times 100}{p} \quad (2)$$

$$R^2 = 1 - \left( \frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \right) \quad (3)$$

$$APE(\%) = \left| \frac{\text{Model prediction values} - \text{Experimental values}}{\text{Experimental values}} \right| \times 100\% \quad (4)$$

Where,

- t : Target value
- O : Output value
- RMSE : Root mean squared error
- MEP : Mean error percentage
- APE : Absolute percentage of error
- R<sup>2</sup> : Coefficient of determination/ absolute fraction of variance
- P : Number of patterns
- j : Processing elements

Here, to judge the performance of each network regression analysis was adopted to find the coefficient of determination value (R<sup>2</sup>) for both training and testing phases. Another index termed as mean absolute percentage of error (MAPE) is also used in this analysis to judge the training and testing performance. Figure 5 shows the ANN prediction values and observed values for chip tool interface temperature in different test cutting conditions. From the graph, it is clear that the proposed model can predict values which are nearly very close to experimental observations for each of the output parameters. The results show that the ANN model can be used easily for prediction of chip tool interface temperature.

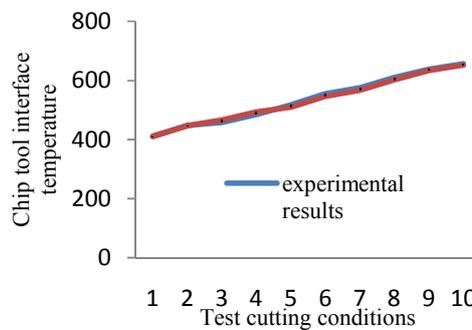


Figure 5: Experimental vs. ANN prediction

## 4. Results and Discussion

Though artificial neural networks are used widely for predicting tool wear and surface roughness in machining steel for different machining conditions, use of ANN for predicting chip tool interface temperature is quietly a new approach. The schematic diagram of artificial neural network for the prediction of tool wear and surface roughness is shown in Figure 1. In this study, an artificial neural network (ANN) with feed-forward back-propagation algorithm was trained and the training epoch (cycles) set for each network is 10,000. The purpose of the training is to minimize the mean squared error (MSE). The training performance of the proposed ANN architecture has been shown in Figure 3. From Figure 3 it is seen that the network error goal is met at 70 epochs.

The numbers of neurons in the hidden layer were found by trial and error method and finally 10 hidden neurons were chosen for the suggested network. The proposed network can be represented as 3-10-1. To find the optimal network architecture, coefficient of determination ( $R^2$ ) and mean absolute percentage of error (MAPE) between the network prediction and experimental values were calculated for every network for both training and testing phases. The performance of the ANN model has been highlighted in Figure 5 for chip tool interface temperature. As shown in the figures, it is clear that the values predicted by ANN are very close to experimental values. The result shows that, the model can be successfully used to forecast chip tool interface temperature.

## 5. Conclusion

One of the primary objectives in machining operation is to control chip tool interface temperature to produce product with low cost and high quality i.e. to obtain machining economics. It involves the optimum selection of machining parameters, e.g. cutting speed, feed rate and depth of cut. These parameters directly affect the cost, productivity and quality of products by affecting cutting temperature. A better predictive model can help as to choose the optimum machining parameters before performing machining operations in order to control chip tool interface temperature. The objective of this work was to develop an ANN model to predict chip tool interface temperature while turning medium carbon steel under dry environment. The model has been proved to be successful in terms of agreement with experimental results. The proposed model can be used in optimization of cutting process for efficient and economic production by forecasting the chip tool interface temperature.

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