

INVESTIGATION AND MODELING OF CUTTING TOOL TEMPERATURE IN TURNING OF INCONEL 625 STEEL BY USING TAGUCHI METHOD AND LONG SHORT TERM MEMORY NETWORK

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Abstract: In this paper, the results of an experimental investigation of cutting tool temperature in turning operations are presented. The cutting tool temperature is a very relevant in order to avoid excessive tool wear and tool damage. This study explains the impact of cutting speed, feed rate and depth of cut on cutting tool temperature during machining of Inconel 625 steel. Taguchi methodology is used to formulate the experimental layout. A Taguchi L27 design of experiment is applied to analyze the effect of each cutting parameter on the cutting tool temperature. Minitab software is used to process the experimental data and to develop a mathematical regression formula among three main cutting parameters and tool temperature. The obtained data in experimental work are used to perform deep learning using the Long Short-Term Memory (LSTM) network in order to predict the cutting tool temperature. The obtained results indicate that feed rate has the largest effect on cutting tool temperature followed by depth of cut and cutting speed. The predicted cutting tool temperature values obtained from LSTM network are very close to those of experimental, where the average percentage error from test base is 1.93%. According to the results, the LSTM predicts well the expected outcomes, and the standard deviation is in acceptable interval for predicting the cutting tool temperatures.

Key words: machining, turning, cutting tool temperature, prediction, Taguchi, deep learning, LSTM.

1. INTRODUCTION

Cutting tool temperature is a very important parameter because it has an impact on the quality of the surface roughness being processed, on tool wear, and on tool life. A turning cutting tool's edges have to cope with severe thermal and mechanical loadings. Temperature affects the cutting tool damage behavior. High temperature causes a significant decrease of the yield strength of the tool materials, which lead to plastic deformation and crack formation [1]. Therefore, to avoid precocious tool failures, quantitative information about the cutting temperature is very relevant.

By creating a mathematical model of cutting tool temperature, the search for the optimal machining solution can be performed. The material selected in this study to investigate the cutting tool temperature is Inconel 625, which is primarily used in the power plant, nuclear power plant, aircraft, and oil refining industries.

The Inconel 625 has high durability and high-temperature resistance; it is also resistant to corrosion and oxidation. Initially, this material was used for steam transfer pipes, then with some modifications for both marine and nuclear use. It is resistant to breakage and has

good adhesion. Many researches have been performed using Taguchi Method to optimize the turning parameters.

Nalbalt [2] has used L9 orthogonal array with nine experiments, to investigate the performance characteristics in turning operations of AISI 1030 steel using Ti coated tools. They found that the insert radius and feed rate are the main parameters that influence the surface roughness.

Mthieselvan [3] has illustrated the procedure used when employing Taguchi method for a turning operation. Cutting depth, spindle speed, feed speed and tool wear are used as process parameters, while feed force and thrust force are selected as operating characteristics.

Manoj et al. [4] have investigated the effects of cutting speed, feed rate, and depth of cut on material removal rate (MRR). They have researched mild steel test piece by changing the (input parameters) cutting conditions with Taguchi Method. They have found that these input cutting conditions have a significant effect on MRR.

Lin [5] has used Deep Learning with Long short Term Memory (LSTM) network to predict the surface roughness in milling process. Based on the analyzed literature, it was found that very little work was done in the area of optimizing the tool temperature with combinations of three main cutting parameters in turning. Therefore, in this paper, the impact of cutting speed, feed rate, and depth of cut on cutting tool temperature during

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machining of Inconel 625 steel are investigated. Taguchi mathematical used for tool temperature modeling and prediction. The aim of the research is to find the changes in the tool temperature with the change of the cutting speed, feed rate and cutting depth.

The paper is organized as follows. In section 2, Taguchi method is explained. In section 3, long short term memory (LSTM) is described; section 4 outlines the designing of experiment according to Taguchi methodology. Section 5 presents the results and finally, section 6 concludes the paper.

2. TAGUCHI EXPERIMENTAL DESIGN APPROACH

The Taguchi method is designed for optimization of process parameters and reducing changes in the process. It is based on conducting and evaluating results of experiments to find the best levels of control factors. The main objective of Taguchi approach is to keep variance in the output very low even in the presence of noise inputs. It has a wide application in many manufacturing fields. It was developed for designing experiments to investigate how many different parameters affect the mean and variance in the process performance characteristics that determines how well the process works. The experimental design involves the use of orthogonal arrays to organize experimental parameters that affect the machining process and the levels at which that process should be changed [6]. Rather than trying all possible combinations like factorial design, the Taguchi method tests a pair of combinations. This allows the collection of data needed to determine the factors that have the most impact on product quality with a minimal amount of experimentation that saves the time and funding resources. The Taguchi method is best used when there are an average number of variables (3 to 50 factors), some combinations between variables, and only a few of these variables appear to be significant [7].

3. LSTM NETWORK

LSTM is a part of recurrent neural network (RNN) used in the field of deep learning, which addresses the vanishing problem and enables learning of long-term dependencies, but is more effective.

They were developed by Hochreiter and Jürgen Schmidhuber [8], and nowadays are very widely used.

The Long short-term memory has unique units that are called memory blocks in the recurrent hidden layer.

Memory block has memory cells with self-relation saving the temporal state of networks in addition to unique units that manage the information. Every memory contains input gate that manages the activations inside the memory cell, and Output gate that manages the output activations inside network. LSTM is used for classifying, processing and making prediction.

LSTM contains 4 input weights (input data and 3 gates), and 4 recurrent weights (output to input data and 3 gates). LSTM unit consists of a cell, input gate, output gate, and a forget gate. Recently, they have shown a very good results and accuracy in language modeling, image captioning, translation, speech recognition etc. In this

research, the LSTM has been used for prediction of tool temperature on the cutting insert [9].

4. EXPERIMENT DESIGN ACCORDING TO TAGUCHI METHOD

Classic experimental design methods are very complex and time consuming. Because Taguchi experiments were selected in the Minitab 17 software, the number of parameters that can affect the turning process can be as high as 86. The parameters that are selected to be analysed are cutting speed (v_c), feed rate (f) and depth of cutting (a_p). Each parameter has three levels: low, middle and high level. These levels are marked respectively with numbers 1, 2 and 3. According to the Taguchi method, if three parameters and 3 levels are used for each parameter, the orthogonal sequence for experimentation is L27. Table 1 shows cutting parameters and their levels for experimentation.

The orthogonal order is made according to the Taguchi method, which uses a unique standard experimental design that requires only a small number of experimental combinations to find the main factors influencing the turning process. According to this method, at least 9 experiments must be taken. Based on this orthogonal range (VO), a design which has at least 9 lines must be selected, requiring a total of 27 attempts to optimize the most influential process parameters. Based on the main factors (v_c , f and a_p), the variables are assigned to the column as determined by the orthogonal order. The last column may not be included, but no row should be left out. Once the orthogonal order is selected, the experiments are selected by level combinations. It is important to carry out all the experiments. The performance parameter (output), in our case the tool temperature is taken for analysis done in Minitab 17 [4].

4.1. The signal-to-noise (S/N) ratio

In the design method according to Taguchi, the design parameters v_c , f and a_p (factors that can be controlled by the technologist) and the vibration factors (factors that cannot be controlled by the technologist) are considered to affect the cutting tool temperature. The S/N ratio is used in this analysis that takes into account both the average and the variation of the experimental result. The S/N ratio depends on the characteristics of the process that has to be optimized. Usually, in the S/N report analysis there are three categories of performance characteristics: lower-best, highest-best and best-nominal performance. The S/N ratio for each response is calculated differently based on the category of performance characteristics and regardless of the category. From the graph on Fig. 1 and 2, the values

Table 1
Cutting parameters and their levels in the design of experiment

Cutting parameters	Levels		
	Level 1	Level 2	Level 3
Cutting speed v_c [m/min]	65	78	91
Feed rate f [mm/rev]	0.04	0.06	0.08
Depth of cut a_p [mm]	0.4	0.7	1.0

were selected as well as the confirmation tests of those values were performed. The largest S/N ratio corresponds to a better performance characteristic. As soon as all S/N reports are calculated for each run of an experiment, Taguchi supports a graphical approach to analyse the data. In the graphical approach, the S/N reports and average responses are completed for each factor versus each of its levels.

4.2. Experimental set-up

The workpiece used for experiment is Inconel 625 steel with diameter $\varnothing 50$ mm and length 405 mm.

Machining is carried out on the lathe machine Tornado 230. Cutting tool holder PCLNR 2525 12 and turning insert CNMG 120408 NN from lamina technologies are used. Pyrometer CELLATEMP PQ 38 AF 4 with measurement range from 30 °C to 2500 °C has been used to measure the temperature on the cutting tool insert.

5. RESULTS

Based on the design of the experimental conditions according to the Taguchi method, the results presented in Table 2 and regression equation of tool temperature (1) it shows the impact of cutting speed, feed rate and depth of cut on tool temperature.

Table 2

Results obtained according to Taguchi plan L27

Exp. No.	Cutting conditions			Tool temperature T [°C]
	Cutting speed v_c [m/min]	Feed rate f [mm/rev]	Depth of cut a_p [mm]	
1	65	0.04	0.4	368.72
2	65	0.04	0.4	355.16
3	65	0.04	0.4	379.60
4	65	0.06	0.7	441.92
5	65	0.06	0.7	458.37
6	65	0.06	0.7	526.90
7	65	0.08	1.0	487.16
8	65	0.08	1.0	480.68
9	65	0.08	1.0	503.19
10	78	0.04	0.7	434.99
11	78	0.04	0.7	453.47
12	78	0.04	0.7	456.00
13	78	0.06	1.0	472.66
14	78	0.06	1.0	436.50
15	78	0.06	1.0	477.80
16	78	0.08	0.4	428.65
17	78	0.08	0.4	451.66
18	78	0.08	0.4	439.70
19	91	0.04	1.0	451.62
20	91	0.04	1.0	445.54
21	91	0.04	1.0	449.84
22	91	0.06	0.4	529.04
23	91	0.06	0.4	462.86
24	91	0.06	0.4	459.02
25	91	0.08	0.7	481.96
26	91	0.08	0.7	498.41
27	91	0.08	0.7	500.91

Normal probability plot for tool temperature is presented in Fig. 3.

Table 3 presents analysis of the variances the impact of cutting speed, feed rate and depth of cut on tool temperature.

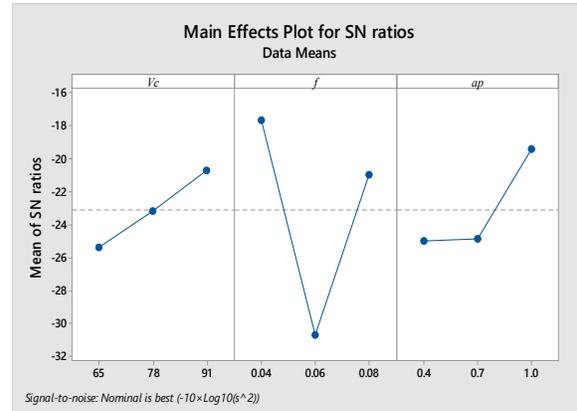


Fig. 1. The average value of the influences of cutting conditions v_c, f and a_p .

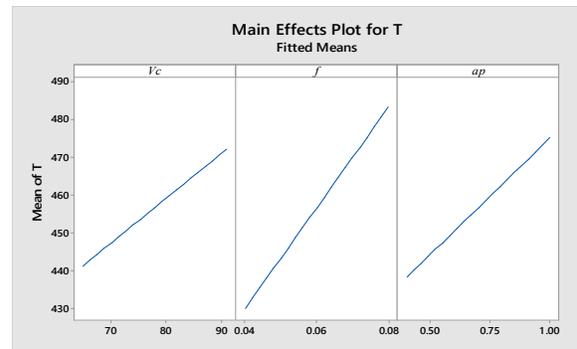


Fig. 2. The influence of each parameter on the cutting tool temperature.

Table 3

Analysis of the variances for temperature

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	23010	7670.0	7.91	0.001
Cutting speed	1	14278	4278.1	4.41	0.047
Feed rate	1	12661	12660.6	13.06	0.001
Depth of cut	1	6071	6071.3	6.26	0.020
Error	23	22296	969.4		
Lack-of-fit	5	12793	2558.6	4.85	0.006
Pure Error	18	9503	527.9		
Total	2645306				

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
31.1351	50.79 %	44.37 %	34.26 %

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	241.8	52.5	4.61	0.000	1.00
Cutting Speed	1.186	0.565	2.10	0.047	
Feed ratio	1326	367	3.61	0.001	1.00
Depth of cut	61.2	24.5	2.50	0.020	1.00

Regression Equation of cutting tool temperature is:

$$T = 241.8 + 1.18 v_c + 132 f + 61.2 a_p \quad (1)$$

Figures 4 and 5 present 3D graphics of temperature for feed rate f_{min} and f_{max} , Figs. 6 and 7 – 3D graphics of temperature for depth of cut a_{pmin} and a_{pmax} , and Figs. 8 and 9 – 3D graphics of temperature for cutting speed v_{cmin} and v_{cmax} .

The following results from analyzes of the experimental values given in Table 2 and from analyzes of the diagrams in Figs. 10 and 11: when optimizing the

minimum and maximal parameters, the feed has the greatest influence on the cutting tool temperature, followed by the depth of cut and the cutting speed.

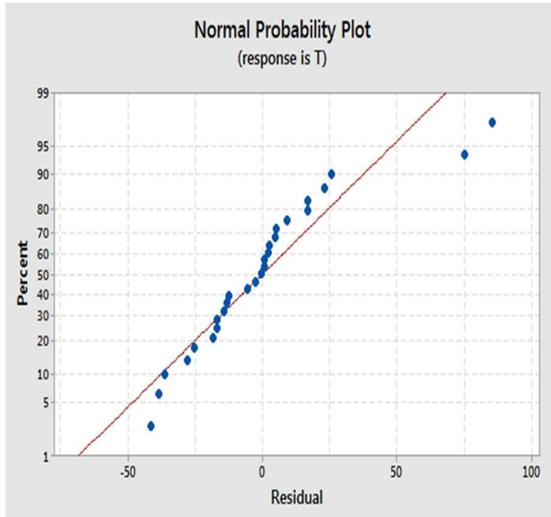


Fig. 3. Normal probability plot for tool temperature.

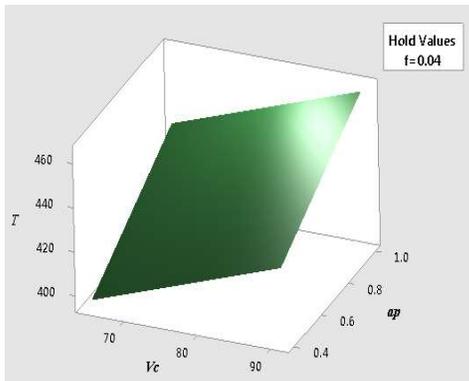


Fig. 4. 3D graphics for $f_{min} = 0.04$ mm/rev.

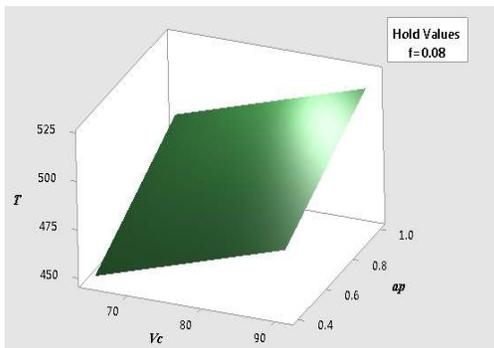


Fig. 5. 3D graphics for $f_{max} = 0.08$ mm/rev.

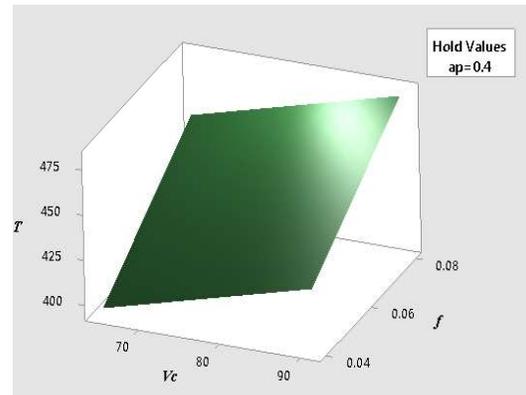


Fig. 6. 3D graphics for $a_{pmin} = 0.4$ mm.

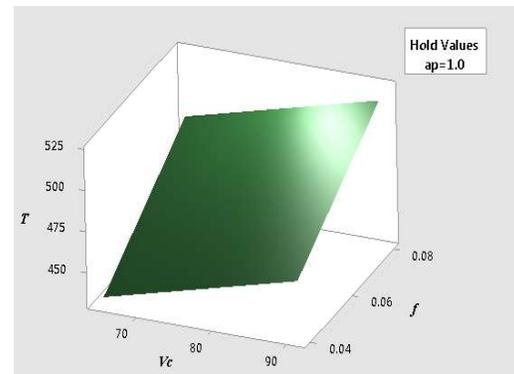


Fig. 7. 3D graphics for $a_{pmax} = 1.0$ mm.

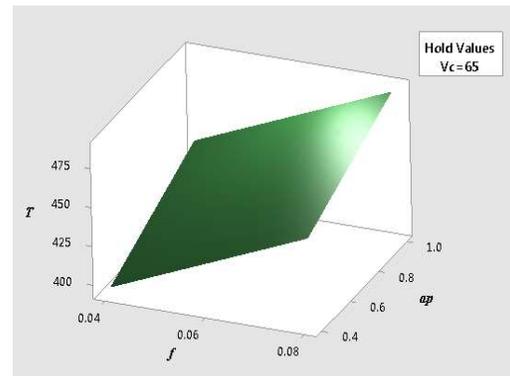


Fig. 8. 3D graphics for $v_{cmin} = 65$ m/min.

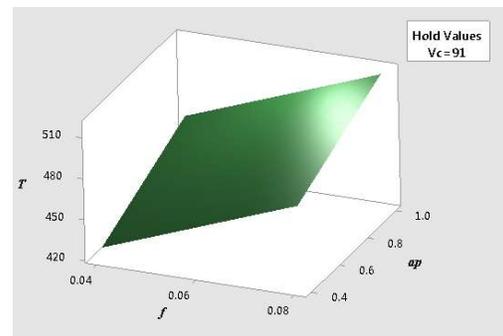


Fig. 9. 3D graphics for $v_{cmax} = 91$ m/min.

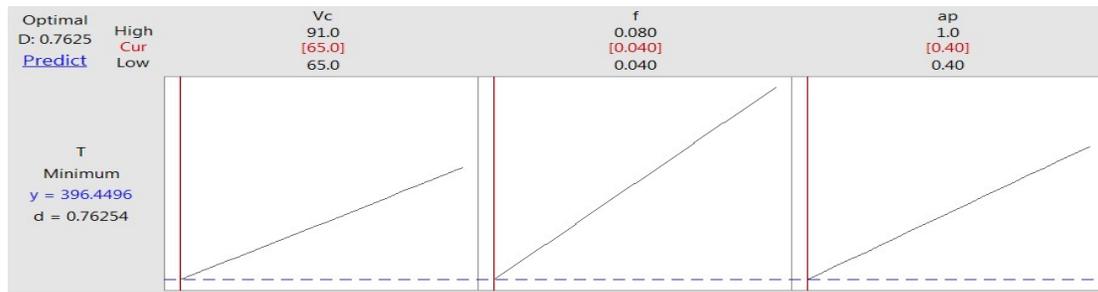


Fig. 10. Optimization of minimal parameters.

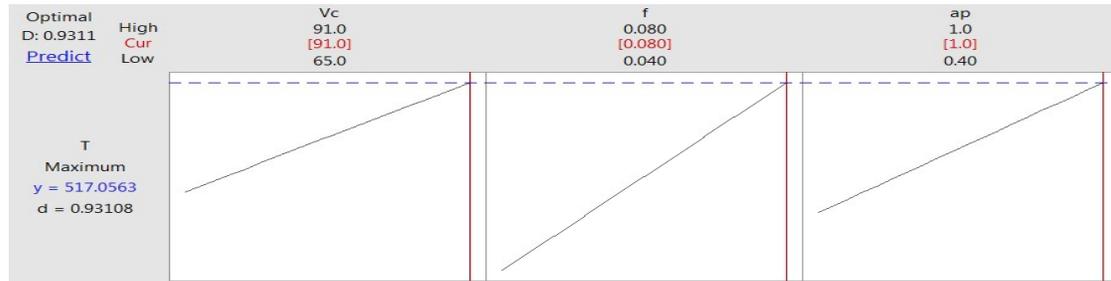


Fig. 11. Optimization of maximum parameters.

5.1. Long short-term memory network for cutting tool temperature prediction

The data given in Table 2 are used to create and train the LSTM network in order to predict the tool temperature.

The three inputs (v_c, f, a_p) are connected to the input layer of the network. The output of the network is temperature. Below is presented Matlab code where the three features cell array is obtained from 27 measurements.

24 measurements are used for training the deep learning network and three measurements are used for testing.

The test data is selected randomly from the 27 experiments by using Matlab code presented below. The "randi" built in function is used for randomly specify the 3 measurements for network testing.

```
>> randomTestSet= randi (24, 3,1)
randomTestSet = 2 20 17
```

The LSTM structure consists of three units in sequence input layer, 200 hidden units in LSTM layer, one fully connected Layer and a Regression Layer. The LSTM code is given below:

```
numFeatures=3;
numHiddenUnits=200;
numResponses=1;
layers = [ ...
    sequenceInputLayer(numFeatures)
    lstmLayer(numHiddenUnits,'OutputMode','last')
    fullyConnectedLayer(numResponses)
    regressionLayer];
```

The results of the trained LSTM network are shown in Table 4.

The average percentage prediction error for test base (highlighted measurements, Table 4) is 1.93%, and the average percentage error for the training base is 3.32%.

The Root mean squared error (RMSE) and loss was used to evaluate the performance of the trained LSTM. Root mean squared error (RMSE) is the standard deviation of the residuals and gives how close predicted

Table 4

The Results of the trained LSTM network

Exp. No.	Cutting speed v_c [m/min]	Feed rate f [mm/rev]	Depth of cut a_p [mm]	Cutting tool temperature T [°]	Predicted cutting tool temperature T [°]	Prediction Error [%]
1	65	0.04	0.4	368.72	359.92	2.38
2	65	0.04	0.4	355.16	359.92	1.34
3	65	0.04	0.4	379.60	359.92	5.18
4	65	0.06	0.7	441.92	465.31	5.29
5	65	0.06	0.7	458.37	465.31	1.55
6	65	0.06	0.7	526.90	465.31	11.6
7	65	0.08	1.0	487.16	484.97	0.44
8	65	0.08	1.0	480.68	484.97	0.89
9	65	0.08	1.0	503.19	484.97	8.52
10	78	0.04	0.7	434.99	460.49	5.86
11	78	0.04	0.7	453.47	460.49	1.55
12	78	0.04	0.7	456.00	460.49	0.98
13	78	0.06	1.0	472.66	465.99	1.41
14	78	0.06	1.0	436.50	465.99	6.75
15	78	0.06	1.0	477.80	465.99	2.47
16	78	0.08	0.4	428.65	452.28	5.51
17	78	0.08	0.4	451.66	452.28	0.13
18	78	0.08	0.4	439.70	452.28	2.86
19	91	0.04	1.0	451.62	447.67	0.87
20	91	0.04	1.0	445.54	447.67	0.47
21	91	0.04	1.0	449.84	447.67	0.48
22	91	0.06	0.4	529.04	468.38	11.4
23	91	0.06	0.4	462.86	468.38	1.19
24	91	0.06	0.4	459.02	468.38	2.03
25	91	0.08	0.7	481.96	496.54	3.02
26	91	0.08	0.7	498.41	496.54	0.37
27	91	0.08	0.7	500.91	496.54	0.87

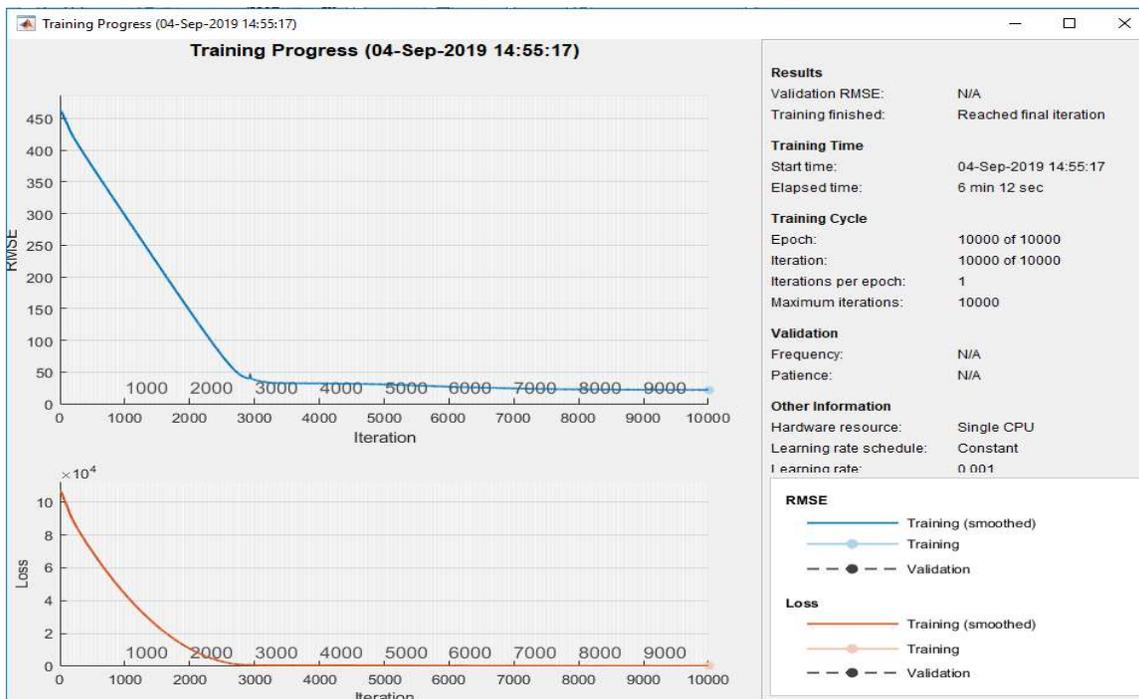


Fig. 12. The results of the LSTM training.

data is to the line of the best fit. The loss instrument gives how good the model predicts the expected outcome. According to the Fig. 12, at approximately 3000 iterations, the RMSE approaches to the standard deviation less than 50 and at 7000 iterations it becomes less than 30. The loss (cost function) approaches to zero after the 3000 iterations.

According to the results, the model predicts well the expected outcomes, and the standard deviation is in acceptable interval for predicting the cutting tool temperatures.

6. CONCLUSION

In this study the impact of cutting speed, feed rate and depth of cut on cutting tool temperature during machining of Inconel 625 steel have been investigated.

Optimization of the process parameters has been done using Taguchi Method and experiments were performed for Taguchi's L27 array.

Long short term memory network has been used for prediction of tool temperature on the cutting tool insert.

From the obtained results the following can be concluded:

- Feed rate has the largest impact on cutting tool temperature.
- The cutting tool temperature increases with increasing depth of cut and cutting speed

The predicted cutting tool temperatures obtained from LSTM network are very close to those of experimental values, where the average percentage error from test base is 1.93%, and the average percentage error for the training base is 3.32%, that means that LSTM have a high level of accuracy and the future of deep learning is very bright.

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