OPTIMIZATION AND PREDICTIVE MODELLING ON SURFACE ROUGHNESS OF DUPLEX STAINLESS STEEL USING ARTIFICIAL NEURAL NETWORK

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Abstract - In this study, a prediction model was developed for surface roughness of Duplex Stainless Steel (1.4462) by using Artificial Neural Network (ANN). Machinability tests were carried out under dry conditions at the CNC lathe with the cutting parameters selected in accordance with ISO 3685. In the experiment, surface roughness depending on cutting parameters (cutting speed, chip angle and feed rate) were measured. These parameters were used for ANN as input parameters (training and testing). Output parameters of ANN were surface roughness and temperature values. The accuracy of ANN performance evaluated by regression analysis with comparing experimental and predicted. ANN model provided highly accurate and consistent prediction for all output parameters.

Keywords - Duplex Stainless Steel, Neural Network, Surface Roughness

I. INTRODUCTION

Stainless steels include high chromium and low carbon. It also contains alloying elements such as Cr, Ni, Mo, and N in their compositions. In order to form stainless steel, at least 12% chromium must be present in the compositions. Stainless steels consist of 5 groups according to their mechanical properties and proportions of alloy elements (Martensitic, ferritic, austenitic, precipitation hardened, double-phase (duplex) stainless steels) [1]. Duplex stainless steels, a new type of stainless steels, have gained importance in recent years. Duplex stainless steel consisting of ferrite and austenite means, "consisting of two parts" in Latin. The austenite in the structure provides ductility and general corrosion resistance while ferrite provides resistance against mechanical strength and tensile corrosion crack. Duplex stainless steels has the characteristics of ferritic and austenitic stainless steels[2]. Duplex stainless steels contain equal proportions of austenite and ferrite phases. Due to their superior mechanical properties and corrosion resistance, it have been widely used in many areas [3, 4].

Recently, there are many studies to develop predictive and optimization models for investigating the influence of machining parameters on machining performance using artificial intelligence techniques. The Artificial Neural Network (ANN) is powerful tool for dealing with the complex nature of the machining of stainless steel [5-8].Some researcher to improve of ANN performance combine other optimizing methods (genetic algorithm, particle swarm optimization, response surface method, etc.). Sangwan et al. used hybrid (ANN and genetic algorithm - GA) approach for determining the optimum machining parameters leading to minimum surface roughness. A real machining experiment has been referred to check the capability of the ANN-GA approach for prediction and optimization of surface roughness [9]. In the study [10], predictive and optimization model (ANN – GA) as an alternative to conventional approaches in predicting the optimal value of machining parameters leading to minimum surface roughness.

Some studies focused on multi parameter or multi objective modelling for machinability one more parameter optimization. Kant and Sangwan developed a multi-objective predictive model for the minimization of power consumption and surface roughness in machining, using grey relational analysis coupled with principal component analysis and response surface methodology, to obtain the optimum machining parameters [11]. Koyee et al., experimental investigations of turning EN 1.4462 and EN 1.4410 duplex stainless steel grades used and nature-inspired metaheuristic bat algorithm is employed to handle the multi-objective optimization of the conflicting performances [12]. Taguchi method is also common to predict machining parameters. Abhang et al. optimized machining parameters in steel turning by Taguchi [13]. In the study [14], the dry turning parameters of two different grades of nitrogen alloyed duplex stainless steel are optimized by using Taguchi method.

II. MATERIAL AND METHOD

2.1. Materials and Procedures

The material used in the present study is a Duplex Stainless Steel (1.4462). The chemical composition and mechanical properties of the material is given in Table 1.

2.2. Cutting Tool and Machine

In the experiments PVD 1105 TiAlN coated cementite carbide cutting tools were used which are commercial quality SNMG120408-QM (9° chip angle) and SNMG120408-SMR (15° chip angle) produced by SANDVIK. Machining Experiments were carried out on the "Johnford TC-35" industrial CNC lathe with the FANUC control unit. The power of the machine is 10 KW, the machine spindle has variable steeples speed and can reach up to 3500 rpm.

Table1: Chemical composition and mechanical properties of Duplex Stainless Steel (1.4462)

Chemical composition							
%C	%Mn	%P	%S	%Si	%Cr	%Mo	%Ni
0.03	2.0	0.035	0.015	1.0	21-23	2.5-3.5	4.5-6.5
Mechanical properties							
Hardness (HB)	270 (max.)						
%0,2 Yield strength (N/mm^2)	450 (min)						
Tensile strength (N/mm^2)	650-880						
% elongation	25 (min)						

2.3. Measuring Devices

The profile method is used for roughness measurement. For this purpose, MAHR-Perthometer M1 portable surface roughness device, which can read the profile change in R_a, R_z and R_{max}, is used. At the beginning of each new experiment, the measurements made on the surfaces where the turning was made were made parallel to the work piece axis and the work piece was rotated about 120° around its own axis, taking three measurement values on each surface. The arithmetic mean of these three values was taken as the average surface roughness value. Cutting length is 0.8 mm and sampling length is 5.6 mm was selected as measuring surface roughness values at the time of the machining process on the work piece.

Raytek MI3 infrared sensor was used for temperature measurement. The measurement was taken one point and its range is 250-1400 °C. The measurements are transferred to the computer via the Data Temp Multi drop program.

2.4. Cutting Parameters

The tests were carried out under dry cutting conditions that are recommended by the cutting tool manufacturer given in Table 2. For each experiment, four different cutting speeds, three different feed rates and a cutting depth were selected. Totally, 24 experiment conducted. Coolant was not used for the tests. In order to provide a fresh cutting surface, insert was replaced each time.
The sensors, test setup and the surface roughness measurement are given Fig. 1 and Fig. 2.

Table 2: Cutting conditions

Cutting Speed, V (m/min)	Feed Rate, f (mm/rev)	Cutting Depth, a (mm)	Chip Angle
50–63–70–80	0,225-0,3-0,375	1	9 -13

Fig.1. The sensor and test setupand temperature measurement

Fig.2. The measurement device for surface roughness

III. ARTIFICIAL NEURAL NETWORK AND PREDICTION MODEL FOR SURFACE ROUGHNESS

The biological nervous system, the brain, which consists of a large number of highly connected elements called neurons, inspires artificial neural networks (ANNs). The brain stores and processes the information by adjusting the linking patterns of the neurons [15]. An ANN can be applied successfully in areas where needs learning, classification, function prediction, finding the most appropriate value, data classification, and the determination and association of features [16]. ANNs are one of the most well known predictive models that are able to estimate output(s) of the machining processes in the range of investigated input parameters [17, 18].

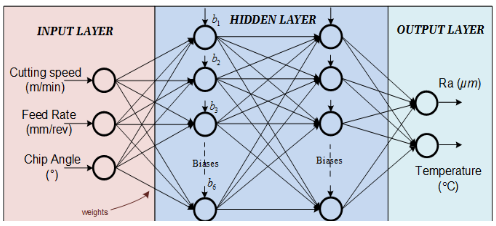

Fig.3. ANN model for surface roughness and temperature prediction

The ANN model is illustrated in Fig. 3. ANN model has three different layers as input, hidden and output. The input variables of ANN are cutting speed, feed rate and chip angle. Outputs are surface roughness and temperature. ANN trained the data in two hidden layers in this study. Different network structures were performed and optimized. Best values were kept by 3-6-6-2 network structures with three inputs, two outputs, and six hidden neurons. In this study, 24 experimental data sets were measured for the training and testing data for the ANN. The ratio for training and testing data was selected as 85:15, i.e. 20 and 4 sets of the data were randomly selected. The logistic hyperbolic tangent transfer function was used as activation function. One of the characteristics of this function is that only a value between 0 and 1 can be produced. The input and output data sets were normalized using the following equation before the training and testing process to obtain the optimal predictions.

$$y = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Table 3: Experimental and predicted data for training and test

	No	INPUTs: Feed Rate (mm/rev)	INPUTs: Chip Angle (degree)	INPUTs: Cutting Speed (m/min)	OUTPUTs (experiment): Surface roughness, Ra (µm)	OUTPUTs (experiment): Temperature (°C)	OUTPUTs (predicted): Surface roughness, Ra (µm)	OUTPUTs (predicted): Temperature (°C)
TRAINING	1	0,225	9	50	2,180	303,510	2,176	303,510
	2	0,225	9	63	2,260	307,170	2,258	307,170
	3	0,225	9	80	2,010	309,360	2,006	309,360
	4	0,3	9	50	3,840	327,870	3,841	327,870
	5	0,3	9	63	3,920	318,450	3,918	318,450
	6	0,3	9	70	3,610	318,810	3,610	318,810
	7	0,375	9	50	5,660	348,290	5,656	348,290
	8	0,375	9	63	5,620	348,040	5,620	348,040
	9	0,375	9	80	5,450	342,390	5,450	342,390
	10	0,225	15	50	2,050	312,960	2,051	312,960
	11	0,225	15	63	2,230	325,540	2,235	325,540
	12	0,225	15	70	2,180	331,110	2,176	331,110
	13	0,225	15	80	1,670	326,880	1,672	326,880
	14	0,3	15	50	3,650	320,970	3,650	320,970
	15	0,3	15	63	3,780	341,630	3,776	341,630
	16	0,3	15	70	3,860	336,740	3,858	336,740
	17	0,375	15	50	5,280	351,010	5,282	351,010
	18	0,375	15	63	5,730	348,610	5,729	348,610
	19	0,375	15	70	6,250	346,140	6,247	346,140
	20	0,375	15	80	5,770	350,130	5,775	350,130
TEST	21	0,375	9	70	5,620	350,550	5,898	341,496
	22	0,3	15	80	3,720	341,560	3,165	345,337
	23	0,3	9	80	3,500	323,950	3,222	323,271
	24	0,225	9	70	2,320	312,730	2,190	307,561

IV. RESULTS AND DISCUSSION

Experimental and predicted data is given in the Table 3. Input data (feed rate, chip angle and cutting speed), output data (surface roughness and temperature) both experiment and predicted are listed. Last four data for test was selected randomly. Surface roughness values predicted after ANN training were compared with values obtained from the experimental study. Predictive accuracy was evaluated using the root mean squared error (RMSE), coefficient determination (R^2), mean absolute error (MAE), and mean percentage error (MPE). The error calculation formulas are represented in Equations (2) – (5).

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left|y_k - \hat{y}_k\right|^2} \quad (2)$$

$$MAE = \frac{1}{n}\sum_{k=1}^{n}\left|y_k - \hat{y}_k\right| \quad (3)$$

$$MPE = \frac{1}{n}\sum_{k=1}^{n}\frac{y_k - \hat{y}_k}{\hat{y}_k} * 100 \quad (4)$$

$$R^2 = 1 - \left(\frac{\sum_{k=1}^{n}\left|y_k - \hat{y}_k\right|^2}{\sum_{k=1}^{n}\hat{y}_k^{\,2}}\right) \quad (5)$$

The accuracy of the predictive estimation results are summarized in Table 4. The regression coefficient (R) for surface roughness were found to be 0.9999 and 0.9920 for training and test. The regression coefficient (R) for temperature were found to be 0.9999 and 0.9997 for training and test. These are close to 1, thus, indicating a strong correlation between the experimental outputs and network outputs.

Table 4: Accuracy of predictions of the neural network model

	Surface Roughness		Temperature	
	Training	Test	Training	Test
R^2	0,9999	0,9920	0,9999	0,9997
RMSE	8,10E-07	3,46E-01	1,64E-06	5,55E+00
MAE	6,15E-07	3,12E-01	1,38E-06	4,67E+00
MPE	2,36E-05	8,40E+00	4,12E-07	1,39E+00

The regression coefficient graphs for training and test value are presented in Fig. 4 and 5, respectively. It is clear that prediction of surface roughness is very close to experimental data. The regression coefficient graphs for training and test value are presented in Fig. 6 and 7, respectively. It is clear that prediction of temperature is very close to experimental data. The changing of the error value between experiment and predicted is given in Fig. 8 during ANN training process. After 300iterations, the error value reached 1e-06.

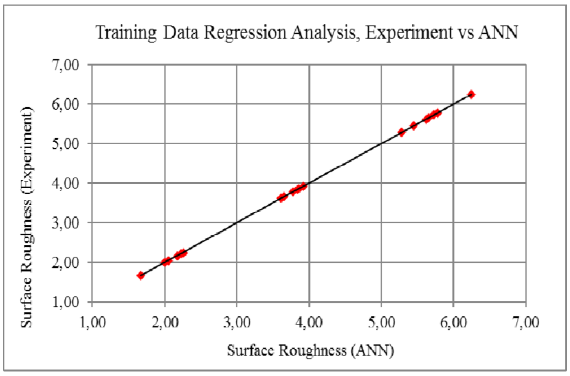

Fig.4. Regression analysis of surface roughness for training data

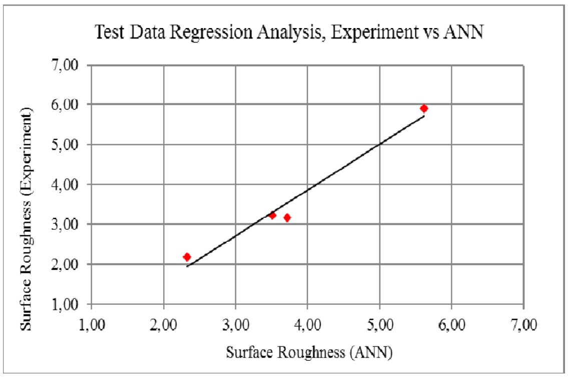

Fig.5. Regression analysis of surface roughness for test data

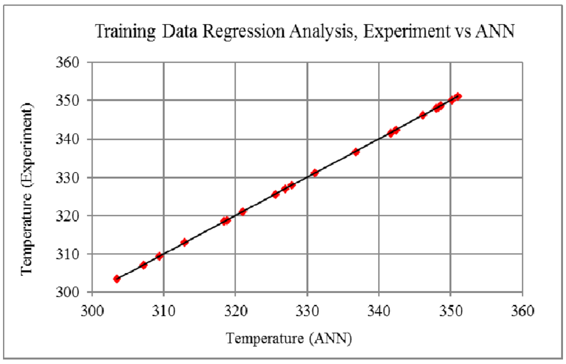

Fig.6. Regression analysis of temperature for training data

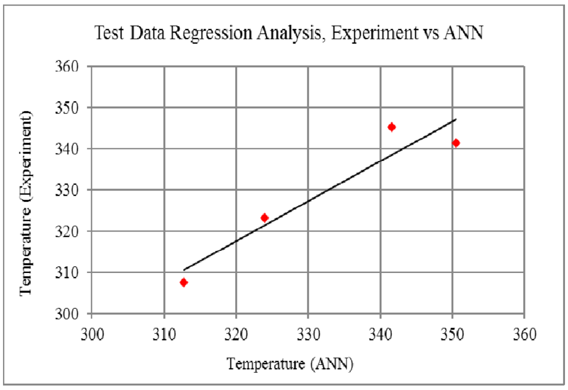

Fig.7. Regression analysis of temperature for test data

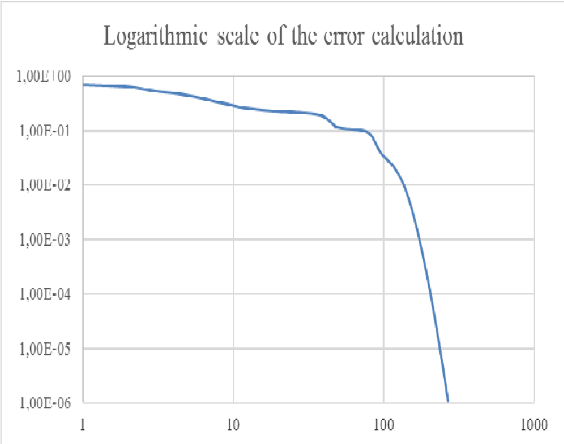

Fig.8. Error changing of the ANN output

CONCLUSIONS

In this study, a model for prediction of surface roughness and temperature was developed depending on experimental results. In modeling design, feed rate, cutting speed and chip angle were selected as input parameters of artificial neural network. The best network structure with minimum error rate was achieved 3-6-6-2. The ANN model provide predicted values of surface roughness and temperature quietly close to the experimental values. Predictive accuracy of neural network model evaluated R^2. The results are for surface roughness 99.99% and 99.20 % for training and test values, for temperature 99.99% and 99.97 %, which are confidence level for the adequacy.

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