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An application of Neural Networks for Prediction of Surface Texture Parameters in Turning

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Abstract— Surface roughness, an indicator of surface quality is one of the most specified customer requirements in a machining process. Mastering of surface quality issues helps avoiding failure, enhances component integrity, and reduces overall costs. Copper alloy (GC-CuSn12) surface quality, achieved in turning, constitutes the subject of the current research study. Test specimens in the form of near-to-net-shape bars and a titanium nitride coated cemented carbide (T30) cutting tool were used. The independent variables considered were the tool nose radius (r), feed rate (f), cutting speed (V), and depth of cut (a). Process performance is estimated using the statistical surface texture parameters Rα, Ry, and Rz. To predict the surface roughness, an artificial feed forward back propagation neural network (ANN) model was designed for the data obtained.

Keywords— Neural Networks, Modelling, Turning, Surface Texture Parameters.

I. Introduction

Copper-based alloys are used in the mass production of electrical components and water pipe fittings. They are usually machined using high speed CNC machines, which are mostly very high speed lathes fed with brass wire of a relatively small diameter, so that the maximum speed is limited to 140-220m/min, although the tooling is capable of a good performance at much higher speeds. When copper alloys are machined, very high forces act on the tool, particularly at low cutting speeds. This is due to the large contact area on the rake face resulting in a small shear plane angle and thick chips [1], contributing in the fact that copper is cosidered as one of the most difficult materials to machine. When feed rate is decreased or the cutting speed is increased the cutting forces are decreased and the surface finish is improved.

Surface properties dominate the quality of the finished component, since they influence features like dimensional accuracy; tribological issues such as the friction coefficient and wear; post processing requirements; appearance and cost. Surface roughness or texture constitutes a measure for achieving finer surface irregularities in the finished product, while three components –i.e., roughness, waviness, and form– are required for its determination [2].

A number of studies –investigating the relation of cutting forces, tool wear, chip morphology, accuracy issues, and dynamic behaviour during turning with the produced surface quality– are reported in literature. A study of the effects of different process parameters: tool radius (r), feed rate (f), cutting speed (V), and depth of cut (a) in turning of a copper alloy (GC-CuSn12), on the surface texture parameters Ra, Rz, and Ry is attempted in the current work, using the Taguchi methodology and Neural Networks modelling.

Thus, an $L_9(3^4)$ orthogonal matrix experiment was conducted [3]. A matrix experiment consists of a set of experiments where the settings of several process parameters to be studied are changed from one experiment to another in a combinatory way. Experimental results are used in order to train a feed forward back propagation neural network (FFBP-NN) in order to predict surface texture parameters in turning of near-to-net shape parts of copper alloy. Using FFBP-NN in combination with orthogonal matrix experiment, an easy way modeling could be achieved, and applied on experimental region in order to predict surface texture parameters.

II. Experimental setup

The material used for cutting is specified as GC-CuSn12. It is a copper alloy containing 84 to 85% Cu, 11 to 14% Zn, under 1% Pb, less than 2% Ni, and finally under 0.2% Sb. The machine used for the experiments was a Cortini F100 CNC machine lathe (3.7kW) equipped with a GE Fanuc Series O-T control unit. The test specimens were in the form of bars, 32mm in diameter and 80mm in length for near-to-net-shape machining. Tailstock was not used (Fig. 1). The cutting tools were titanium nitride screw-on positive inserts, CCMT 09T30, with a 0.4 and 0.8mm tool nose radii, accordingly (Fig. 2).

Surface roughness is a widely used index characterising a product's quality, and is measured off-line –when the

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component is already machined. The surface texture parameters measured during this study are: the average surface roughness (also known as centre line average – CLA), Rα; average maximum peak to valley height of the profile, R_z; and maximum peak to valley height; R_y; all measured in μm. Measurements are being conducted using the Mitutoyo, surftest RJ-210 tester.

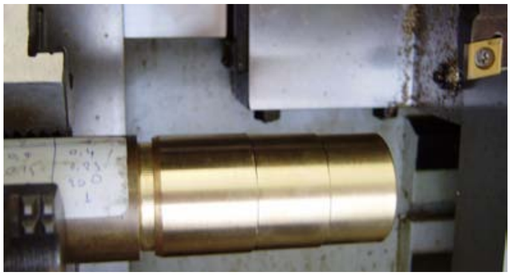

Fig. 1: Cortini F100 CNC machine lathe

Fig. 2: Machined specimens and inserts

The CLA Ra (Fig. 3) can be obtained by taking the arithmetic mean of the absolute values of 1150 different positional deviations over a 4 mm standard length with a cut-off at 0.8 mm according to the relation,

$$R_a = \frac{1}{1150}\sum_{1=1}^{1150}\left|y_i\right| \quad (1)$$

The average maximum peak to valley height of the profile (Rz) is defined according to the relation,

$$R_z = \frac{1}{5}\left(\sum_{i=1}^{5}\left|y_{p_i}\right| + \sum_{i=1}^{5}\left|y_{v_i}\right|\right) \quad (2)$$

where Ypi are the five tallest peaks, and Yvi, the five lowest valleys within the sample considered (Fig. 3). Finally, the maximum peak to valley distance of the filtered profile (Ry) over an evaluation length sensitive to large deviations from the mean line and scratches is defined according to the relation,

$$R_y = R_p + R_v \quad (3)$$

where Rp and Rv are the absolute values of the maximum peak and maximum valley within the measured standard length (Fig. 3). A four parameter design was performed as shown in Table 1. Note that Level 1 and level 3 for the parameter (r) assign the same value. This is not an obstacle for the methodology followed.

The Taguchi design method is a simple and robust technique for process parameters optimisation. The method involves the damping (reduction) of variation in a manufacturing process through robust design of experiments. Taguchi's emphasis on minimising deviation from target, led him to develop measures of the process output that incorporate both the location of the output as well as its variation.

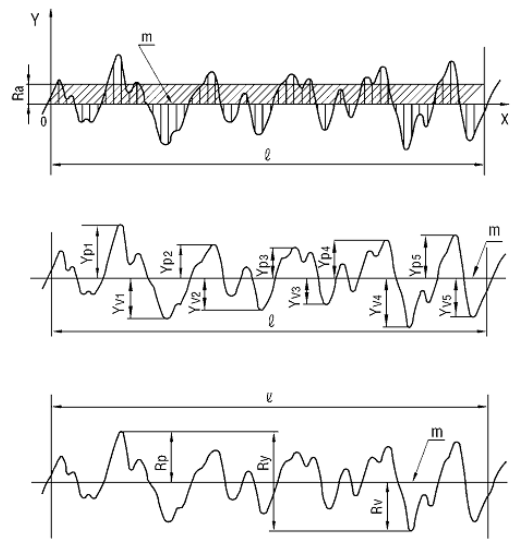

Fig. 3: Surface texture parameters

Table 1: Parameter design.

		Levels		
No	Process Parameters	1	2	3
1	Tool Radius (r, mm)	0.4	0.8	0.4
2	Feed Rate -(f, mm/rev)	0.05	0.15	0.25
3	Cutting Speed (V, m/min)	100	150	200
4	Depth of cut (a, mm)	0.2	0.6	1

These measures are called *signal-to-noise* ratios. The signal-to-noise ratio provides a measure of the impact of noise factors on performance.

Table 2: Orthogonal array $L_9(3^4)$.

	Column			
No Exp	1	2	3	4
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

Calculation of the S/N ratio depends on the *experimental objective* according to which the experiment is conducted –i.e., bigger-the-better, smaller-the-better, and nominal-is-best with corresponding calculation formulae [5]. The standard ($L_9(3^4)$) orthogonal matrix experiment was used (Table 2). Columns 1, 2, 3, and 4 are assigned to tool radius (r), feed rate (f), cutting speed (V) and depth of cut (a), respectively.

III. Experimental Results

The Taguchi design method is a simple and robust technique for optimizing the process parameters. In this method, main parameters, which are assumed to have an influence on process results, are located at different rows in a designed orthogonal array. With such an arrangement randomized experiments can be conducted. In general, signal to noise (S/N) ratio (n, dB) represents quality characteristics for the observed data in the Taguchi design of experiments. In the case of surface roughness amplitude [4][6][7], lower values are desirable. These S/N ratios in the Taguchi method are called as the smaller-the-better characteristics and are defined as follows:

$$\eta = -10\log_{10}\left[\frac{1}{n}\sum_{i=1}^{n} y_i^2\right] \qquad (4)$$

where y_i is the observed data at the i^{th} trial and n is the number of trials. From the S/N ratio, the effective parameters having an influence on process results can be obtained and the optimal sets of process parameters can be determined. Based on Robust design, the standard orthogonal array ($L_9(3^4)$) has been selected in order to perform the matrix experiment (Table 3). Three levels for each factor were selected (Table 1). Following the ($L_9(3^4)$) orthogonal array nine experiments were performed with each experiment producing a test part which was tested for R_a, Rz, and Ry all measured in μm.

Table 3: Matrix experiment

Ex. No.	r	f	V	a	R_a	R_z	Ry
1	0.4	0.05	100	0.2	1.713	9.238	11.154
2	0.4	0.15	150	0.6	1.384	9.020	11.001
3	0.4	0.25	200	1	4.576	19.290	22.488
4	0.8	0.05	150	1	1.278	7.972	9.947
5	0.8	0.15	200	0.2	1.674	10.151	12.024
6	0.8	0.25	100	0.6	2.352	13.688	16.055
7	0.4	0.05	200	0.6	1.549	9.208	10.663
8	0.4	0.15	100	1	1.995	13.862	16.604
9	0.4	0.25	150	0.2	5.149	22.005	24.761
Mean (m)					2.407	12.714	14.966

IV. Neural Network Architecture

Aiming in the prediction of the produced surface roughness parameters (Ra, Rz, and Ry) during longitudinal turning of a Cooper alloy, a NN model has been developed. The four (4) factors studied were used as input parameters of the NN model. Previous studies [8] indicate that by using Taguchi's DoE methods, a structured method of NN parameter-setting can be implemented, which identify NN and training parameter settings resulting in enhanced NN performance. Training samples are presented to the NN during training, and the network is adjusted according to its error. The nine (9) experimental data samples (Table 3), were separated into three groups, namely the training, the validation and the testing samples. Training samples are presented to the network during training and the network is adjusted according to its error. Validation samples are used to measure network generalization and to halt training when generalization stops improving. Testing samples have no effect on training and so provide an independent measure of network performance during and after training (confirmation runs).

In general, a standard procedure for calculating the proper number of hidden layers and neurons does not exist. For complicated systems the theorem of Kolmogorov or the Widrow rule can be used for calculating the number of hidden neurons [9]. In this work, the feed-forward with back-propagation learning (FFBP) architecture has been selected to analyze the surface texture parameters. These types of networks have an input layer of X inputs, one or more hidden layers with several neurons and an output layer of Y outputs. In the selected ANN, the transfer function of the hidden layer is hyperbolic tangent sigmoid, while for the output layer a linear transfer function was used. The input vector consists of the four process parameters of Table 3. The output layer consists of the performance measures, namely the Ra, Rz, and Ry surface texture parameters. According to ANN theory FFBP-NNs with one hidden layer are appropriate to model each mapping between process parameters and performance measures in engineering problems [10].

In the present work, five trials using FFBP-NNs with one hidden layer were tested having 10, 11, 12, 13 and 14 neurons each; see Figure 5. This one that has 13 neurons on the hidden layer gave the best performance as indicated from the results tabulated in Table 4.

The one-hidden-layer 13-neurons FFBB-NN was trained using the Levenberg-Marquardt algorithm (TRAINLM) and mean square error (MSE) used as objective function. The data used were randomly divided into three subsets, namely the training, the validation and the testing samples.

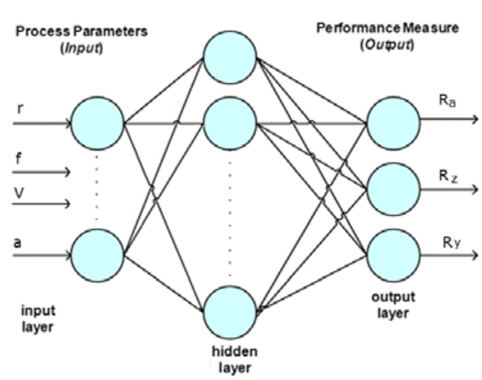

Fig. 4: The selected ANN architecture (feed-forward with back-propagation learning).

Table 4. Best performance of ANN architecture.

	ANN Architecture				
	4x10x3	**4x11x3**	**4x12x3**	**4x13x3**	**4x14x3**
Training	1	1	1	1	1
Validation	0.8963	0.8440	0.8719	0.9544	0.7224
Test	0.1265	0.8557	0.8292	0.99.06	0.8492
All	0.8547	0.9333	0.9541	0.998-	0.9246
Best val. perf.	9.88	11.64	11.17	**2.91**	14.82
epoch	1	2	4	1	1

Back-propagation ANNs are prone to the overtraining problem that could limit their generalization capability [8]. Overtraining usually occurs in ANNs with a lot of degrees of freedom [10] and after a number of learning loops, in which the performance of the training data set increases, while the performance of the validation data set decreases. Mean Squared Error (MSE) is the average squared difference between network output values and target values. Lower values are better. Zero means no error. The best validation performance is equal to 2.91 at epoch 1; see Figure 5.

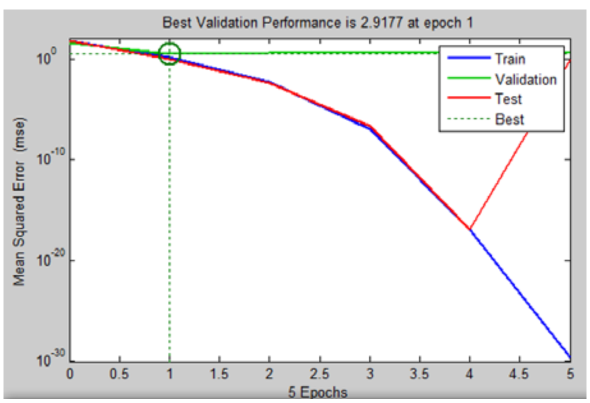

Fig. 5: The selected ANN architecture (feed-forward with back-propagation learning).

Another performance measure for the network efficiency is the regression (R); see Figure 6. Regression values measure the correlation between output values and targets. The acquired results show a good correlation between output values and targets during training (R=1), validation (R=0.9544), and testing procedure (R=0.9906).

The trained ANN model can be used for the optimization of the cutting parameters during longitudinal turning of a cooper alloy.

This can be done by testing the behaviour of the response variable (Ra, Rz, and Ry) under different variations in the values of tool radius (r), feed rate (f), cutting speed (V), and depth of cut (a) (Fig. 7).

V. Conclusions

The surface texture parameters (R_a, R_z, and R_y) of copper alloy near-to-net-shape parts during turning was measured according to a matrix experiment. The results were used to train a feed forward back propagation neural network with a topology of 4X13X3 neurons. The proposed NN can be used to predict the surface texture parameters as well as to optimize the process according to each one of the surface texture parameters. As a future work Authors plan to improve the performance of FFBP-NN incorporating more experiments as well as investigate the performance of alternatives training algorithms. In addition a comparison among other approaches such as regression and additive modeling will be performed. Using the extracted NN the surface response of R_a, R_z, and R_y can be drawn and the effects of process parameters be estimated inside the experimental region in which the designed experiment is conducted. This methodology could be easily applied to different materials and initial conditions for optimization of other material removal processes.

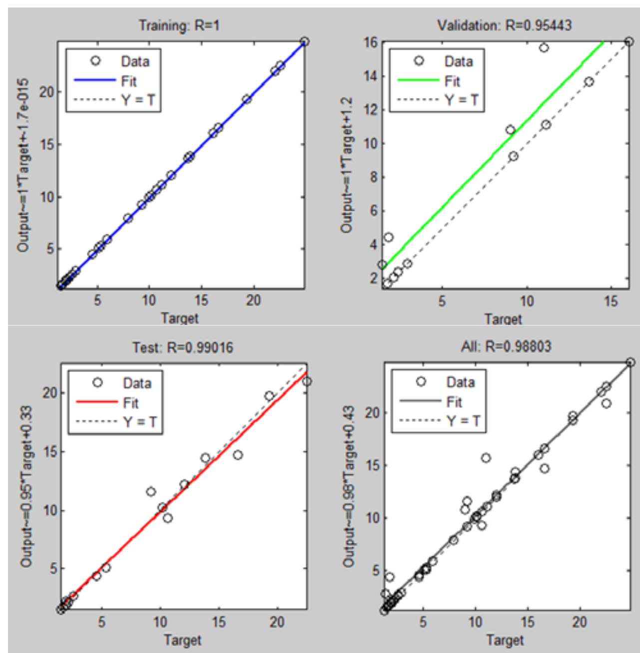

Fig. 6: Regression plots

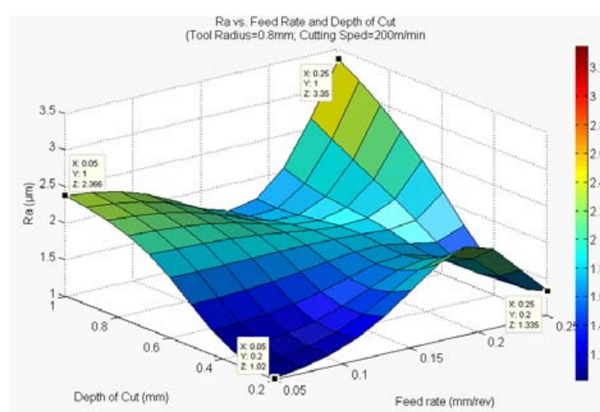

Fig. 7: CLA Ra according feed rate and depth of cut (r=0.8mm, V=200m/min)

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