PREDICTION OF SURFACE ROUGHNESS IN TURNING USING ORTHOGONAL MATRIX EXPERIMENT AND NEURAL NETWORKS

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Abstract: A neural network modeling approach is presented for the prediction of surface texture parameters during turning of a copper alloy (GC-CuSn12). 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 cutting speed, feed rate, cutting depth and tool nose radius. The corresponding surface texture parameters that have been studied are the R_a, R_q, and R_t. A feed forward back propagation neural network was developed using experimental data which were conducted on a CNC lathe according to the principles of Taguchi design of experiments method. It was found that NN approach can be applied in an easy way on designed experiments and predictions can be achieved, fast and quite accurate. The developed NN is constrained by the experimental region in which the designed experiment is conducted. Thus, it is very important to select parameters' levels as well as the limits of the experimental region and the structure of the orthogonal experiment. This methodology could be easily applied to different materials and initial conditions for optimization of other manufacturing processes.

1 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 (Trent and Wright, 2000).

This is the main reason why copper is considered to be one of the most difficult materials to machine. Generally, when the cutting speed is increased the cutting forces are decreased and the surface finish is improved.

A study of the effects of different process parameters: tool radius (r), feed rate (f), cutting speed (V), and cutting depth (a) in turning of a copper alloy (GC-CuSn12), on the surface texture parameters Ra, Rq, Rt, 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 (Phadke, 1989). A matrix experiment consists of a set of experiments where the settings of several process parameters to be studied are changed

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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.

2 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 (Figure 1).

The cutting tools were titanium nitride screw-on positive inserts, CCMT 09T30, with a 0.4 and 0.8mm tool nose radii, accordingly (Figure 2).

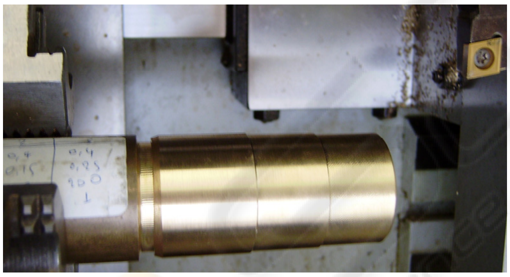

Figure 1: Cortini F100 CNC machine lathe.

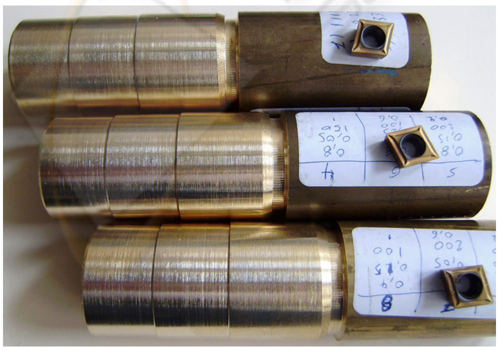

Figure 2: Machined specimens and inserts.

The surface texture parameters; average surface roughness (R_a, μm), root mean square roughness (R_q, μm), and maximum height of peaks (R_p, μm) were measured using the Taylor Hobson, Talysurf 10 tester (Figure 3).

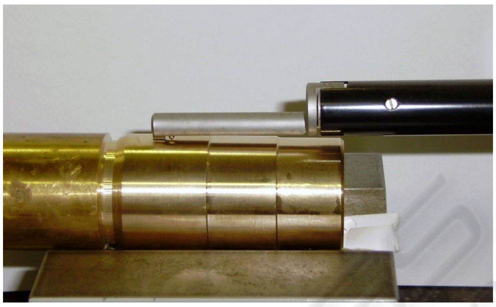

Figure 3: Surface roughness measurements.

Average roughness (R_a) can be obtained by taking the average of 1150 different positional deviations over a 4 mm length with a cut-off at 0.8mm. The equation of average surface roughness is given as

$$R_a = \frac{1}{1150}\sum_{1=1}^{1150}|z_i| \tag{1}$$

where z_i is the value of surface roughness in irregular measurement points.

Root mean square roughness R_q can be obtained by the form:

$$R_q = \sqrt{\frac{1}{1150}\sum_{1=1}^{1150}(z_i)^2} \tag{2}$$

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.

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	Cutting Depth (a, mm)	0.2	0.6	1

The standard (L9(34)) 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.

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

Table 3: Matrix experiment.

Ex. No.	r	f	V	a	R_a	R_q	R_t
1	0.4	0.05	100	0.2	0.24	0.33	1.4
2	0.4	0.15	150	0.6	1.51	1.95	11.4
3	0.4	0.25	200	1	0.54	0.75	4.4
4	0.8	0.05	150	1	0.44	0.61	3.4
5	0.8	0.15	200	0.2	0.27	0.38	2.4
6	0.8	0.25	100	0.6	0.69	0.92	5.4
7	0.4	0.05	200	0.6	0.34	0.4	1.4
8	0.4	0.15	100	1	0.84	1.03	4.1
9	0.4	0.25	150	0.2	0.32	0.43	1.8
Mean (m)					0.57	0.75	3.96

3 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 (Kechagias, 2007; Petropoulos et al, 2008; Tsao, 2009), 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:

$$\eta = -10\log_{10}\left[\frac{1}{n}\sum_{i=1}^{n} y_i^2\right] \tag{3}$$

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 average surface roughness (R_a, μm), root mean square roughness (R_q, μm), and maximum height of peaks (R_p, μm).

4 NEURAL NETWORK SET-UP

In general, NNs are parallel distributed information processing systems that demonstrate the ability to learn, recall, and generalize from training patterns or data. Models of NN are specified by three basic entities: models of synaptic interconnections and structures, models of the neurons, and the training rules for updating the connecting weights (Lin and Lee, 1996; Jiao et al, 2004; Ozel and Karpat, 2005; Kechagias and Iakovakis 2008).

A NN consists of a set of highly interconnected neurons such that each neuron output is connected through weights, to other neurons or to itself. Hence, the structure that organizes these neurons and the connection geometry among them should be specified for a NN.

A neural network consists of at least three layers, where input vectors (p_i) applied at the input layer and output vectors (a_i) are obtained at the output layer (Figure 4).

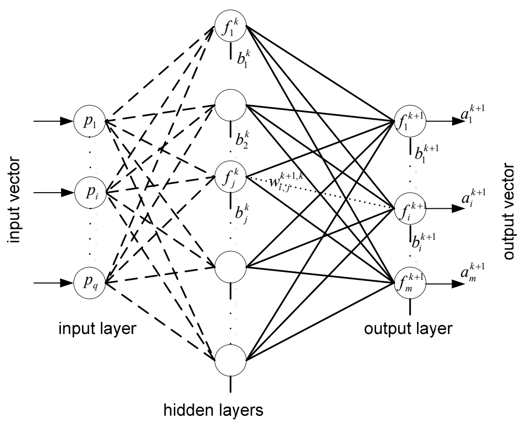

Figure 4: A multilayer feed-forward NN.

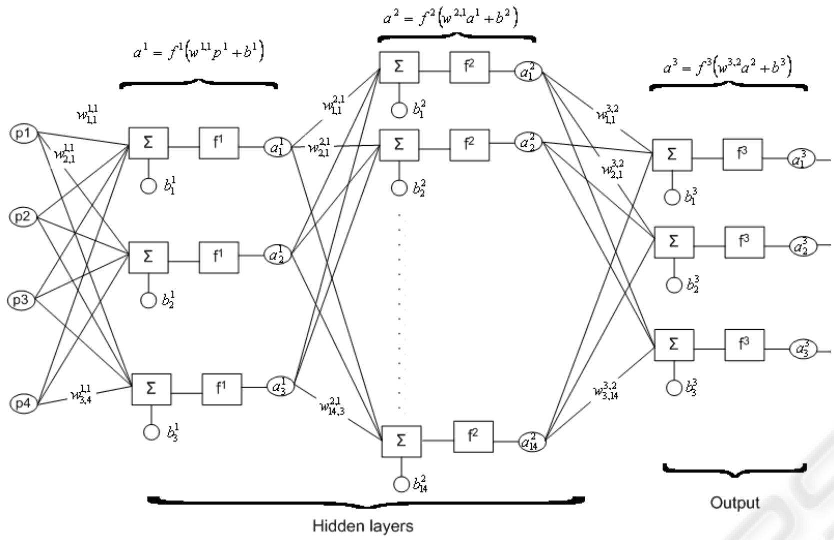

Figure 5: FFBP-NN details.

Each layer consists of a number of neurons which are also called processing elements (PE). PEs can be viewed as consisting of two parts: input and output. Input of a PE is an integrated function which combines information coming from the net. Considering a feed forward NN (Figure 4), the net input to PE i in layer k+1 is:

$$n_i^{k+1} = \sum_j w_{i,j}^{k+1,k} a_j^k + b_i^{k+1} \qquad (4)$$

where $w_{i,j}$ and b_i are the corresponding weights and biases.

The output of PE i will be

$$a_i^{k+1} = f^{k+1}(n_i^{k+1}) \qquad (5)$$

where f is the transfer function of neurons in $(k+1)^{th}$ layer.

Training of the network uses training rules to adjust the weights associated with PE inputs. Unsupervised training uses input data alone while supervised training works by showing the network a series of matching input and output examples $\{(p_1,t_1), (p_2,t_2), \ldots(p_q,t_q)\}$.

MATLAB version 6.5 program was used to create, train, and test the FFBP-NN (Feed Forward Back Propagation Neural Network) through network data manager. Generally, MATLAB NN toolbox refers to the input layer as the input vector. A layer that produces the network output is called output layer. All the other layers are called hidden layers.

A number of trials was executed to select the appropriate topology of the FFBP-NN, which is shown in Figure 5.

Tool radius (r), feed rate (f), cutting speed (V), and the depth of cut (a) were used as the input vector into the NN. Roughness parameters (Ra, Rq, Rt) were used as the output layer. Two hidden layers were selected, after a number of trials, having 3 and 14 neurons respectively. This network had the best performance among them that have one or two hidden layers (Figure 6).

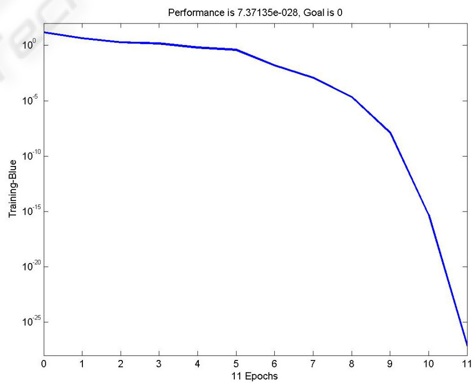

Figure 6: FFBP-NN training process.

Hyperbolic tangent sigmoid transfer function (tansig) was used as transfer function for the hidden layers (Eq. 6, Fig. 7). The transfer function for the output layer was the linear function (Eq. 7, Fig. 7).

$$a^1 = f^1(w^{1,1}p^1 + b^1) = tansig(w^{1,1}p^1 + b^1) = tansig(n) = [2/(1+e^{-2n})] - 1 \qquad (6)$$

$$a^2 = f^2(w^{2,1}a^1 + b^2) = purelin(w^{2,1}a^1 + b^2) = purelin(n) = n \qquad (7)$$

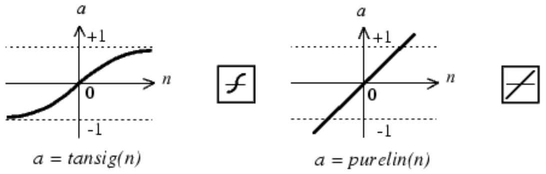

Figure 7: Hyperbolic tangent sigmoid and linear transfer function.

Training functions repeatedly apply a set of input vectors to a network, updating the network each time, until some stopping criteria are met. Stopping criteria can consist of a maximum number of epochs, a minimum error gradient, an error goal, etc.

The Levenberg–Marquardt (TRAIN-LM) algorithm selected for training the FFBP-NN, which is a variation of the classic back-propagation algorithm that, unlike other variations that use heuristics, relies on numerical optimization techniques to minimize and accelerate the required calculations, resulting in much faster training.

LEARNGDM is used as 'adaption learning function' which is the gradient descent with momentum weight and bias learning function. Biases (b^j) simply being added to the product ($w^{j,i}+b^j$).

The performance of FFBP-NN was measured with the mean squared error (MSE) of the testing subset which calculated by the form:

$$MSE = \frac{1}{2}\sum_{q=1}^{Q}(t_q - a_q^M)^T(t_q - a_q^M) = \frac{1}{2}\sum_{q=1}^{Q}e_q^T e_q \qquad (8)$$

where a_q^M is the output of the network corresponding to q^{th} input p_q, and $e_q=(t_q-a_q^M)$ is the error term.

It must be noted that the outcome of the training greatly depends on the initialization of the weights, which are randomly selected. Training process can be seen in Figure 6.

5 EVALUATION

Using the extracted FFBP-NN the surface texture parameters can be predicted quickly and easy. In order to evaluate the NN model an evaluation experiment was conducted and the result shows that the NN model gives values close to the actual ones (Table 4).

Below the surface response of the performance of the R_a, R_q, and R_t can be seen for all the combination of V and f keeping constant the tool nose radius (r=0.4mm) and the cut of depth (a=1mm).

Table 4: Evaluation experiment (r=0.8mm, f=0.05mm/rev, V=200m/min, a=0.2mm).

	R_a (μm)	R_q (μm)	R_t (μm)
Actual	0.17	0.21	1.3
Predicted	0.23	0.34	1.94

The surface responses show that generally when increasing the cutting speed the surface texture parameters decreasing. Also, when increasing the feed rate the response is getting worse when it takes a value of about 0.15mm/rev (see Figure 8).

Also, using the NN model, all the ` of the parameter levels were predicted and the process was optimized according to average surface roughness (R_a). It was found that the best combination (that gives R_a=0.2μm) is: r=0.4mm, f=0.05mm/rev, V=150m/min, and a=0.06mm.

6 CONCLUSIONS

The surface texture parameters (R_a, R_q, and R_t) 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 4X3X14X3 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_q, and R_t 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.

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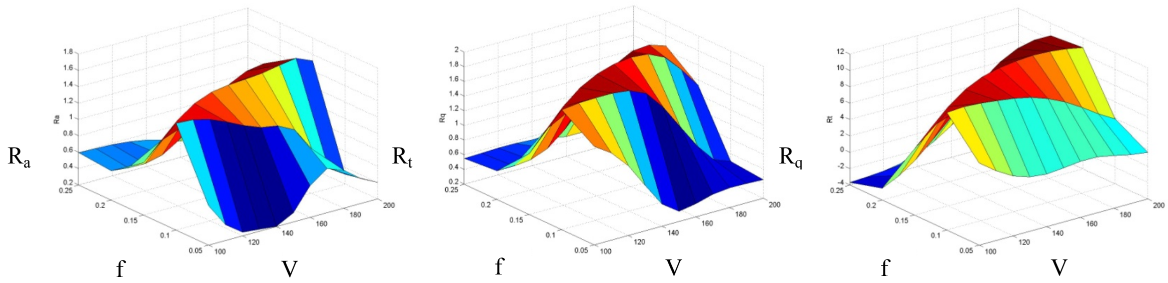

Figure 8: Surface response for R_a, R_q, and R_t using NN model (r=0.4mm, a=1mm).

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