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20^{th} International Research/Expert Conference
"Trends in the Development of Machinery and Associated Technology"
TMT 2016, Mediterranean Sea Cruising, 24^{th} September - 1^{st} October, 2016

IMPROVED NEURAL MODELS FOR ROUGHNESS IN HONING PROCESSES

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ABSTRACT
In the present work improved neural network models for average roughness Ra in rough honing processes are studied. Four different adaptive models were tested, which integrate previously obtained direct and indirect models. Such models allow defining values for process variables from required average roughness Ra values. A control parameter d is employed for determining the error of the model, and a sensitivity parameter m measures the convergence speed of the models. Models were tested for m=1, m=10, m=100 and m=1000. Best model was selected having lowest relative error between experimental and simulated values.
Keywords: neural network, roughness, honing, adaptive model

1. INTRODUCTION
Neural network models can be used for modelling roughness in abrasive machining processes. However, few authors have modelled roughness in honing processes by means of artificial neural networks. For example, Feng et al. predicted roughness parameters related to Abbott-Firestone curve in honing operations a function of process parameters [1]. In a previous work by the authors, a direct neural network was selected to define average roughness Ra as a function of process parameters in rough honing processes [2]. Later, an indirect model was obtained in order to predict process parameters from Ra values [3]. In the present paper, indirect model was improved by means of an adaptive model that combines both indirect and direct models. The adaptive model will allow predicting process parameters grain size of abrasive GS (FEPA) [4], density of abrasive DE (ISO 6104) [5], pressure of abrasive stones on the workpiece's surface PR (N/cm^2), linear speed VL (m/min) and tangential speed VT (m/min) for different average roughness Ra values.

2. ADAPTIVE CONTROL MODELS
From the general structure of the adaptive model (Figure 1), four different models were tested, in order to select best one among them.

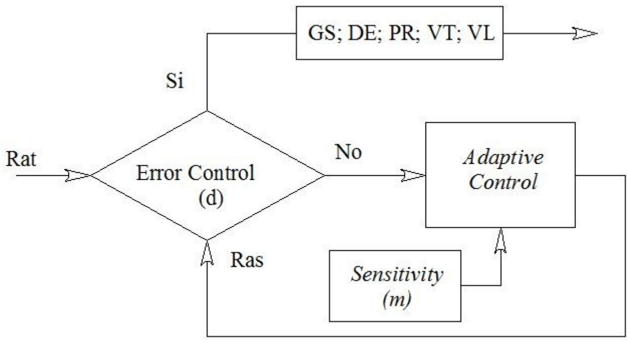

Figure 1. General adaptive control model

Where Rat is the target value for roughness (μm),
Ras is simulated value for roughness (μm),
d is error control parameter, d=Rat-Ras (μm), and
m is a parameter that defines sensitivity of the system and is related to convergence speed of the model. Calculation of m parameter is different for each model considered.

Model I is the simplest one. It consists of a single loop where first indirect or reverse model and then direct model are applied consecutively, with a single m parameter for convergence speed control and a single d parameter for error control (Figure 2).

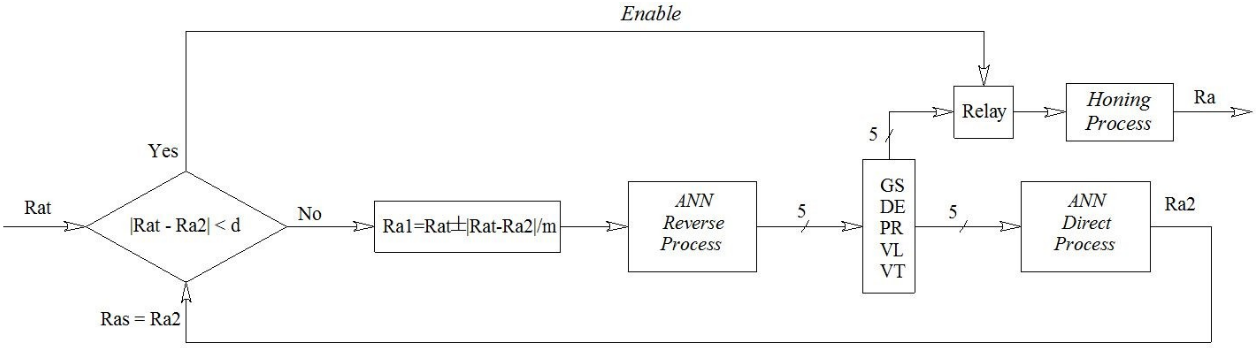

Figure 2. Model I

Model II consists of one loop with a single error control parameter d and a single speed convergence parameter m. However, unlike model I, process variables are obtained, not from one indirect model but from the combination of results of two indirect networks. One of the networks modifies its results according to loop iterations.

Model III is more complex. It consists of two loops working sequentially, with two different error control parameters, d1 and d2, and two different speed convergence parameters, m1 and m2.

Model IV has two independent loops, with control parameters d1 an d2 respectively, and two speed convergence parameters m1 and m2 respectively. However, parameters corresponding to the two loops work together. From combination of results of each loop, final process variables are obtained, which have their own speed convergence parameter m3.

3. PROCEDURE

First, the convergence speed m that optimizes each model is configured. For doing this, 100 iterations of the model were performed, and successive values of error parameter d were studied. Four different m values were tested, in a logarithmic scale, m=1, m=10, m=100 and m=1000. Finally, the four models were compared in order to select the most efficient model having lowest error parameter d.

In order to build adaptive models, both direct and indirect models had been previously obtained from results of 33 experimental tests [2, 3]. In the present paper, three additional experiments were performed, as described in Table 1, with the purpose of comparing different adaptive models. The table also contains experimental Ra values, which were measured with a Hommel Etamic W-5 roughness meter.

Table 1. Experimental tests performed

Experiment	GS (FEPA)	DE (ISO6104)	PR (N/cm^2)	VT(m/min)	VL(m/min)	Ra(µm)
1	181	30	450	20	20	2.92
2	181	75	600	20	32	2.03
3	76	75	600	45	20	1.08

The four models were compared of d error parameter as well as relative error d/Rat (%). Error parameters were calculated for each one of the three experiments considered, and average error values were obtained.

4. RESULTS

Four different values were tested for parameter m: 1, 10, 100 and 1000. Best results having lowest relative error d/Rat(%) values are presented for each one of the four models (Table 2).

Table 2. Parameters d and d/Rat(%) for the different models

	Model I (m=100)		Model II (m=100)		Model III – loop 2 (m1=m2=100)		Model IV – loop 2 (m1=100, m2=m3=10)	
Experiment	d	d/Rat (%)	d	d/Rat (%)	d	d/Rat (%)	d	d/Rat (%)
1	0.107	3.654	0.033	1.130	0.469	16.063	0.059	2.010
2	0.082	4.018	0.002	0.118	0.002	0.118	0.062	3.043
3	0.046	4.267	0.123	11.405	0.122	11.350	0.045	4.201
Average	0.078	3.980	0.053	4.218	0.198	9.177	0.055	3.085

Model III and model IV contain two loops. In both cases, the first loop coincides with Model I. For this reason, Table 2 only includes results for the second loop of Model III and Model IV.

Among all models studied, best results were obtained for Model I and for model IV (first loop). Model I was chosen since it allows much easier calculations than Model IV.

As an example, results for parameter d according to Model I are depicted in Figure 3 as a function of iteration number.

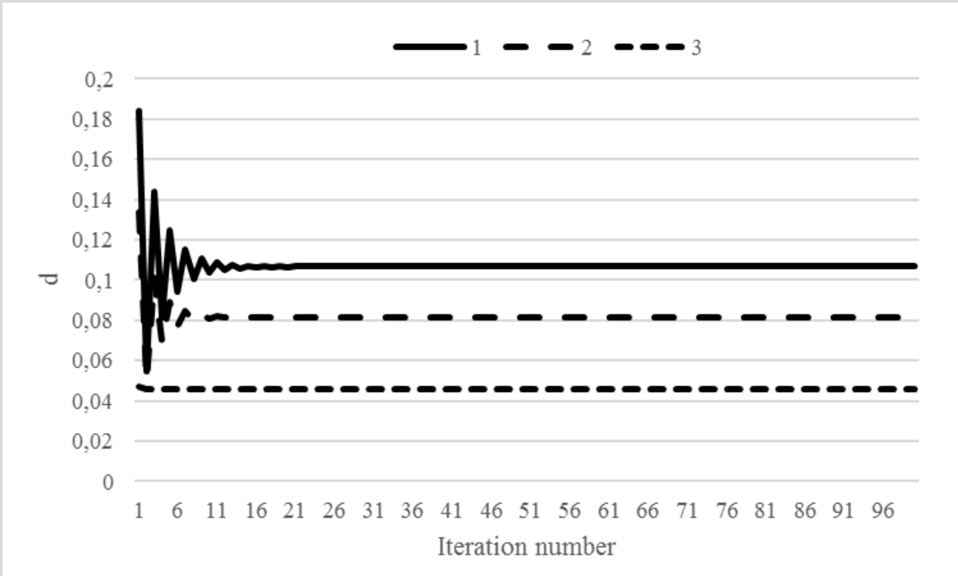

Figure 3. Model I: d values vs. iteration number

Experiment 1 was considered to converge from iteration 25 on, experiment 2 from iteration 15 on, and experiment 3 from iteration 3 on.

5. CONCLUSIONS

Four different adaptive neural network models were tested for predicting process parameters as a function of required average roughness Ra values. Both model I and model IV provided lowest average relative error between experimental and simulated values. However, model I is simpler than model IV. For this reason, model I was selected.

6. ACKNOWLEDGEMENTS

The authors thank Mr. Joan Vivancos-Calvet for his valuable comments, as well as Mr. Alejandro Domínguez-Fernández and Mr. Ramón Casado-López for his help with experimental tests. They are also grateful to Spanish Ministry of Economy and Competitiveness for project DPI2011-26300.

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