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NEURAL NETWORK MODEL FOR SURFACE ROUGHNESS IN SEMIFINISH HONING

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ABSTRACT
In the present work, neural networks were used for modelling average roughness Ra as a function of process parameters: grain size, density of abrasive, pressure of honing stones on the workpiece's surface, linear speed and tangential speed. For doing this, first experimental semifinish honing tests were performed. Then results were used for selecting best configuration of the neural network, taking into account either one or two hidden layers. In addition, neural models were compared to regression models.
Keywords: neural networks, honing, regression

1. INTRODUCTION
Neural networks have been used for modeling roughness in different machining processes such as turning [1] or milling [2]. In the present paper, an artificial neural network was selected to model the semifinish honing process. It was compared to a statistical model developed by means of design of experiments (DOE). Both models predict average roughness Ra from most relevant honing variables. Selection and training of neural networks was performed from data of DOE tests. Both models were compared according to methodology employed by Ben Fredj et al. [3].

2. MATERIALS AND METHODS
St-52 steel cylinders of 80 mm internal diameter and 100 mm length were used. Honing stones were made of cubic boron nitride (CBN) with metallic bond. Experiments were performed in a test horizontal honing machine which allows controlling process variables such as pressure, tangential speed and linear speed. Two more variables were varied, abrasive grain size and abrasive density. Average roughness Ra was measured on the workpiece's surface by means of a Hommel Etamic W-5 roughness meter. A fractional factorial model design was used, with five central points and ten face-centred points. Values of variables are presented in Table 1.

Table 1. Factors considered with values for low and high levels

Factor	GS (FEPA)	DE (ISO6104)	PR (N/cm^2)	VT(m/min)	VL(m/min)
Low level	46	15	400	30	20
High level	76	45	700	50	40

In the present study response considered was average roughness Ra.

A total amount of 27 datasets was obtained: 16 from factorial design, 10 for face centered points and one for central points. Datasets were divided into training data (81,5 %of data or 22 datasets) and validation data (18,5% of data or 5 datasets).

3. CONFIGURATION OF THE NEURAL NETWORK

Feed forward multilayer perceptron was employed, with back propagation algorithm. Networks with either one or two hidden layers were taken into account. They were configured with a tangential sigmoidal function in the hidden layer and a pure linear function in the output layer. Use of such networks is based on research by Liao [4] and Li, Mills and Rowe [5] in grinding processes and Feng et al. [6] in honing processes.

For networks with one hidden layer, in order to select most efficient network number of neurons between 4 and 30 were tested, according to the work by Lawrence and Petterson [7]. For networks with two hidden layers, total number of neurons was defined as best number of networks for one hidden layer but increasing it by 50 %. Total number of neurons was divided into two groups: 2/3 for first hidden layer and 1/3 for second hidden layer. Obtained number was used as initial network and different combinations with variation of ±1 neurons in each layer, in a way that total number of neurons remains constant.

In order to compare networks having different number of neurons, mean quadratic error mqe from validation results (5 datasets not used for training the network) and mean quadratic error from training + validation results were calculated (27 datasets). Average value of both errors was calculated.

4. SELECTION OF BEST NEURAL NETWORK WITH ONE HIDDEN LAYER

For networks with one hidden layer, lowest mqe values correspond to 11 neurons. Thus, best configuration is BP 5_11_1, where BP means backpropagation algorithm; number 5 means that 5 input variables are considered; number 11 means that there are 11 neurons in the hidden layer, and number 1 means that 1 response is considered. Corresponding mqe from validation results is 0.0002 while mqe from training + validation results is 0.0715. Average mqe value is 0.0359.

Figure 1 depicts experimental and modeled values (11 neurons in the hidden layer) for the 27 different conditions that were studied. Experiments were arranged according to increasing roughness values.

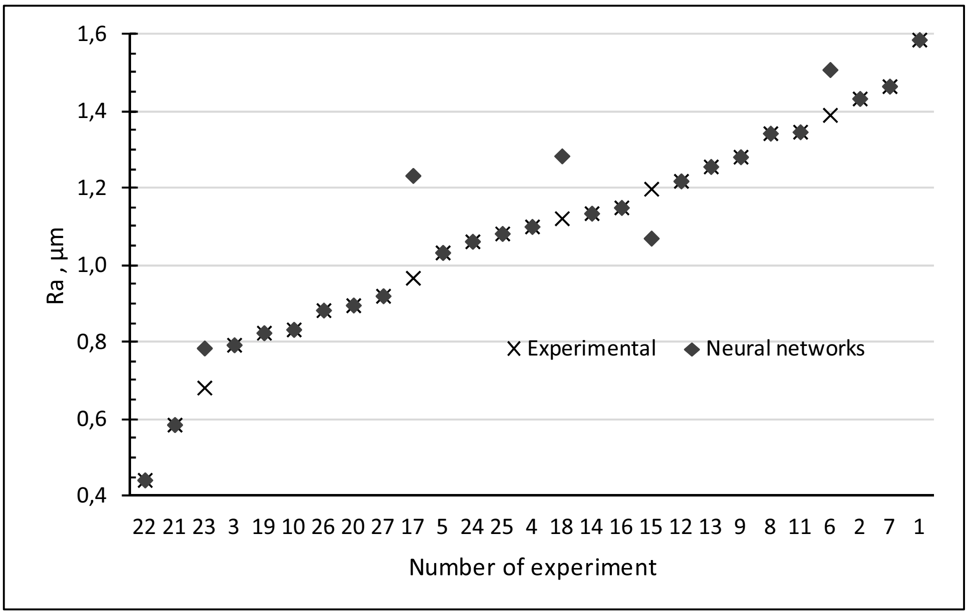

Figure 1. Comparison between experimental and simulation results for 11 neurons in the hidden layer

5. SELECTION OF BEST NEURAL NETWORK WITH TWO HIDDEN LAYERS

Since best neural network with one hidden layer corresponds to 11 neurons, 17 neurons were used for two hidden layers. Number of neurons tested was 6-11, 7-10, 8-9, 9-8, 10-7, 11-6, 12-5, 13-4, 14-3, 15-2 and 16-1.

Best configuration with two hidden layers corresponds to 7 and 10 neurons respectively: BP 5_7_10_1. This means backpropagation algorithm with 5 input variables, 7 neurons in the first hidden layer, 10 neurons in the second hidden layer and 1 response. Corresponding mqe from validation data is 0.0076 and mqe from training + validation data is 0.0580. Average mqe value is 0.0328.

Figure 2 shows comparison between experimental and modeled values for 7 and 10 neurons in the hidden layers.

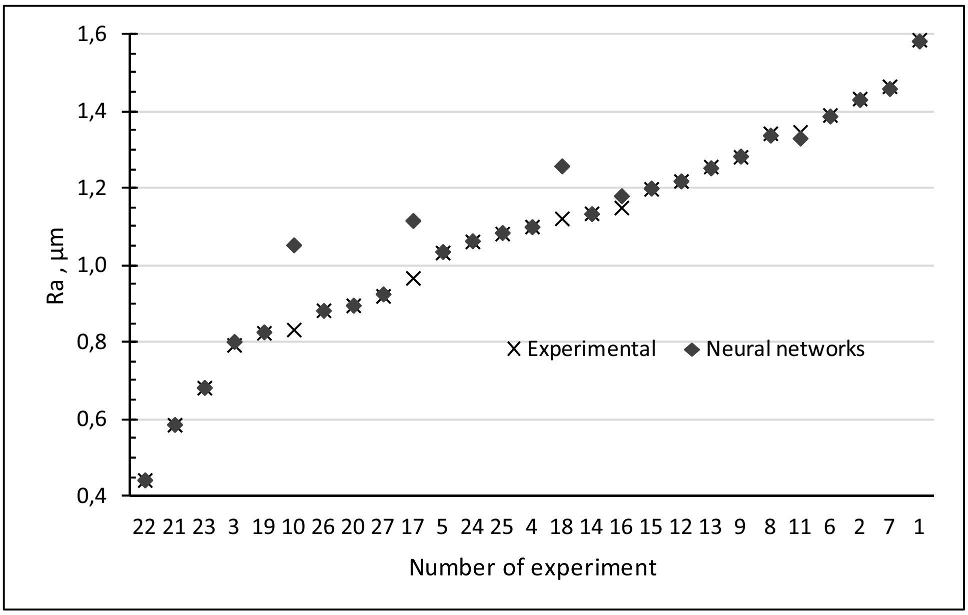

Figure 2. Comparison between experimental and simulation results for 7 and 10 neurons in the hidden layers.

6. COMPARISON BETWEEN NEURAL AND STATISTICAL MODELS

Second order regression models were obtained from experimental data. Table 2 presents mean quadratic error values for neural model with one hidden layer, neural model with two hidden layers and statistical model.

Table 2. Mean quadratic error for neural model with one hidden layer, neural model with two hidden layers and statistical model

Model	BP_5_11_1	BP_5_7_10_1	Statistical
Mqe	0.0715	0.0580	0,0579

Mean quadratic error is very similar for the neural model with two hidden layers and for the statistical model, while neural model with one hidden layer has higher mqe value. For this reason, neural model with one hidden layer was discarded.

7. CONCLUSIONS

In order to model average roughness Ra in semifinish honing processes both neural networks with one and with two hidden layers were employed. For one hidden layer best network corresponds to 11 neurons and for two hidden layer best network corresponds to 7 and 10 neurons respectively. Neural models were compared to a statistical model. Similar mean quadratic error was obtained for the neural model having two layers and the statistical model.

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