INDIRECT MODEL FOR ROUGHNESS IN ROUGH HONING PROCESSES BASED ON ARTIFICIAL NEURAL NETWORKS

Abstract

In the present paper an indirect model based on neural networks is presented for modelling the rough honing process. It allows obtaining values to be set for different process variables (linear speed, tangential speed, pressure of abrasive stones, grain size of abrasive and density of abrasive) as a function of required average roughness Ra. A multilayer perceptron (feedforward) with a backpropagation (BP) training system was used for defining neural networks. Several configurations were tested with different strategies, number of layers, number of neurons and transfer function. Best configuration for the network was searched by means of two different methods, trial and error and Taguchi design of experiments (DOE). In both cases, best configuration corresponds to a single network with two hidden layers. Once best configuration was found, a network was defined for obtaining honing parameters as a function of required roughness parameters related to Abbott-Firestone curve, Rk, Rpk and Rvk.

Keywords: Honing, surface roughness, artificial neural networks, indirect model

NOMENCLATURE

A Weight of number of neurons Na for data division a

ANN Artificial neural networks

A(i, k) Matrix containing differences between real and simulated values for each one of the i validation tests and each one of the k variables when 5 neural networks are considered

B(k) Vector containing differences between real and simulated values for each one of the k validation tests

BP Backpropagation algorithm

DE Density of abrasive according to ISO6104:2013

Dif(%) Relative difference between real and simulated values

DOE Design of Experiments

GS Grain size of abrasive according to FEPA

mqe Mean quadratic error between real and simulated roughness Ra values

n Number of validation tests

N Number of neurons of the best neural network

PR Pressure of abrasive stones on the workpieces' surface (N/cm^2)

Ra Average roughness (μm)

Rk Core height (μm)

Rpk Reduced peak height (μm)

Rvk Reduced valley height (μm)

ti Real value for Ra (μm)

tDE(i) Vector containing real values for DE for each one of the i validation tests

tGS(i) Vector containing real values for GS for each one of the i validation tests

tPR(i) Vector containing real values for PRS for each one of the i validation tests

tVL(i) Vector containing real values for VL for each one of the i validation tests

tVT(i) Vector containing real values for VT for each one of the i validation tests

tV(i) Real process value of the ith pattern corresponding to Ra

Vi Each one of the process variables

VL Linear speed (m/min)

VT Tangential speed (m/min)

yi Simulated value for Ra (μm)

yDE(i) Vector containing simulated values for DE for each one of the i validation tests

yGS(i) Vector containing simulated values for GS for each one of the i validation tests

yPR(i) Vector containing simulated values for PRS for each one of the i validation tests

yVL(i) Vector containing simulated values for VL for each one of the i validation tests

yVT(i) Vector containing simulated values for VT for each one of the i validation tests

yV(i) Simulated process value of the ith pattern corresponding to Ra

1. Introduction

Many variables influence responses. such as surface roughness or material removal rate in abrasive machining processes. Since such processes are complex and non linear, statistical techniques of design of experiments have great difficulties to model them. Another option to model them consists of using artificial intelligence techniques, in order to overcome non linearity of such abrasive machining processes[1]. Artificial neural networks (ANN) have provided satisfactory results in machining processes like turning [2] or milling [3]. Moreover, different authors showed an improvement in results obtained when using artificial neural network models with respect to statistical models [4], [5]. They have also been proved to be useful for modeling grinding processes. For example, Sathyanarayanan et al. [6] predicted surface finish, force and power from input variables: feed rate, depth of cut, and wheel bond type, by means of ANN. Liao established a model for a flat finishing process with diamond stones using ANN [7]. Li, Mills and Rowe developed ANN for selecting grinding wheels in finishing operations [8]. Ben Fredj et al. predicted roughness parameters Ra and Rt from cutting speed, depth of cut, grain size of abrasive and number of passes, in a cylindrical grinding process, using BP algorithm and data from design of experiments (DOE) to train the neural network [5].

Honing is a mechanical process in which material is removed by means of friction between abrasive stones and the workpieces' surface, thanks to simultaneous rotation and translation movements. This leads to a cross-hatch pattern on the workpieces' surface, which is very important in order to retain oil as well as to reduce friction between surfaces that are in contact. Hegemier and Steward demonstrated that honing and plateau-honing processes produce the best surface finish on cylinders for four stroke diesel engines, since they optimize oil consumption, minimize ring wear and liner wear

[15]. Drozda [10] and ASM [11] proved that honing is currently the only process that is able to achieve the double requirement for surface finish and cross-hatch pattern that are necessary for manufacturing cylinder liners. Relative speed of the two parts as well as pressure of abrasive stones on the workpiece's surface determines material removal rate and surface roughness of the liner. Other parameters that influence surface finish and productivity are those related to the abrasive stone: type of abrasive material, grain size and density of abrasive, as well as bond employed.

Regarding honing processes, Feng et al. used ANN with three hidden layers and trained by means of BP learning algorithm for obtaining roughness parameters related to Abbott-Firestone curve [12]. They also showed improvements in results obtained when using artificial neural networks with respect to statistical models [4]. Neagu and Dumitrescu used BP learning algorithm in three layer ANN for modeling roughness, roundness and cylindricity as a function of process variables [13]. Wen et al used ANN for solving multiobjective optimization of both quality and efficiency in the honing process of titanium parts [14]. Lawrence et al. used ANN for predicting roughness parameters related to Abbott-Firestone curve from image based parameters [15]. However, all previously mentioned papers solved the direct problem, in which values for responses, for example surface roughness, are predicted from known variables' values.

With respect to selection of best neural configuration, Zhong et al. stated that there is no exact solution for this purpose [16]. Although number of neurons is often obtained by means of trial and error approach, several attempts have been made to use systematic methods. For example, Pontes et al. used Taguchi design of experiments for selecting best configuration for neural networks used to predict roughness in turning processes [17]. Ortiz-Rodriguez et al. also used Taguchi DOE for designing neural networks [18].

They considered number of neurons in the first hidden layer, number of neurons in the second hidden layer, momentum and learning rate. Zanchettin et al. used design of experiments for identifyging most influential factors affecting a neuro-fuzzy inference system [19]. Mohana Rao et al. used genetic algorithms to optimize weights used in neural networks for modelling surface roughness in electro discharge machining [20]. On the other hand, Özel and Karpat presented a systematic approach for choosing number of hidden layers and number of neurons in turning processes, by using the output parameters of Bayesian regularization algorithm [21].

In the present paper the indirect problem is addressed in honing processes by means of ANN for roughness. This implies that the input variable for the network is desired average roughness Ra, and output variables are process' variables. Thus, networks only have one input variable and many output variables, and this complicates obtaining results with low error. ANN configuration that best models the honing process was selected by means of two different methods: trial and error and Taguchi DOE. In both cases configuration having lowest mean quadratic error mqe was considered to be the best one. Alternative methods for solving the indirect problem are time series analysis [22] and real time procedures for regression models [23]. Indirect approach involves support for honing machine users in decision making, when defining most appropriate values for the process variables to obtain required surface roughness. This will help users to reduce amount of experimental tests to be performed before serial production.

2. Experimental data

Experiments were performed in a test machine with the aim of working under controlled and stable conditions. Input parameters that can be modified by the user are linear speed

of the honing head VL, tangential speed of the workpiece VT (unlike industrial machines where usually the honing head rotates) and pressure of abrasive stones on the cylinders' surface PR (Figure 1). Output signals can be visualized and registered. In addition, two properties of the honing stones were varied: grain size of abrasive GR according to FEPA [24] (*Federation of European Producers of Abrasives*) and abrasive density DE according to ISO-6104:2005 [25].

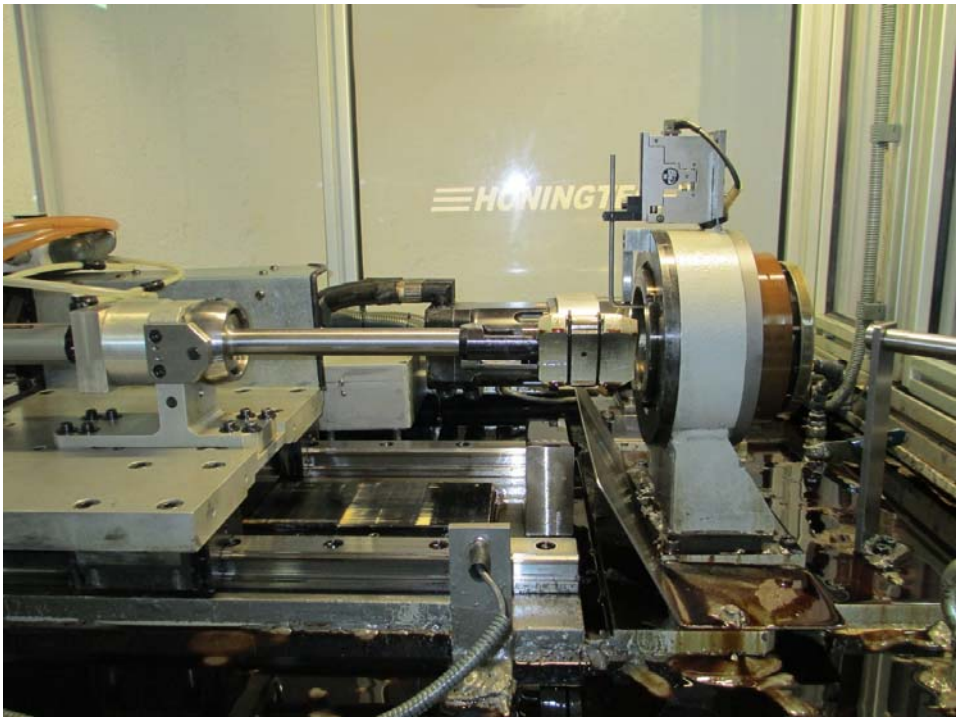

Figure 1. Test machine

Minitab® 17 was used for all statistical analysis. Central composite design was defined, with a two-level fractional factorial design 2^{5-1} with 16 points and 5 central points. 10 face-centered axial points were added to the design in order to consider second order models. Thus, total number of experiments was 31, with two replicates. Levels selected for the five variables are presented in Table 1.

Table 1. Variables and levels employed in factorial design (DOE)

Variable	Levels
GS [FEPA]	91 – 181
DE [ISO 6104]	30 – 60
PR [N/cm^2]	400 – 700
VT [m/min]	30 – 50
VL [m/min]	20 – 40

Tests were performed on steel St-52 cylinders of length 100 mm, 90 mm external diameter and 80 mm internal diameter. It was assured that, for each experiment, honing time is long enough to completely erase previous machining marks. In addition, it was assured that the surface of the honing stone was completely stabilized and had the shape of the cylinder before each experiment was performed.

For each cylinder 9 roughness measurements were performed on a diametral plane (separated 40 º), at 50 mm from the end of the cylinder. A Taylor Hobson Talysurf series 2 roughness meter was employed. Extreme values were discarded according to the Chauvenet criterion, as it was explained elsewhere [26]. Finally, an average value for each experiment was calculated.

3. Methodology

Networks are based on a multilayer perceptron (feedforward) with a backpropagation (BP) training system, as recommended for different machining processes, for example Aguiar et al. [27] and Feng and Wang [4] for turning processes, and Tsai [28] an Razfar [29] for milling processes. In accordance with Hornik et al., a multilayer perceptron network with one hidden layer and nonlinear activation function and a sufficiently high number of neurons will work as a universal model and will approximate any function. On the contrary, output function can be linear [30]. If a network with more than one hidden layer is used, it is also possible to approximate any function, although there is no theory that defines the structure to be used.

3.1 Network for average roughness Ra

Different network configurations were defined with Matlab software for average roughness Ra. According to support documentation by Demuth et al. [31], first the *train* function was used two consecutive times to train the networks, so as to improve its learning process. Previously, values of the weight and bias matrices had been initialized by means of the *initlay* function. Then, networks were trained and validated. Available data were divided into three groups: 82 % for training and 18 % for validation. Training of the neural networks stopped when decrement in mqe obtained with validation data was lower than 1.00 e^{-10}. As Guyon noticed [32], there is no universal rule that is accepted to divide data. On the contrary, depending on complexity degree of the problem and of number of data used, proportion of data partition varies significantly. Finally, most effective configuration was chosen by minimization of mqe.

Two ways for finding best configuration for networks regarding Ra are employed in the present paper: trial and error and Taguchi DOE.

Since a strong relationship between variables was found in previous studies, a single ANN with one input (desired Ra surface roughness value) and five outputs (process variables GS, DE, VL, VT and PR) was used as shown in Figure 2.

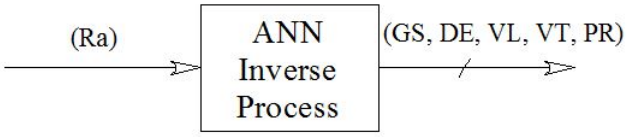

Figure 2. Functional diagram of the indirect problem with a single ANN

Thus, the perceptron was configured with one input variable (Ra) and one or two hidden layers with nonlinear function, and one output layer with linear function. As an example, network with one hidden layer and tan-sigmoidal transfer function is shown in Figure 3.

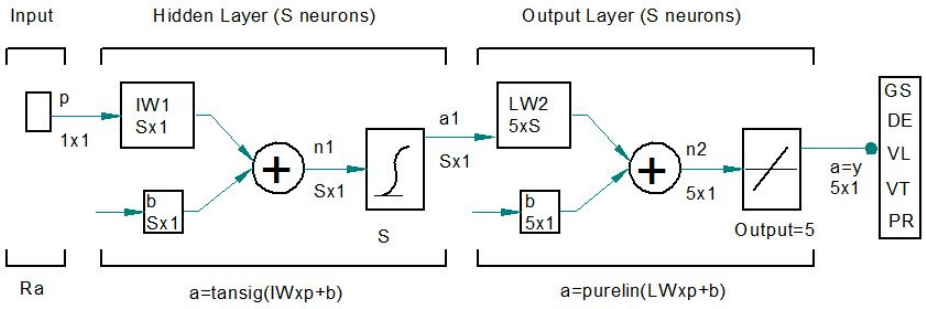

Figure 3. Configuration of one ANN with one hidden layer

3.1.1 Trial and error method

Parameters considered are as follows:

- Type of transfer function: tangential-sigmoidal nonlinear function (Figure 4a).

- Number of layers: either 1 or 2 hidden layers.
- Number of neurons in the first hidden layer: between 4 and 50.

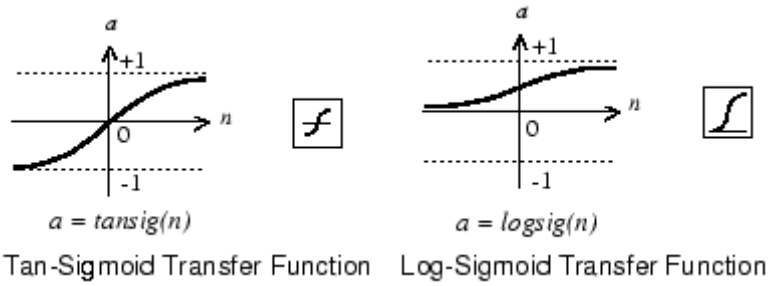

Figure 4 Transfer function: (a) Tan-Sigmoid, (b) Log-Sigmoid

For networks with one hidden layer, a number of neurons between 4 and 100 was trained and compared, in accordance with Laurence and Petterson [33]. No recommendation was found for networks with two hidden layers. For this reason, first number of neurons of the best configuration with one hidden layer was determined. As start point, the same number of neurons but increased by 50 % was used for the second layer. Neurons were distributed in proportions 2/3 and 1/3 between the first and second hidden layer respectively. Later successive variations of ±1 neurons in each layer were tested, in a way that total number of neurons remains constant.

3.1.2 Taguchi DOE

In this case, only some experiments were performed, according to Taguchi method. Three factors were considered:

- Type of function in the hidden layer (F3): either tan-sigmoidal (Figure 4a) or log-sigmoidal transfer function (Figure 4b).
- Number of layers (F2): either one or two layers.

- Number of neurons in the first hidden layer (F1); 25, 50, 75 or 100. In the second layer, 50% more neurons were considered than in the first layer (37, 75, 113 and 150 respectively).

L8 orthogonal array employed is shown in Table 2.

Table 2. L8 orthogonal array with 3 factors F1, F2 and F3

Experiments	F1	F2	F3
1	25	1	Tan-Sigmoid
2	25	2	Log-Sigmoid
3	50	1	Tan-Sigmoid
4	50	2	Log-Sigmoid
5	75	1	Log-Sigmoid
6	75	2	Tan-Sigmoid
7	100	1	Log-Sigmoid
8	100	2	Tan-Sigmoid

3.2 Network for Abbott-Firestone parameters

After choosing best configuration for average roughness Ra, a network was built for solving the indirect process regarding Abbott-Firestone parameters Rk, Rpk and Rvk.

4. Selection of best network

In order to choose best ANN configuration, mean quadratic error of validation data was employed, according to Equation 1.

$$mqe = \sqrt{\frac{\sum_{k=1}^{n} B(k)}{n}}$$

(Eq. 1)

Where

n = number of validation tests, and

different parameters are explained in Equations 2 to 13.

$$B(k) = \left(\frac{\sum_{i=1}^{5} A_{i,k}}{5}\right)_{k=1,\dots,n}$$

(Eq. 2)

$$A(i,k) = \begin{pmatrix} (tGS_1 - yGS_1)^2 & \cdots & (tGS_n - yGS_n)^2 \\ \vdots & \ddots & \vdots \\ (tPR_1 - yPR_1)^2 & \cdots & (tPR_n - yPR_n)^2 \end{pmatrix}_{\substack{k=1,\dots,n \\ i=1,\dots,5}}$$

(Eq. 3)

$$tGS(i) = (tGS_1, \dots, tGS_i, \dots, tGS_n)_{i=1,\dots,n}$$

$$yGS(i) = (yGS_1, \dots, yGS_i, \dots, yGS_n)_{i=1,\dots,n}$$

(Eq. 4 and 5)

$$tDE(i) = (tDE_1, \dots, tDE_i, \dots, tDE_n)_{i=1,\dots,n}$$

$$yDE(i) = (yDE_1, \dots, yDE_i, \dots, yDE_n)_{i=1,\dots,n}$$

(Eq. 6 and 7)

$$tVL(i) = (tVL_1, \dots, tVL_i, \dots, tVL_n)_{i=1,\dots,n}$$

$$yVL(i) = (yVL_1, \dots, yVL_i, \dots, yVL_n)_{i=1,\dots,n}$$

(Eq. 8 and 9)

$$tVT(i) = (tVT_1, \dots, tVT_i, \dots, tVT_n)_{i=1,\dots,n}$$

$$yVT(i) = (yVT_1, \dots, yVT_i, \dots, yVT_n)_{i=1,\dots,n}$$

(Eq. 10 and 11)

$$tPR(i) = (tPR_1, \dots, tPR_i, \dots, tPR_n)_{i=1,\dots,n}$$

$$yPR(i) = (yPR_1, \dots, yPR_i, \dots, yPR_n)_{i=1,\dots,n}$$

(Eq. 12 and 13)

where

tGS(i) = real value of variable GS of the ith pattern for Ra

yGS(i) = simulated value of variable GS of the ith pattern for Ra

tDE(i) = real value of variable DE of the ith pattern for Ra

yDE(i) = simulated value of variable DE of the ith pattern for Ra

tVL(i) = real value of variable VL of the ith pattern for Ra

yVL(i) = simulated value of variable VL of the ith pattern for Ra

tVT(i) = real value of variable VT of the ith pattern for Ra

yVT(i) = simulated value of variable VT of the ith pattern for Ra

tPR(i) = real value of variable PR of the ith pattern for Ra

yPR(i) = simulated value of variable PR of the ith pattern for Ra

5. Results

5.1 Roughness profiles

In Figure 5 a roughness profile for an experiment having high values for process variables is presented.

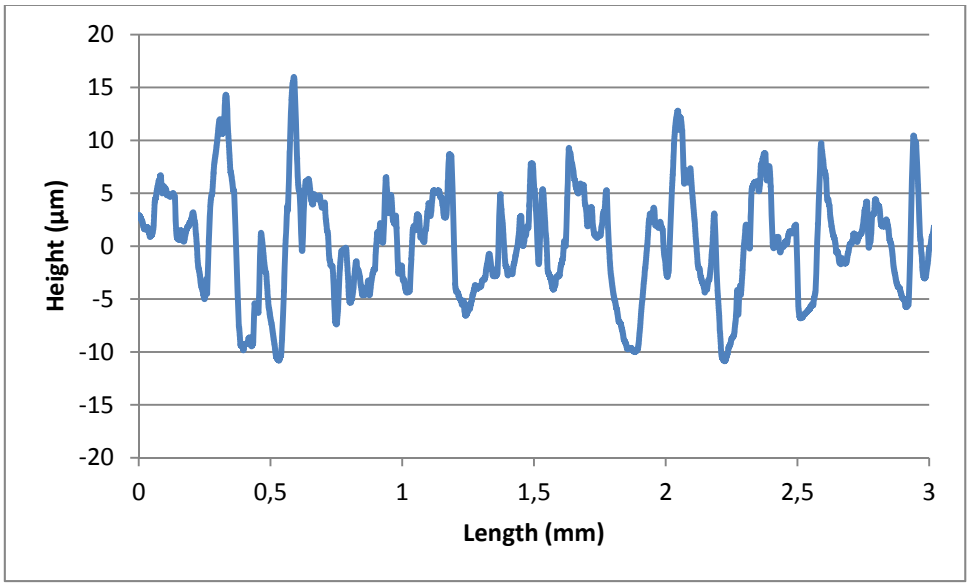

Figure 5 Roguhness profile for an experiment with GS=181, DE=60, PR=700 N/cm^2, VL= and VT=…

Figure 6 corresponds to a roughness profile for an experiment having low values for process variables.

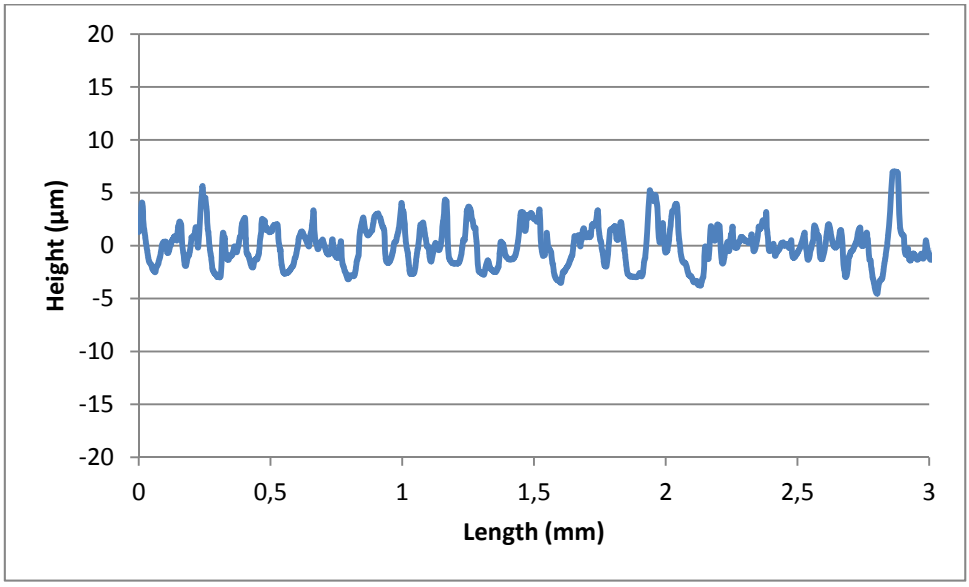

Figure 6 Roughness profile for an experiment with GS=91, DE=30, PR=400 N/cm^2, VL= and VT=…

5.2 Average roughness Ra

5.2.1 Trial and error method

Best configuration corresponds to N=7 neurons in the hidden layer (Table 3).

Table 3. Selected network with one hidden layer

	mqe	N
Final configuration	0.4346	7

For two layers, best network corresponds to 24 and 9 neurons respectively (Table 4).

Table 4. Selected network with two hidden layers

	mqe	N
Final configuration	0.3125	24-9

Overall, best configuration consists of using 2 hidden layers with 24 and 9 neurons in the first and second layer respectively, since mqe value is lower.

5.2.2 Taguchi DOE method

Results of Taguchi DOE are presented next. Table 5 corresponds to values for main effects. It contains a rank, where number 1 means most influential factor and number 3, less influential factor.

Table 5. Values for main effects

Level	Number of neurons	Number of layers	Function
1	0.6926	0.7127	0.6376
2	0.7181	0.5676	0.6427
3	0.5888		
4	0.5611		
Delta	0.1570	0.1450	0.0051
Rank	1	2	3

Figure 7 shows main effects on mean.

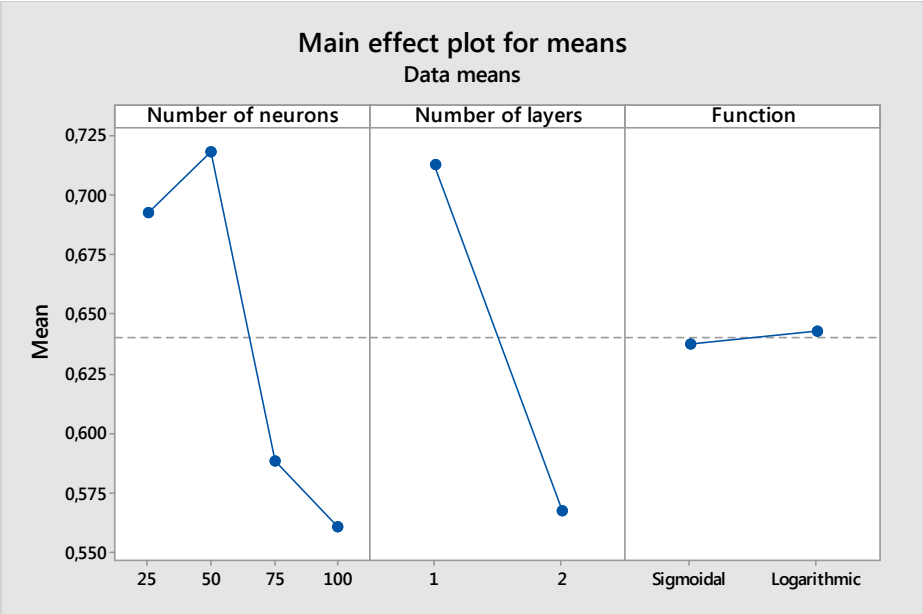

Figure 7. Main effects on mean

According to Table 5 and Figures 7, most influential factor on response mqe is number of neurons, followed by number of layers and type of transfer function. Use of either sigmoidal or logarithmic function does not significantly influence results. Two layers are preferred to one, with 100 neurons in the first hidden layer. Thus, best configuration for the network is 100-2-Sigmoidal Tangential, which corresponds to 100 neurons in the first hidden layer, 50 neurons in the second layer, 2 layers and Sigmoidal Tangential function.

5.3 Parameters related to Abbott-Firestone curve Rk, Rpk and Rvk

For one hidden layer, best configuration corresponds to N=46 neurons in the hidden layer (Table 6).

Table 6. Selected network with one hidden layer

	mqe	N
Final configuration	0.3274	46

For two layers, best network corresponds to 46 and 23 neurons respectively (Table 7).

Table 7. Selected network with two hidden layers

	mqe	N
Final configuration	1.7483	46-23

Overall, best configuration consists of using 1 hidden layer with 46 neurons, since mqe value is lower.

6. Validation of selected neural model

In order to validate selected neural model, some experimental tests at different cutting conditions were performed. For each experiment relative difference Dif (%) between experimental and simulated values for Ra was calculated (Equation 14).

$$Dif\ (\%) = \left(\frac{Ra\ sim - Ra\ exp}{Ra\ sim}\right) \cdot 100 \quad \text{(Eq. 14)}$$

Where Ra exp is experimental Ra value in μm, and

Ra sim is simulated Ra value in μm.

Results are presented in Table 8.

Table 8. Results of validation tests

Experiment	GS (FEPA)	DE (ISO 6104)	PR (N/cm^2)	VT (m/min)	VL (m/min)
1	181	45	533	46.2	40.2
2	91	45	624	38.9	28.3
3	126	45	542	44.0	28.0
4	181	60	581	38.9	42.9
5	126	45	545	42.8	24.9

All relative differences between simulated and experimental values for Ra are below 15 %. For this reason, the model is considered to be validated.

7. Statistical analysis of results

Correlation between response average roughness Ra and the different variables was investigated. As an example, Figs. 10 and 11 correspond to scatter plots of Ra vs. GS and De repectively. Correlation coefficients between Ra and the rest of the variables are quite lower: 0.303 for DE, 0.121 for PR, -0.049 for VT and 0.016 for VL.

Regression analysis was performed with experimental data, considering second order models. Main factors affecting roughness Ra were grain size GS, density DE and pressure PR. GS-DE interaction was also significant. According to Figure 12 roughness Ra takes lowest values at low grain size and medium density of abrasive.

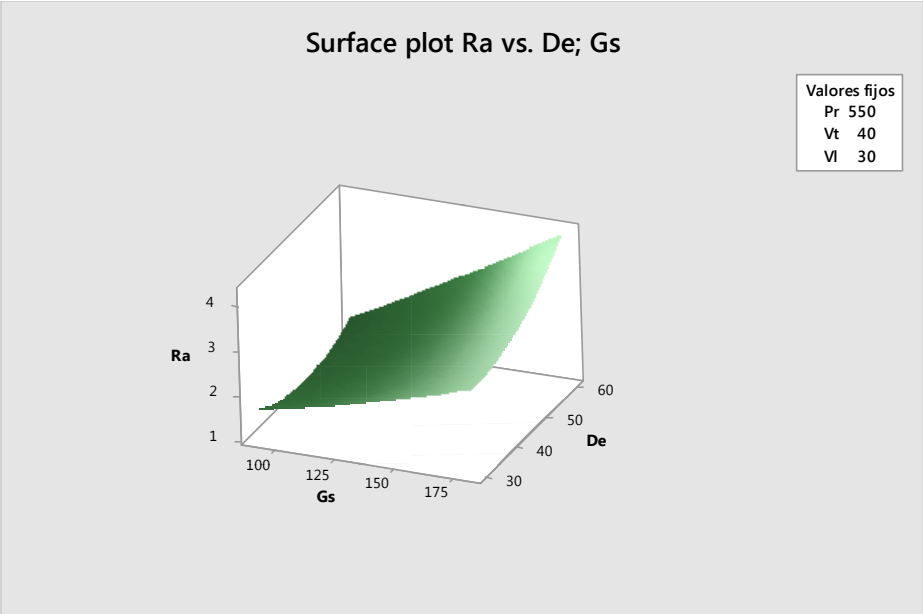

Figure 12. Surface plot Ra vs. DE;GS

Results agree with a previous study, in the sense that grain size, pressure and density were main factors influencing roughness. Main interaction was also that between grain size and density [34]. In accordance with a study by Troglio main factor affecting roughness is grain size. Other factors considered were lubricating oil and workpiece material [35]. Kanthababu et al., who did not take into account grain size as a factor, found that pressure was one of the main parameters affecting roughness, together with honing time [36].

8. Conclusions

In the present paper an indirect neural network model for predicting the honing process variables (grain size of abrasive, density of abrasive, linear speed, tangential speed and pressure) as a function of roughness parameters is proposed. Two different methods for determining best network configuration are presented and compared: trial and error methodology and Taguchi DOE.

With the trial and error methodology one and two hidden layers were studied and number of neurons between 4 and 100 were tested. Tan-sigmoid function was taken into account. Configuration that minimizes mean quadratic error for Ra consists of a network with two hidden layers having 24 and 9 neurons respectively. Configuration that minimizes mean quadratic error for Rk, Rpk and Rvk consists of one hidden layer having 46 neurons.

With the Taguchi DOE methodology one or two hidden layers were studied with number of neurons 25, 50, 75 or 100. Both tan-sigmoid and log-sigmoid functions were taken into account. Configuration that minimizes mean quadratic error for Ra consists of a two hidden layers having 100 and 50 neurons respectively, with tan-sigmoid function.

For Ra both methods coincide in selecting two-layer networks, although number of neurons is different. Trial and error has the advantage that it provides sweep of different combinations for different number of neurons. On the contrary, it requires performing many tests. Taguchi methodology studies different factors at the same time and reduces significantly number of tests. Its main drawback is that it does not consider all possible values for number of neurons.

Use of the indirect model allows improving the honing process. It is a direct support to decision taking and reduces the need to perform experimental tests, with an important cost reduction.

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