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SELECTION OF AN NEURAL NETWORK FOR MODELLING THE HONING PROCESS

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ABSTRACT
Roughness obtained in honing process depends on many different process parameters, such as grain size of abrasive stones, pressure of stones on the workpiece's surface, density of abrasive, tangential speed of the honing head and linear speed of the honing head. This fact makes it difficult to study the process from an analytical point of view. For this reason, use of empirical methods or use of artificial intelligence is recommended in this case. In the present paper, results about use of neural networks for obtaining average roughness Ra as a function of honing parameters are presented. Best neural network was chosen among different possibilities. For doing this, experimental results were divided into three groups: 70 % of results were used for training, 15 % of results were used for validation and 15 % of results were used as test to compare networks with other models. The best neural network was considered to be the one with lowest errors using the validation experimental results.
Keywords: roughness, neural networks, honing

1. INTRODUCTION
Manufacturing processes have been widely modelled by means of neural networks. For example, surface roughness in grinding processes was studied by Liao and Chen. [1]. However, few studies are known on use of neural networks in interior honing processes. Feng et al. obtained models for surface roughness parameters that are related to the Abbott-Firestone curve for both rough and finish processes [2]. Variables considered were grit size, honing time and pressure. Pu et al. used neural networks to optimize the honing process [3]. They varied parameters such as oilstone granularity, stroke length, stroke speed and spindle speed. In the present paper interior honing process for cylinders was modelled by means of artificial neural networks in order to obtain average roughness Ra from 5 relevant variables in the process: grain size of abrasive (Gs), abrasive density (D), linear speed of abrasive stones with respect to workpiece (VL), tangential speed of abrasive stones with respect to workpiece (VT), and pressure of abrasive stones on workpiece (P).

2. EXPERIMENTAL TESTS

Honing experiments were conducted in a honing test machine, to 33 steel St-52 cylinders of dimensions 300 mm in length, 90 mm external diameter and 80 mm internal diameter. For each cylinder 9 roughness measurements were taken equidistant one from the other along a circumference in a diametral plane at 150 mm from the end of the cylinder. A Taylor-Hobson Talysurf 2 roughness meter was employed. In Table 1 honing conditions as well as roughness Ra results are presented.

Table 1.Process variables and Ra values (average value of replicates) obtained when machining 33 cylinders in the test honing machine

Cylinder	GS (FEPA)	D (FEPA)	VL (m/min)	VT (r.p.m.)	P (N/cm2)	Ra (μm)
1	76	30	20	80	450	1.25
2	181	30	20	80	450	2.83
3	76	75	20	80	450	1.09
4	181	30	32	80	450	2.93
5	76	75	32	80	450	0.88
6	181	75	32	80	450	1.40
7	181	30	20	180	450	2.57
8	76	75	20	180	450	0.86
9	181	30	32	180	450	3.10
10	76	75	32	180	450	1.11
11	181	75	32	180	450	1.70
12	76	30	20	80	600	1.48
13	181	30	20	80	600	2.89
14	76	75	20	80	600	1.14
15	181	75	20	80	600	2.53
16	76	30	32	80	600	1.20
17	181	30	32	80	600	3.06
18	181	75	32	80	600	2.10
19	76	30	20	180	600	1.40
20	181	30	20	180	600	3.11
21	76	75	20	180	600	1.04
22	76	30	32	180	600	1.61
23	181	30	32	180	600	3.21
24	76	75	32	180	600	1.24
25	181	75	32	180	600	1.93
26	76	50	26	130	525	1.12
27	126	50	20	130	525	2.12
28	126	50	26	80	525	2.12
29	126	50	26	180	525	2.10
30	126	50	26	130	600	2.13
31	126	50	26	130	525	1.74
32	126	50	26	130	525	1.86
33	126	50	26	130	525	2.10

3. DATA TREATMENT

A total amount of 33 x 9 data were collected. However, from each cylinder extreme values were statistically discarded. Final amount of 207 data groups (Gs, D, VL, VT, P, Ra) were considered. Data groups were randomly divided into training, validation and test groups in a proportion 70% (145 groups), 15% (31 groups), and 15% (31 groups) respectively. In order to generalize results this random division process was repeated three times, in a way that initial 207 data groups were randomly divided into three different data divisions (called divisions a, b and c) each one containing training, validation and test data. If training data are used for training each network in an iterative way by modifying the weight matrix, validation data are used to stop training when reduction in quadratic average error is lower than a certain previously defined gradient ($1.00\ e^{-10}$). Test data are not used in the training process and are kept in order to evaluate and compare neural network performance with other models performance.

4. NEURAL NETWORK CONFIGURATION

Different configurations for a multilayer perceptron neural network were tested, with a Back Propagation supervised training algorithm and Cross Validation system. The neural network model was chosen according to literature about neural networks in abrasive machining processes [1,4,5,6,7]. The study was conducted with two different perceptron configurations, first on with one hidden layer (Figure 1), and second one with two hidden layers. Second one is similar to first one but with a hidden layer in the middle. A higher number of layers were discarded in order to avoid overtraining, which would mean memorizing of training data rather than training.

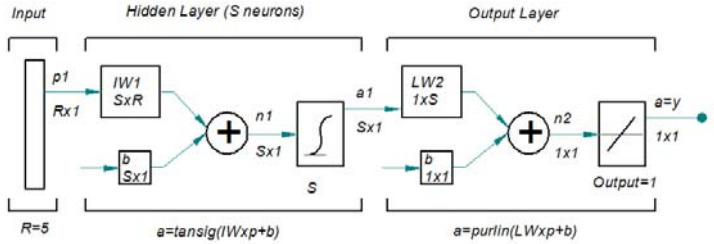

Figure 1. Configuration of the perceptron with one hidden layer of "S" neurones.

5. METHODOLOGY FOR SELECTING THE MULTILAYER PERCEPTRON

For each data division 'a', 'b', and 'c' the perceptron configuration that better models training and validation data is searched, for both networks with one and two hidden layers. Mean quadratic error (mqe) of the validation group is used as selection parameter. Since mqe results of the three data divisions do not coincide completely, a final configuration or number of neurones N considered being best is calculated. Best configuration is obtained by weighting number of neurones of each division according to mqe for each division. For a network with two hidden layers the same process for determining number of neurones will be applied separately to each one of the two hidden layers. So as to compare and decide the best configuration between one hidden layer and two hidden layers, a new division 'd' of training, validation and test data is performed. With such data division, mqe is calculated for the two previously selected networks, after training them with the new data division 'd'.

6. RESULTS

6.1. Perceptron configuration with one hidden layer

From training and calculation of mqe of neural networks with one hidden layer (Table 2), best configuration is N = 39.6 corresponding to a **perceptron with 40 neurones in the hidden layer**.

Table 2.Mean quadratic error of perceptrons with one hidden layer, for the three data divisions considered

N	8	9	10	11	12	14	16	18	20	25	30	35	40	45	**50**	75
Mqe a	0.143	0.113	0.148	0.134	0.120	0.126	0.130	0.155	0.122	0.120	0.129	0.151	0.115	0.117	**0.110**	0.121
N	8	9	10	11	12	14	16	18	20	25	**30**	35	40	45	50	75
Mqe b	0.143	0.144	0.153	0.140	0.118	0.213	0.140	0.159	0.136	0.172	**0.097**	0.172	0.108	0.133	0.126	0.155
N	8	9	10	11	12	14	16	18	20	25	30	35	**40**	45	50	75
Mqe c	0.183	0.176	0.135	0.130	0.145	0.250	0.129	0.143	0.221	0.103	0.150	0.188	**0.098**	0.109	0.122	0.112

6.2. Perceptron configuration with two hidden layers

According to calculation methodology to select the best network with two hidden layers (Table 3), best configuration was found for N = 41.8 in the first hidden layer and N = 18.4 in the second hidden

layer, which corresponds to a **perceptron with 42 neurones in the first hidden layer and 18 neurones in the second hidden layer.**

Table 3.Mean quadratic error of perceptrons with two hidden layers, for the three data divisions considered

N	45-30	46-29	47-28	48-27	49-26	50-25	51-24	**52-23**	53-22	54-21	55-20
Mqe a	0.107	0.145	0.133	0.123	0.153	0.154	0.110	**0.098**	0.105	0.127	0.111
N	25-20	26-19	27-18	28-17	29-16	30-15	31-14	32-13	33-12	**34-11**	35-10
Mqe b	0.146	0.114	0.137	0.150	0.112	0.166	0.184	0.136	0.164	**0.103**	0.157
N	35-25	36-24	37-23	38-22	**39-21**	40-20	41-19	42-18	43-17	44-16	45-15
Mqe c	0.128	0.149	0.129	0.110	**0.100**	0.144	0.169	0.122	0.139	0.147	0.105

6.3. Final configuration of the perceptron network

From calculation of mqe of selected perceptrons with 1 and 2 hidden layers, trained with data division 'd' it can be deduced that best configuration is **perceptron network with one hidden layer of 40 neurones.** The reason for this is that for one hidden layer with N = 40, Mqe d is 0.163, which is smaller than Mqe d of 0.173 for two hidden layers with N= 42-18.

7. CONCLUSIONS

Although the honing process is not linear, it is enough to use a network with one hidden layer to model the process. Increasing complexity of the network by increasing number of hidden layer does not improve results. A future line of work is to compare the selected network with other statistical models that also model the interior honing process.

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