THE COST ESTIMATION OF A WATER JET CUTTING PROCESS USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT: The paper presents a neural model used to control an abrasive water jet cutting machine and predict the cost of the process. The material features, the orifice diameter and the abrasive consumption are considered to be the input parameters. The output parameters are the feed rate, the energy consumption and the water consumption. A neural model with back propagation algorithm was used. A set of data obtained from the "Waterjet Web Reference Calculator" was used to model the process. The training and the validation data were calculated based on the values presented by the waterjet cutting machines manufacturers. In another paper [1] the authors have presented a neural model for controlling the speed of cutting and the abrasive consumption.
KEYWORDS: waterjet, processing, neural, network, model

1. INTRODUCTION

Waterjet machines can manufacture parts to very good tolerances. Today the modern waterjet cutting machines can create parts with a tolerance as small as 0.05 mm, although it is usually easier to obtain tolerances under 0.1 mm [1,4]. The productivity and cost of processing are other important factors which determine the parameters of the abrasive jet processing and sometimes they may be even critical in choosing this process.

Numerous models and approaches like design of experiments, regression modelling, ANOVA analysis, fuzzy logics and artificial neural networks are known for determining the process parameters. Some of these studies are based on mathematical equations developed for predicting the process parameters [3].
Models based ANN and regression was presented by Caydas and Hascalik [2] in order to estimate the minimum value of the machining performance value in comparison of the experimental data. Zain et al. 2011 [5] used neural model to estimate the quality of the cutting of machined-material considered process parameters include traverse speed, waterjet pressure, standoff distance, abrasive flow rate.

The purpose of this paper is to develop a neural model for determining the process parameters for the waterjet cutting machines. Besides the feed rate, other parameters that can be used in cost determination were sought. For this reason, the neural model was built to also provide the energy and water consumption, components that are necessary to calculate the processing cost.

The energy consumption used in the training data was calculated based on the pump energy and the time required cutting a length of one meter of varying thickness. Water consumption was calculated the same way considering the link between power, pressure and flow and the cutting time.

Considering the notations explained in Table 1, the formulas used to determine the cutting parameters are shown by the equations (1) - (11).

Table 1. Notations used in equations (1) - (11)

C_P - processing cost	P_E- energy price	n- number of pieces
C_A - cost of abrasive	P_L - labour price	t_c-effective cutting time
C_E - cost of electricity	P_W- water price	t_r- time for positioning
C_L - cost of labour	L_c- cutting length	t_p- perforation time
C_C - cost of nozzles	L_r- length of positioning movement	n_1 – perforation number/piece
C_D - depreciation cost	EP - Energy consumption	t_{po}- time/perforation
P_M- waterjet machine price	A-abrasive flow rate	t_{prep} – set-up time
P_{FN} - focusing nozzle price	W-water consumption	T_{FN}, T_{MN} – nozzles life
P_{MN}- mixing nozzle price	f-cutting feed	T_M – waterjet machine life
P_A- abrasive price	f_{rmed}- medium rapid feed rate	

$$C_P = C_L + C_E + C_A + C_W + C_C + C_D \quad (1)$$

$$t = t_c + t_r + t_p \quad (2)$$

$$t_c = \frac{L_c}{f} \quad (3)$$

$$t_r = \frac{L_r}{f_{rmed}} \quad (4)$$

$$t_p = n_1 \cdot t_{po} \quad (5)$$

$$C_L = P_L(t + t_{prep}) \quad (6)$$

$$C_E = P_E \cdot EP \quad (7)$$

$$C_A = P_A \cdot A \cdot (t - t_r) \quad (8)$$

$$C_W = P_W \cdot W \cdot (t - t_r) \quad (9)$$

$$C_C = t \cdot \left(\frac{P_{FN}}{T_{FN}} + \frac{P_{MN}}{T_{MN}}\right) \quad (10)$$

$$C_D = (t + t_{prep}) \cdot \frac{P_M}{T_M} \quad (11)$$

2. STRUCTURE OF THE NEURAL MODEL

Figure 1 presents a model used to calculate the process parameters and the cutting cost. The diagram contains a neural model and other information processing blocks in order to obtain the cost value.

A neural network with a backpropagation learning algorithm is considered in order to obtain the neural model. The network topology has three input nodes which represent the material thickness, the orifice diameter and the abrasive consumption and three output nodes that represent the feed rate f_0, energy consumption EP and the water consumption W. 25 neurons were chosen for the hidden layer. The activation function for the hidden layer is the sigmoid function and the output one uses the pureline function.

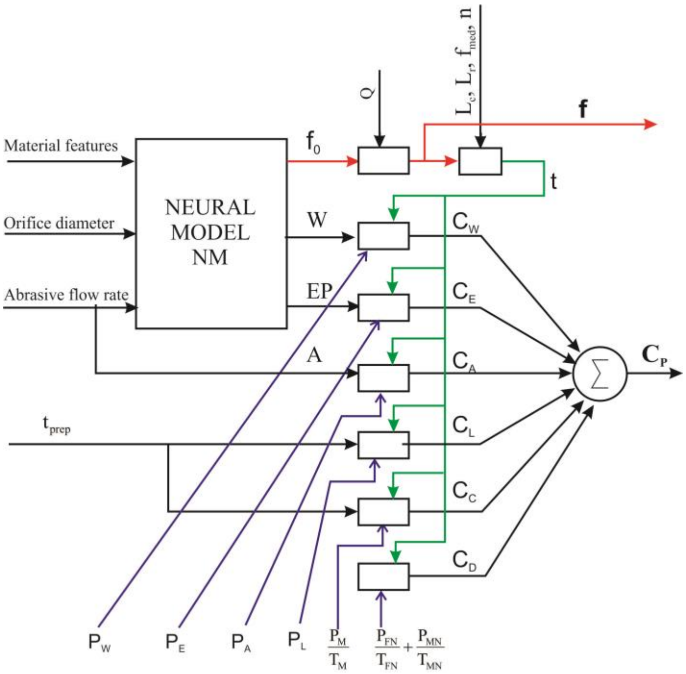

Figure 1. Neural model for AWJ process

Table 2 presents the training data set.

Table 2. Training data set

No.	Thickness [mm]	Orifice diameter [mm]	Abrasive flow rate [kg/min]	Cutter feed rate [mm/min]	Energy consumption [kWh]	Water consumption [l/min]	No.	Thickness [mm]	Orifice diameter [mm]	Abrasive flow rate [kg/min]	Cutter feed rate [mm/min]	Energy consumption [kWh]	Water consumption [l/min]
1.	3	0.25	0.30	0.95	2.79	0.22	24.	5	0.30	0.50	0.86	4.43	0.35
2.	3	0.25	0.40	1.07	2.49	0.20	25.	5	0.35	0.30	0.90	5.78	0.46
3.	3	0.25	0.50	1.16	2.28	0.18	26.	5	0.35	0.40	1.01	5.16	0.41
4.	3	0.30	0.30	1.27	3.01	0.24	27.	5	0.35	0.50	1.10	4.72	0.37
5.	3	0.30	0.40	1.42	2.69	0.21	28.	7.5	0.25	0.30	0.33	8.00	0.63
6.	3	0.30	0.50	1.55	2.46	0.19	29.	7.5	0.25	0.40	0.37	7.14	0.56
7.	3	0.35	0.30	1.62	3.21	0.25	30.	7.5	0.25	0.50	0.41	6.54	0.52
8.	3	0.35	0.40	1.81	2.87	0.23	31.	7.5	0.30	0.30	0.44	8.63	0.68
9.	3	0.35	0.50	1.98	2.63	0.21	32.	7.5	0.30	0.40	0.50	7.71	0.61
10.	4	0.25	0.30	0.68	3.88	0.31	33.	7.5	0.30	0.50	0.54	7.06	0.56
11.	4	0.25	0.40	0.77	3.47	0.27	34.	7.5	0.35	0.30	0.56	9.21	0.73
12.	4	0.25	0.50	0.84	3.17	0.25	35.	7.5	0.35	0.40	0.63	8.22	0.65
13.	4	0.30	0.30	0.91	4.19	0.33	36.	7.5	0.35	0.50	0.69	7.53	0.59
14.	4	0.30	0.40	1.02	3.74	0.30	37.	10	0.25	0.30	0.24	11.14	0.88
15.	4	0.30	0.50	1.11	3.43	0.27	38.	10	0.25	0.40	0.27	9.94	0.78
16.	4	0.35	0.30	1.16	4.47	0.35	39.	10	0.25	0.50	0.29	9.10	0.72
17.	4	0.35	0.40	1.30	3.99	0.32	40.	10	0.30	0.30	0.32	12.02	0.95
18.	4	0.35	0.50	1.42	3.66	0.29	41.	10	0.30	0.40	0.36	10.73	0.85
19.	5	0.25	0.30	0.53	5.02	0.40	42.	10	0.30	0.50	0.39	9.82	0.78
20.	5	0.25	0.40	0.59	4.48	0.35	43.	10	0.35	0.30	0.41	12.82	1.01
21.	5	0.25	0.50	0.65	4.11	0.32	44.	10	0.35	0.40	0.45	11.45	0.90
22.	5	0.30	0.30	0.70	5.42	0.43	45.	10	0.35	0.50	0.50	10.49	0.83
23.	5	0.30	0.40	0.79	4.83	0.38							

In table 2, the first three columns (1-3) show the input parameters (material thickness, orifice diameter and abrasive flow rate) and the next three columns (4-6) show the output parameters (cutter feed rate, energy consumption and water consumption). The output parameters were calculated by a “waterjet web reference calculator” [7]. The network training was done using a set of 45 input-output pairs of values.

The process parameters for cutting an aluminium plate and an average quality processing on machine which has the following features were chosen as input: 50 HP pump (pressure 4000 bar) and one cutting head. The abrasive nozzle diameter was chosen as the nearest value from twice the orifice diameter. The training data from table 2 were normalized by scaling, as follows: thickness was divided by 10 and, water consumption, divided by 100. Both, the training and validation of the neural network was done with normalized data. The simulated results obtained in the operational phase were also scaled using the same normalization factors. It was found that through data normalization we obtained an improvement of the results for the same training data set.

The neural network resulting from the training process was validated with a set of 27 pairs of input-output. The validation results of the network trained are presented in figure 2.

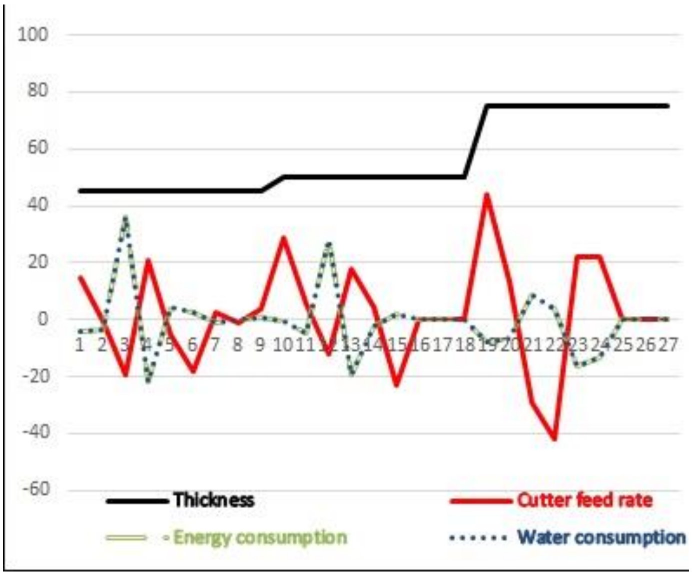

Figure 2. Validation errors

Relative errors in the range of ±43% for the cutter feed rate and ±36% for the energy and water consumption were obtained when the outputs were calculated. Analysing figure 2 shows that the neural model gives better results for energy and water consumption compared to feed rate. We also concluded that the error of the feed rate increases with the material thickness.

3. CASE STUDY. DETERMINING COSTS FOR CUTTING THE ACTIVE MOLD PLATES

The case study examines the economics of making a mould for the thermoforming of sofa sides out of composite material. This particular material is composed of hemp and polypropylene fibres [6]. Figure 3 shows the finished sofa side and the active mould elements, the core and the cavity. The section in figure 4 shows the shape of the active elements of the mould.

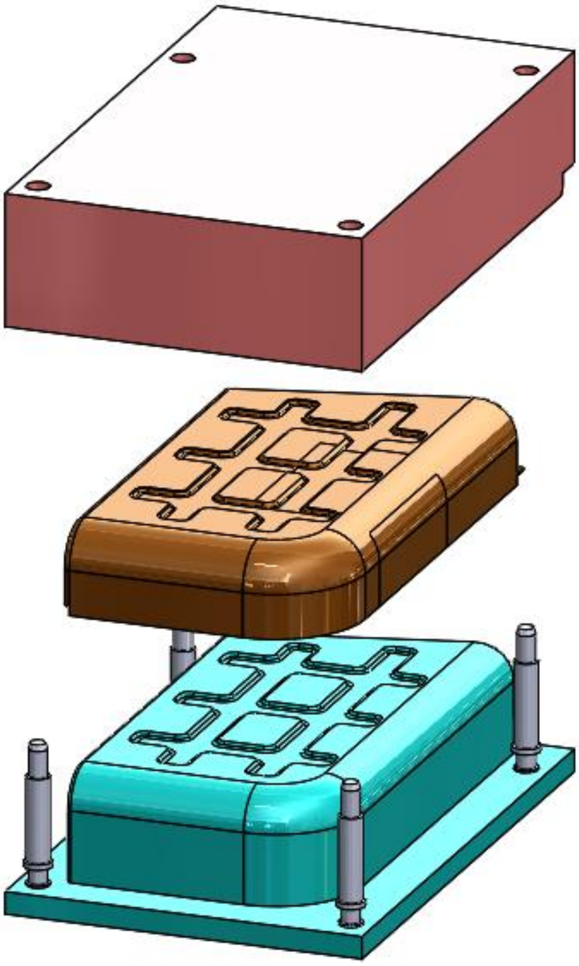

Figure 3. Mould for thermoforming a sofa side

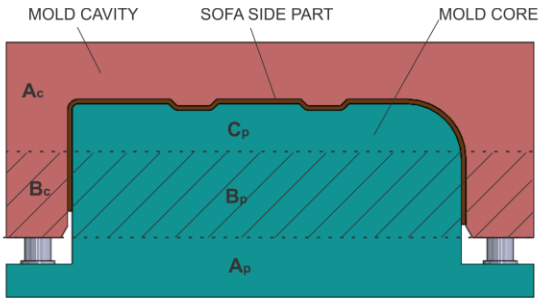

Figure 4. Cross section through the mould

The core and the cavity are made by machining on CNC machine tools. These active parts are made of aluminium plates (EN-AW 7075 alloy) of a large size (650x450x150mm). Figure 4 shows that a large part of the material is removed as chips. Such a mould is expensive not only because of the material, but also because of the machining. Milling complex surfaces at greater depths requires special tools and a drastic reduction of the depth of cut and feed because of tool chatter, which in turn increases machining time and costs.

The paper also examines a possibility of splitting the cavity and core each into multiple parts and then, later, assembling it. The cavity could be made of parts Ac and Bc and the core of parts Ap, Bp and Cp. Figure 4 shows that part Bp can be obtained from Bc by waterjet cutting. In order to cut Bp from Bc some extra material must be considered for the width of the cut. The sofa side thickness, 3,5-4 mm, allows cutting part B on an intermediate contour between the final surface of the cavity and core.

In order, with the data in table 3, for cutting the plates, is considered for the cost calculation.

Table 3. Values of the constants in table 1

L_c [mm]	L_r [mm]	P_M (€)	P_{FN} (€)	P_{MN} (€)	P_A (€/kg)	P_E(€/kW)	P_L (€/h)	P_W (€/m^3)
1547	178	130000	9.7	60	0.35	0.25	10.5	1
n [pcs]	n_1 [perf/pcs]	f_{rmed} [mm/min]	t_c [min]	t_r [min]	t_p [min]	T_{FN} [h]	T_{MN} [h]	T_M [h]
2	1	6000	0.047	0.039	0.12	40	100	13500

The neural model was used for simulating the data for cutting out the mould plates from a material of 80 mm thicknesses and different settings of the machine. The results are presented in table 4.

Table 4. Results for cutting of mould plates

Input data			Simulated data		
Thickness	Orifice diameter	Abrasive flow	Feed rate	Energy	Water
[mm]	[mm]	[kg/min]	[mm/min]	[kWh]	[l/m]
80	0.25	0.3	40.90212	8.53174	67.33512
80	0.25	0.4	35.71634	7.93697	62.64100
80	0.25	0.5	41.51288	7.36531	58.12930
80	0.30	0.3	40.35183	9.00647	71.08184
80	0.30	0.4	30.48734	8.67716	68.48286
80	0.30	0.5	60.90042	7.53555	59.47291
80	0.35	0.3	37.65820	9.92229	78.30976
80	0.35	0.4	71.87214	8.77113	69.22449
80	0.35	0.5	74.23828	8.24482	65.07063

Equations 1 – 11, the data in table 3 and the simulated results in table 4 (the last three columns) were used to determine the cutting costs. Based on experimental data, the set-up time t_{prep} is assumed to be equal to 30 min for two parts. The model offers the cutting feed rate for the best quality class Q5.

Table 5. Cutting costs for mould plates

No.	Thickness [mm]	Orifice diameter of nozzle [mm]	Abrasive flow rate [kg/min]	Cutting cost Quality class Q5 [€]	Cutting cost Quality Class Q4 [€]	Cutting cost Quality Class Q3 [€]
1.	80	0.25	0.3	**23.29**	19.83	16.80
2.	80	0.25	0.4	**27.06**	22.80	19.08
3.	80	0.25	0.5	**25.18**	21.26	17.82
4.	80	0.30	0.3	**23.71**	20.20	17.13
5.	80	0.30	0.4	**31.00**	26.01	21.64
6.	80	0.30	0.5	**19.03**	16.35	14.00
7.	80	0.35	0.3	**25.32**	21.56	18.27
8.	80	0.35	0.4	**16.73**	14.60	12.74
9.	80	0.35	0.5	**16.92**	14.71	12.78

For classes Q4 and Q3 the cutting feed rate was multiplied by 1.25, respectively 1.6, the other machine parameters being maintained at class Q5 value.

Table 5 shows the evolution of cutting cost for cutting the material thickness combining with values set of orifice diameter and abrasive flow rate. Similarly, with table 5, figure 5 show the cutting cost for the best three classes of quality.

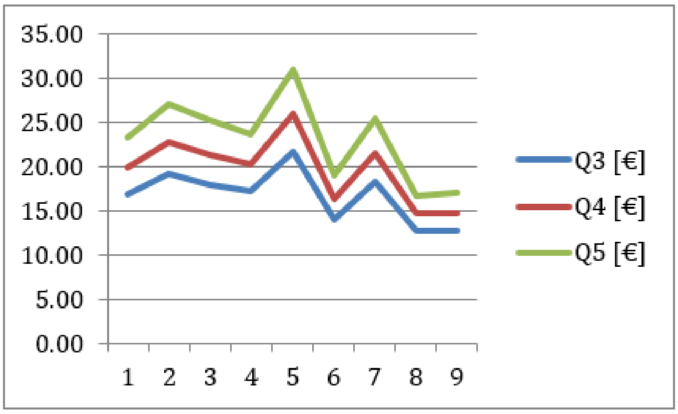

Figure 5. AWJ Cutting costs

4. CONCLUSIONS

This research shows that a neural computing model can be used to control AWJ process parameters and to determinate the cutting cost. The experimental program should consider the material properties, the cutting machine features and must contain many experiments, with a smooth variation of the input parameters.

The following steps need to be followed in order to develop a neural model that accounts for all the technological parameters of a waterjet cutting machine: selecting the input parameters; sorting the parameters into categories; determining the number of input variables; determining the output parameters; creating separate models for different types of machined materials; preparing the training data and the validation data; choosing the network structure and begin training; validating the model and using it commercially.

It is necessary to train the network with a set of data as large as possible in order to obtain an acceptable error. It is also recommended that the domain covered by training data is greater than the domain covered by normal work data. Another way to improve the results is to normalize the training data using different scaling factors.

For the example that involves cutting two mould plates, the model supplies different costs depending on the thickness of the material, the quality class and the machine features. The minimum cost 16,73 euros, for the best class of quality (Q5) of AWJ cutting is obtained using the following machine settings: orifice diameter of nozzle 0,35 mm, abrasive flow rate 0,4 kg/min and cutter feed rate 71,87 mm/min.

By cutting the Bp part of the Bc plate and using it in the core of mold construction, savings over 60 kg of aluminum and the cost of the material amounts to 600 Euros.

In addition, from the CAM simulations, the cavity processing time is reduced by 4, 5 hours and the core by about 4 hours. Taking into account the cost of CNC machinining processing of 35 Euro/hour, that means reducing the cost about 300 euros.

5. REFERENCES

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