Application of neural networks for optimization of metal cutting parameters in AWJ

Oleg Rudenko [1], Oleksandr Bezsonov [1], Oleg Ilyunin [1] and Nataliia Serdiuk[1]

[1] *Kharkiv National University of Radioelectronics, Nauky ave., 14, Kharkiv, 61166, Ukraine*

Abstract

Abrasive Water Jet (AWJ) is a modern technology where the process of cutting various materials is carried out using a stream of water mixed with an abrasive, which ensures a minimum of waste. AWJ is the safest and most effective tool to ensure cutting quality. This technology surpasses many other cutting methods in the variety of material processing, as a result of which it has found wide application in many branches of production. The article proposes a neural network model of direct propagation for identification of the maximum cutting speed with given limitations of other parameters with an adequacy coefficient of r^2=0.9891. The presented neural network can be used to develop soft-applications for operative adjustment of cutting modes for numerical software control of AWJ units.

Keywords

Artificial neural network, machine learning, abrasive water jet technology, optimization

1. Introduction

The rapid development of industry and technology drives continuous improvements in material processing, aligning with the concept of Industry 4.0 [1]. One of the most promising innovations in this sector is Abrasive Water Jet (AWJ) technology, where the material cutting process is powered by a high-pressure stream of water mixed with abrasive particles. This method significantly enhances cutting force and precision.

A key feature of AWJ is its versatility. AWJ cutting can be applied to a wide range of materials, including metals, glass, stone, concrete, plastics, and more. The technology's high precision allows for the cutting of complex and detailed shapes, making it ideal for high-precision manufacturing tasks. The advantages of AWJ include:

1. Water is inexpensive, non-toxic, readily available, and easy to dispose of.
2. The water jet functions as an almost ideal single-point cutting tool, facilitating the design of efficient automated systems.
3. Any contour can be cut with clean edges, allowing for intricate shapes and sharp corners. The process can be carried out in both horizontal and vertical positions.
4. Cutting does not have to start from the edge; no pilot hole is needed when cutting in the middle of a sheet.
5. Even if you already have plasma, laser, or gas cutting machines, a waterjet is an ideal partner, expanding the range of materials you can cut, providing superior quality on high-finish materials, and extending the thickness range for conventional materials such as steel.
6. The narrow cut width in some materials reduces waste and lowers costs.
7. The method does not generate heat, preventing the re-welding of edges in laminated materials, a common issue with traditional plastic cutting methods.

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oleh.rudenko@nure.ua (O. Rudenko); oleksandr.bezsonov@nure.ua (O. Bezsonov); oleh.iliunin@nure.ua (O. Ilyunin); nataliya.serdyuk@nure.ua (N. Serdiuk)

0000-0003-0859-2015 (O. Rudenko); 0000-0001-6104-4275 (O. Bezsonov); 0000-0002-7751-4814 (O. Ilyunin); 0000-0002-0107-4365 (N. Serdiuk)

8. No heat generation means no thermal degradation of the work material.
9. Fire hazards are minimized, making the process suitable for explosive environments.
10. Blade clogging is avoided, which is a problem when mechanically cutting sticky materials.
11. Fewer moving parts reduce the need for maintenance.
12. Cutting forces are directed in a single direction, with negligible lateral forces allowing cuts close to the edge.
13. A dust-free environment is particularly advantageous for cutting asbestos and glass fiber insulations, which typically produce dust.

There are numerous potential applications for AWJ technology: the method can be more effective across a wide range of structural materials with specific thicknesses, including aluminum, titanium alloys [3], steel [4], brass, front-hardened steel, tool steel [5], stainless steel, mild steel [6], copper, plastic, quartz, ceramics [7], laminates, composites [8], easy-to-use materials, leather, stone [8-9], granite, marble [10], deep-frozen fish and meat [11]. After drying, the thickness of the cut materials can be typical for stainless steel up to 100 mm, aluminum 120 mm, glass 100 mm and stone 140 mm [12]. Figure 1 shows some examples of production using AWJ technology [2]. Intelligent models can become powerful tools for enhancing the accuracy, smoothness, and efficiency of sheet metal cutting with AWJ, making the process more precise, efficient, and cost-effective.

Figure 1: Application of AWJ technology

Developing these models involves data collection and analysis, a deep understanding of AWJ processes, and the implementation of machine learning algorithms and other artificial intelligence technologies, which will further advance this innovative technology.

2. Problem analysis

Thus, the procedure for identifying the depth of the AWJ technology using an additional fuzzy logic (FL) system is presented in [13]. As a result, the parameters of the cutting depth are determined by the pressure of the water, the mass of the abrasive, the diameter of the focusing nozzle and the transverse fluidity of the jet. In [14], the modeling of AWJ is presented using the mathematical apparatus of fuzzy logic, optimization of the rule base, the data base from subsequent genetic algorithm (GA) and double GA code. Regardless of the modeling of additional fuzzy logic, the output parameters, but the surface roughness R_a, and *MRR* - the softness of the material (metal), were transferred for various combinations of parameters in the AWJ process, such as the pressure in on the exit diameter of the nozzle, the movement of the jet of the abrasive mix, the mass concentration of water and the mass concentration of abrasive particles, the speed of feeding the mixture to the nozzle, and the speed of movement of the mixture between the nozzle and the material surface. In [15], an advanced algorithm for optimizing a process parameter based on "teaching-learning-based optimization (TLBO) algorithm" is presented for finding optimal process parameters. In [16] it is conducted experiments on cutting borosilicate glass using the AWJ method. The depth of cutting is determined by various adjustments of process parameters - water pressure, fluidity of abrasive flow, fluidity of movement and delivery to the material. The model of cutting depth, broken down in this way, reveals the infusion of various parameters into the cutting of an amorphous borosilicate glass with the help of AWJ. The optimal adjustment of the parameters of the server depends on the additional swarm algorithm (PSO).

Parameters associated with the AWJ machining process are presented in [17]. Many predecessors focused on the wide range of material parameters, such as the softness of the material, the roughness of the surface, the depth of the cut and the microstructural strength of the selected material. Even a small number of previous researchers have proposed methods for painting the surface of the bone and cutting [18]. Based on the thorough knowledge of the AWJC metal forming mechanism, various methods such as polishing, turning, drilling [19], milling and surface finishing [20] were subdivided with an emphasis on economy. It was determined that the AWJ processing is the best for 2D and 3D processing [19, 20]. There are no differences between cutting mild structural steel, or materials made of stainless steel, cast iron - all are processed equally well, and the main thing: the accounting parameters for the same type of material (metal) are the same. If there are high quality requirements during the machining process, the parameters must be selected correctly, and the machining process must be completed before the cut deformation areas appearance or excessive surface erosion. Optimization of parameters for a wider range of material and reduction of the recommended surface shortness was achieved [21] by integrating the Taguchi method with analysis of variance of variation of alternatives (ANOVA). The analysis shows that the surface area increases the MRR, while the surface roughness greatly increases the fluidity of the abrasive flow. It has been discovered [22] that the most important factors for working material made of stainless steel 403 are the pressure of water, which is followed by reaching the wet surface and the fluidity of the abrasive flow. By means of response surface methodology (RSM) [23] the optimal combination of factor set points was determined that ensures a minimum roughness of the surface machined by AWJ. In [24] it was adopted the RSM with the Box-Behnken Design (BBD). The research results showed that the transverse fluidity is the flow factor due to the water pressure, the abrasive flow fluidity and the sharp pressure. Despite the large volume of scientific works, no studies devoted to intellectual models of the influence of operating parameters on the cutting speed of abrasive particle size and density have been found. Another important issue is the reuse of rather expensive abrasives in TP. After the initial use in the TP cycle, abrasives change their: particle size, density, but the main cutting characteristic - hardness - remains almost unchanged. The cost of the abrasive will reach zero [25] after the fourth use. Taking into account that the speed is one of the main indicators of the efficiency of the cutting process, it is advisable to develop an intelligent model for identifying the maximum speed of AWJ cutting of sheet metal under the given limitations and characteristic parameters of the process, in order to the properties changes of the abrasive during repeated use.

3. Intelligent model of the cutting speed estimation

3.1 Description of AWJ cutting process

The tool for AWJ cutting of materials is a fluid jet formed in a certain way, which comes out of a special nozzle with a diameter of 0.08-2.5 mm with a supersonic speed (1000 and more m/s) and provides a working pressure on the workpiece of 400 MPa and more. The liquid in the form of a jet under pressure acts on the material by area, compresses it in the direction of the jet movement, as a result, a compaction core is formed in the material, which expands perpendicular to the jet velocity vector. The latter can damage the material. Since the distance from the nozzle cut to the surface of the material is several millimeters, the jet pressure exceeds the strength limit of the material - due to this, cutting is carried out. The liquid jet acts on the material similarly to a solid tool. A depression is formed in the material, and if the jet is moved, a gap of a certain depth is formed, which depends both on the pressure in the jet and on the hardness of the abrasive and the strength of the material. The energy of the jet decreases with an increase in its length due to an increase in its cross-section, turbulent motion, disintegration into parts, etc., therefore, the nozzle tends to be brought closer to the processed material. The general view of the AWJ unit (a) and the scheme of the cutting head (b) is presented in Fig. 2.

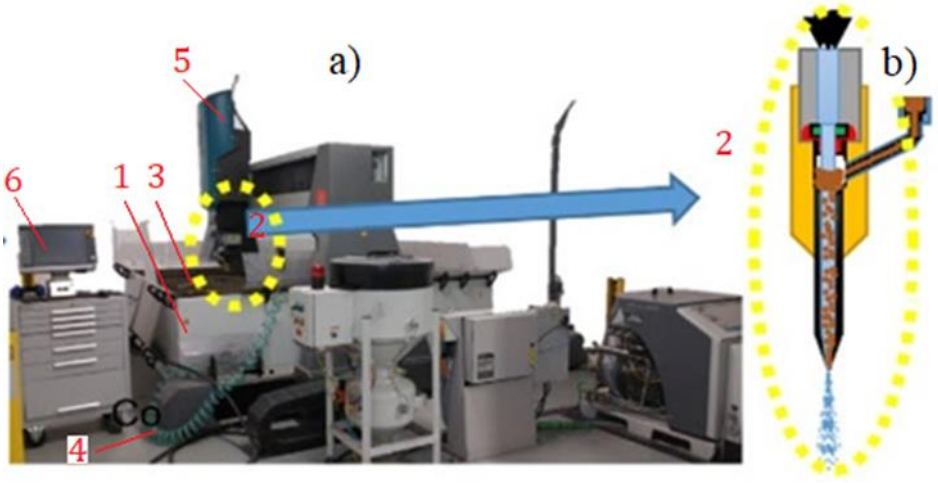

Figure 2: General view of AWJ unit (a) and (b) diagram of the cutting head

The complex for AWJ necessarily includes: 1 – a high-pressure pump; 2 – cutting head; 3 – coordinate table and drives for moving the cutting head; 4 – hydraulic system for supplying high-pressure liquids; 5 – abrasive supply system (for hydroabrasive cutting); 6 - numerical software control system.

Additionally, the complex can be equipped with: a device to prevent the cutting head from colliding with the workpiece; a system of several cutting heads; mechanical system of preliminary over-drilling; a water jet trap that quenches its energy and also serves to collect spent abrasive, and a number of others.

3.2 A generalized empirical model of AWJ cutting

In general, until recently, empirical AWJ models were developed based on a set of experimental data using regression analysis techniques. The common generalized AWJ model with a fairly high degree of agreement (2÷0.2%) of experimental and model-calculated data [26] connects the process variables:

$$D_c = A\frac{\dot{m}_a}{\rho_w d_j u}\left(\frac{P}{E}\right)^{\alpha} \cdot \left(\frac{s}{d_p}\right)^{\beta} \cdot \left(\frac{\dot{m}_a s}{d_p^3 \rho_p u}\right)^{\gamma} \cdot \left(\frac{\rho_p u^2}{P}\right)^{\delta}, \quad (1)$$

namely: D_c – cutting depth;

A, α, β, γ, δ – are constants of the cutting depth power function $D_c = A \cdot P^{\alpha} \cdot s^{\beta} \cdot \dot{m}_a^{\gamma} \cdot u^{\delta}$, empirical indicators that take into account the real conditions of the process and the specifics of the model application;

P – water pressure, (MPa); u – speed of movement of the nozzle (cutting) (mm/s);

s – distance from the nozzle to the target material, (mm);

$\dot{m}_a$ – mass flow of abrasive, (g/s);

ρ_p – particle density, (kg/m^3);

ρ_w – density of water (kg/m^3);

d_j – jet diameter, (mm);

d_p – the average diameter of the abrasive particle, (mm);

E – modulus of elasticity of the material (MPa).

The most important variables influencing the process [27] are: cutting depth, water pressure, abrasive mass consumption, nozzle movement speed, distance from the nozzle to the surface (Fig. 3).

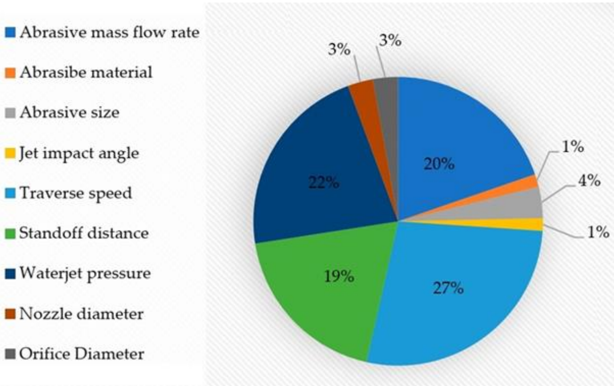

Figure 3: The most influential variables in the AWG cutting process

3.3 Experimental data

Mild steel is the most common form of steel because its relatively low price corresponds to material properties acceptable for many applications. It is used in very large quantities, for example, as structural steel. This is the most versatile form of steel. M250 mild steel plates were used as samples. The dimensions of these mild steel plates were 150 x 100 x 60 mm.

The equipment used for processing the samples was an AB Best Matic - Ingersoll Rand Water Jet Sweden KMT head cutter (Fig.4 [28], with author's corrections) equipped with a pump with a design pressure of 500 MPa and stepwise pressure regulation.

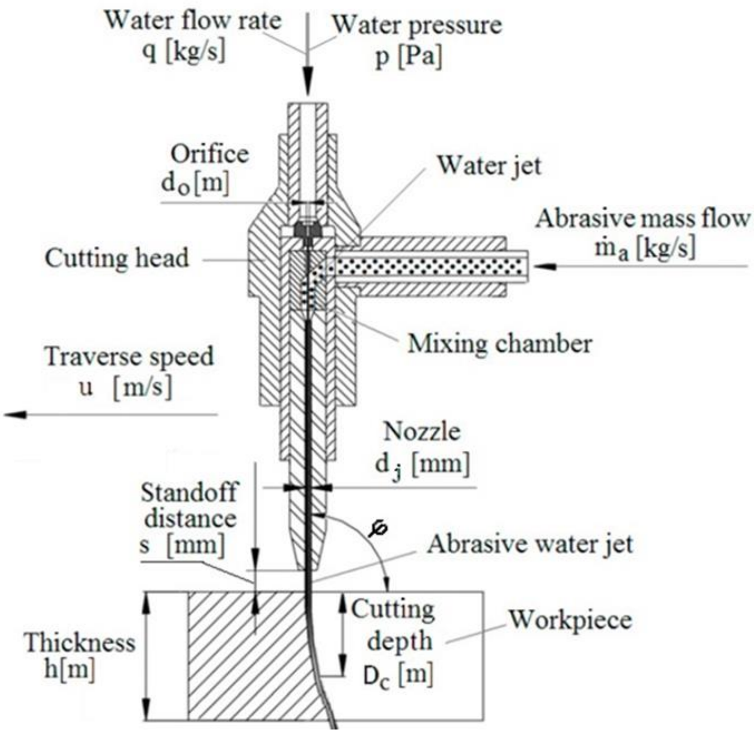

Figure 4: The cutting head scheme [27] (with author's corrections)

Table 1 shows the AWJ parameters that will be included in the model, the gray background highlights the non-influential parameters or constants.

The most favorable conditions for effective implementation of AWJ cutting can be achieved by choosing its optimal parameters: the pressure of the working fluid, the shape and diameter of the nozzle opening, the distance of the nozzle from the surface to be cut, the feed rate, the number of passes (or the number of nozzles per unit cutting length), material cutting is required.

After transformations of equation (1) taking into account the values of empirical coefficients *α, β, γ, δ* given in [29] and real data, the reference calculation expression was obtained:

$$u = \left(\frac{12.106 \cdot P^{0.311} \cdot \dot{m}_a^{0.119} \cdot d_P^{1.77} \cdot \rho_P^{0.867}}{D_c \cdot s^{0.008} \cdot \rho_w \cdot d_j} \right)^{\frac{1}{0.147}}, \quad (2)$$

where in the formula:
u – speed of movement of the jet (cutting), (mm/s);
P – water pressure, (MPa);
$\dot{m}_a$ – mass flow of abrasive, (g/s);
d_p – the average diameter of the abrasive particle, (mm);
ρ_p – particle density, (kg/m^3);
D_c – cutting depth, (mm);
s – distance from the nozzle to the target material, (mm);
ρ_w – density of water (kg/m^3);
d_j – jet diameter, (mm).

Table 1
Categories of AWJ cutting parameters and their ranges

N	Technologies	Hydraulics	Abrasive/ material	Mixing
	Distance, s =(1.8; 3.5; 5.0)x10^{-3}*m*	Water pressure, P =(265÷400) x 10^6, step 5 x 10^6 Pa	Type of abrasive (hardness) - granite	The length of the focusing tube, l_f (*m*)
2	Head speed, u = (0.5; 1.5; 2.5)x10^{-3} *m·s*$^{-1}$	Orifice diameter, d_o, = 1.05 x10^{-3}*m*	Size/ density ρ_p = 4100 ÷ 5150 *kg/m*^{3}	Diameter of the focusing tube/jet, d_j = 0.35 x10^{-3}*m*
3	The movement direction of is linear, z = 180°	Orifice material: artificial sapphire	The shape is a cube	The focusing tube material is steel
4	Attack angle, φ =90°		Particle diameter, d_p =(0.18; 0.105)·10^{-3}*m*	Abrasive supply direction, f_d =90°
5	Depth of cutting, D_c, x10^{-3}*m*		Abrasive feed rate, m_a = 8; 12.5; 15 *g·s*$^{-1}$	
6	The material is steel M250, ρ_s=7850 *kg/m*^{3}		Elasticity modulus, E = 210000 x10^6Pa	

The general nature of the AWJ process model behavior, depending on the some pairs of parameters extracted from experimental data set, is shown in the graphs (Fig.5).

Experimental data set (1943 measurements [30], where every third record corresponds to the use of a secondary abrasive with the characteristics ρ_p = 5150 *kg/m*^{3}, d_p = 0.105·10^{-3}*m*; a new abrasive characteristics ρ_p = 4100 *kg/m*^{3}, d_p = 0.18·10^{-3}*m*), pre-processed using weighted principal component analysis method (WPCA) similar to that presented in study [31], was provided by ScienceLabNURE#11 Computational Intelligence. Abrasive mass flow $\dot{m}_a$ and fluid pressure P have the greatest influence on AWJ performance. The AWJ process is possible when the pressure of the liquid jet per unit surface area of the cut exceeds the strength limit of the material being processed. All things being equal, a further increase in the pressure of the liquid jet (due to an increase in its kinetic energy) will lead to a potential increase in the thickness of the material cut in one pass.

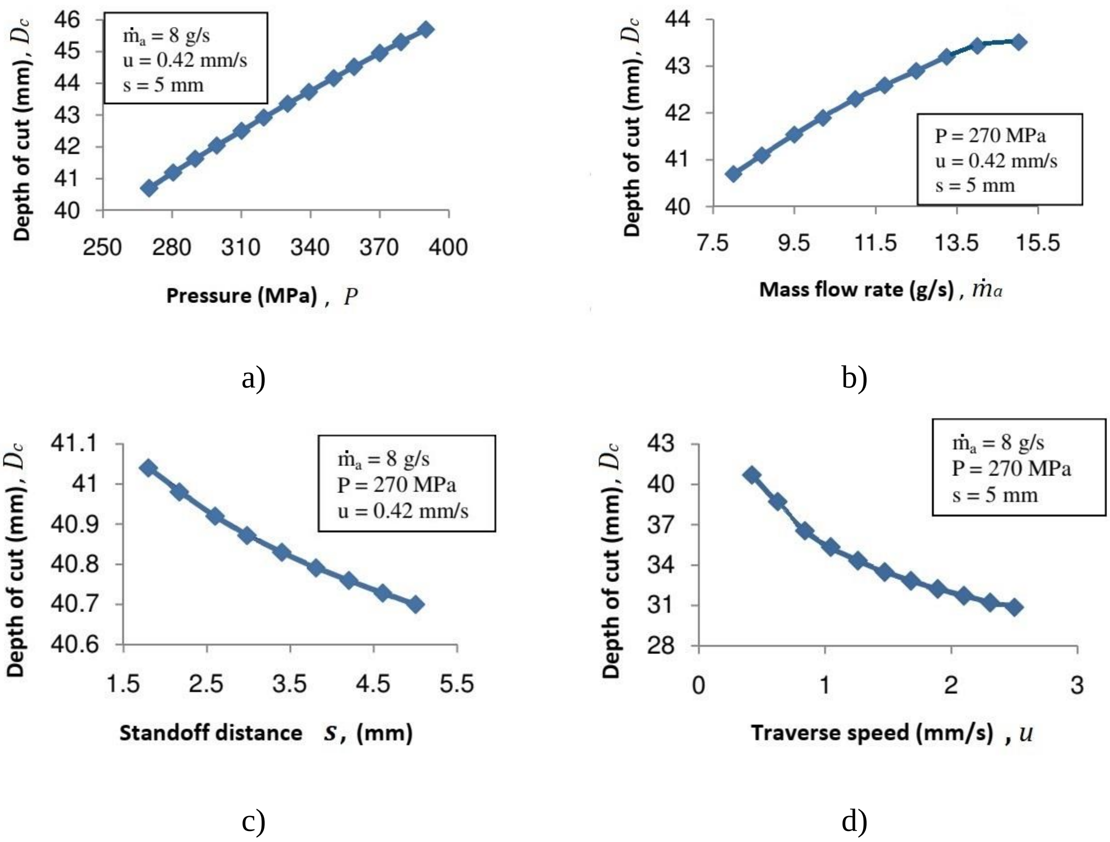

Figure 5: The influence of combinations of some parameters pairs on AWJ cutting [27]

3.4 Model configuration

Considering equation (2), in general, the AWJ model can be presented as follows:

$$u = F(P, \dot{m}_a, d_P, \rho_P, D_c, s, \rho_w, d_j), \quad (3)$$

where, according to experimental measurements (Table 1), the following parameters are assumed to be conditionally constant: d_p, ρ_p, ρ_w, d_j.

A pair of variables (d_p, ρ_p) characterizes the properties of abrasive particles, and are present in power-law form in the D_c parameter. Variables (d_p, ρ_p) are present in measurements in two combinations: new abrasive (0.00018; 4100) and abrasive after the first cycle of use (0.000105; 5150). About 1300 measurements correspond to the first combination.

In this way, using WPCA, the dimensionality of model (3) can be reduced:

$$u = F(P, \dot{m}_a, D_c, s), \quad (4)$$

choosing the artificial neural network structure 4 – N – 1, where N =10 is the number of neurons in the hidden layer. In the MathLab 6.23 environment, a number of experimental tests were conducted with the number N with sigmoidal activation functions, and as a result, the following structure was chosen (Fig. 6).

The input values of the independent variables for training and testing were randomly assigned to the training and test sets in the ratio of 70% to 30% and normalized according to the following procedure:

$$\overline{d} = \left(\frac{d - d_{min}}{d_{max} - d_{min}}\right) \times (n_{max} - n_{min}) + n_{min}, \quad (5)$$

where $\overline{d}$ – normalized data values,

d – numerical data values of each independent variable;

d_{max}, d_{min} – maximum and minimum data values, respectively, of each variable;

n_{max}, n_{min} are the minimum and maximum values, respectively, of the new range.

In our case, $n_{min} = 0$ and $n_{max} = +1$.

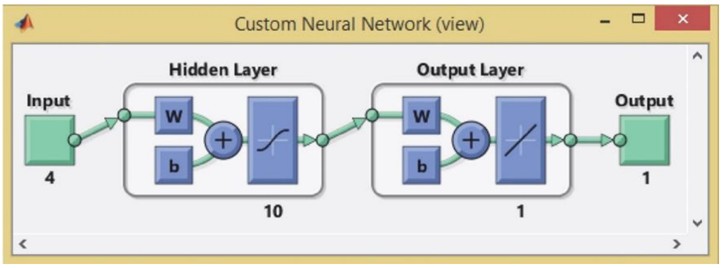

Figure 6: The simulated ANN structure

Equation (5) takes the form:

$$\overline{d} = \left(\frac{d - d_{min}}{d_{max} - d_{min}}\right). \quad (6)$$

The network was trained using a back-propagation algorithm.

The training, validation and test errors of several ANN configurations were evaluated using four statistical parameters, namely absolute average relative deviation (AARD%), mean squared error (MSE), root mean squared error (RMSE) and correlation coefficient r^2. The mathematical equations of these parameters [32] are given below:

$$AARD\% = \frac{100}{N}\sum_{i=1}^{N}\frac{\left|u_i^{exp} - u_i^{ANN}\right|}{u_i^{exp}}, \quad (7)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(u_i^{exp} - u_i^{ANN})^2, \quad (8)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(u_i^{exp} - u_i^{ANN})^2}, \quad (9)$$

$$r^2 = \sum_{i=1}^{N}\left(u_i^{exp} - \overline{u}\right)^2 - \frac{\sum_{i=1}^{N}\left(u_i^{exp} - u_i^{ANN}\right)^2}{\sum_{i=1}^{N}\left(u_i^{exp} - \overline{u}\right)^2}, \quad (10)$$

where u – is the cutting speed;
u^{exp} and u^{ANN} – represent experimental (u^*) and ANN-estimated cutting speed;
$\overline{u}$ – is the average value of the experimental cutting speed;
N – is the number of pairs of values used.

In the training, validation, and testing processes, the $AARD\%$, MSE, and $RMSE$ values on the corresponding validation datasets become smaller than those of the other configurations, while the r^2 value becomes higher. Changing the number of neurons in the hidden layer and changing the type of activation functions to tangential or radial-basis did not improve the predicted results: the values of r^2 continuously decreased, while the values of other errors increased. The optimal configuration of ANN (4–10–1) was chosen for the investigated AWJ cutting process with the following values of testing errors: $AARD\% = 0.921$, $MSE = 4.5248 \cdot 10^{-11}$ та $RMSE = 6.7267 \cdot 10^{-6}$, $r^2 = 0.9891$.

3.5 Simulation results

The developed ANN behavior is presented with three-dimensional surfaces. A weak nonlinearity of the relationship between the parameters P, D_c, s is shown in Fig. 7: with an increase in water pressure P and a decrease in the distance from the jet to the surface of the material being processed s, the cutting depth D_c increases at a constant processing speed u. Fig. 8 shows a nonlinear dependence of the parameters $P, \dot{m}_a, D_c$ with an obvious minimum region of the cutting depth parameter D_c. Fig. 9 shows dependence of the parameters u, P, D_c with an obvious maximum region of the cutting depth parameter u – speed of the jet movement (surface cutting).

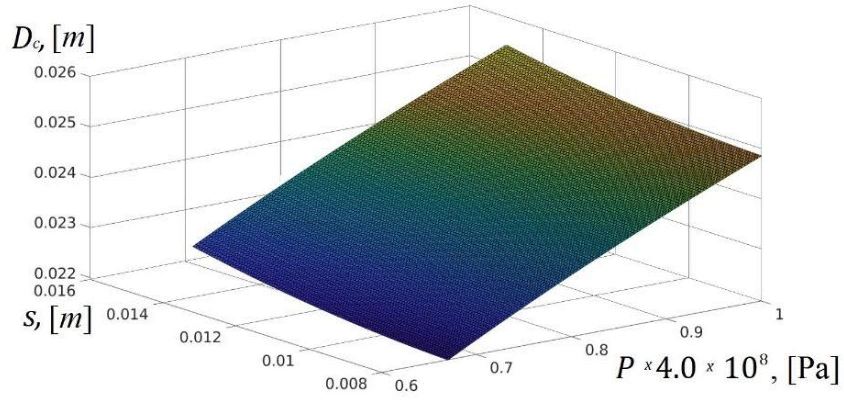

Figure 7: The 3D surface D_c=F (s, P)

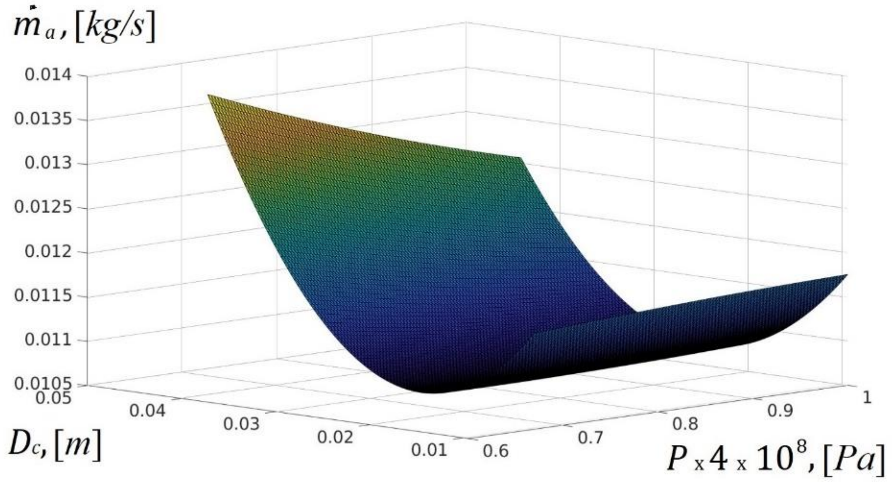

Figure 8: The 3D surface m_a=F (D_c, P)

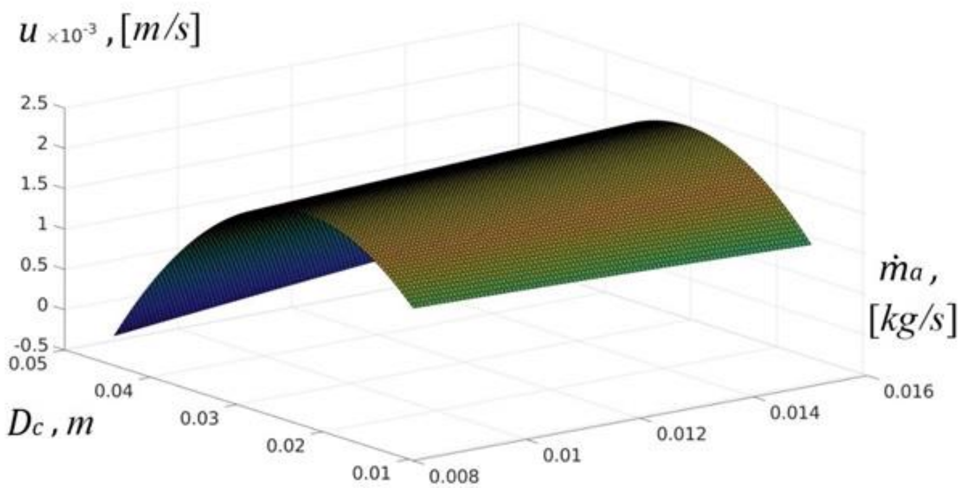

Figure 9: The 3D surface u=F (D_c, m_a)

The regulated parameters P – water pressure and $\dot{m}_a$ – abrasive mass flow have an ambiguous effect on the output of the model u: the ANN training was carried out taking into account two types of abrasives with different characteristics d_p – the average diameter of the abrasive particle and ρ_p – particle density.

To choose the optimal design, as in most similar processes, it is necessary to evaluate several options for setting parameters. For this purpose, it is necessary to use the value criterion appropriately, solving the optimization problem of minimizing the operational costs of C_{OPM} to fulfill the task u and constraints D_c – cutting depth and s – distance to processed surface.

Fig. 10 shows an example of the identification of the optimal parameters set of waterjet cutting using a neural model (white line on the graph interval $P = (320; 368)\ MPa$). It leads to the need to solve the optimization task according to criterion [33] with the following structure:

$$C_{OPM} = \begin{cases} \dfrac{max(u)}{for(B_1 \cdot \alpha_1 \cdot P + B_2 \cdot \alpha_2 \cdot \dot{m}_a) \rightarrow min} \end{cases}, \quad (11)$$

where B_1 is the specific cost of ensuring the necessary pressure of the water-abrasive mixture, taking into account the cost of electricity per 1 m of cut with a given depth;

B_2 – the specific cost of ensuring the mass circulation of the required diameter d_p and density ρ_p of the abrasive or an equivalent mixture of abrasives;

α_1, α_2 – weight coefficients of the importance of factors, determined by expert-technologists.

As can be seen in Fig.10, there is a set of solutions that satisfy the conditions $s = 5mm$, restriction $D_c = 35mm$ and task $u = 1.5mm/s$ (highlighted in white for parameters $\dot{m}_a = (0.008; 0.016)\ g/s$, $P = (320; 368)MPa$). So in Fig.10 point a corresponds to the use of a secondary abrasive with the process parameters $\dot{m}_a = 0.0115\ g/s$, $P = 368\ MPa$, and abrasive characteristics $\rho_p = 5150$ *kg/m*^{3}, $d_p = 0.105 \cdot 10^{-3} m$; point a' corresponds to the use of a new abrasive with characteristics $\rho_p = 4100$ *kg/m*^{3}, $d_p = 0.18 \cdot 10^{-3} m$ and process parameters $\dot{m}_a = 0.008\ g/s$, $P = 320\ MPa$. To select the type of abrasive used in order to improve the efficiency of the cutting process, criterion (11) is applied.

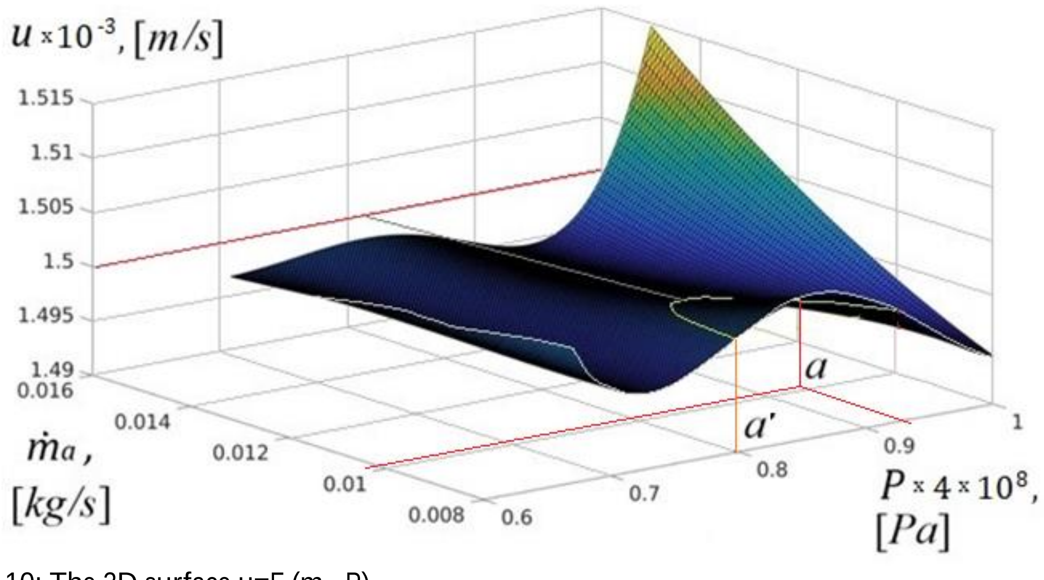

Figure 10: The 3D surface u=F (m_a, P)

4. Discussions

The production of abrasives is a fairly energy-intensive and resource-intensive production that has a negative impact on the environment [25]. In the article [28] the problem for simultaneously optimizing two objectives (productivity and operating cost) with three factors (travel speed, abrasive mass flow rate, and standoff distance) and three constraints (perpendicularity tolerance, surface roughness limit, and travel speed for separation cut) was solved using the multi-objective genetic algorithm (MOGA). The presented model implements a two-stage intelligent procedure that works with experimental data pre-processed by the PCA method, is easier to debug and is aimed only at the operational assessment of the efficiency of reusing abrasives. The model can be integrated into the AWJ machine control system as a software application.

5. Conclusions

Optimization of AWJ cutting performance aims to achieve better product quality, increase productivity and cost efficiency.The article offers an intellectual approach to the identification of optimal metal cutting parameters using AWJ technology. After machine learning, the ANN model with structure 4-10-1, which takes into account the changed parameters of the abrasive when it is reused, was achieved. The proposed ANN model determines the cutting speed when other parameters are set with an adequacy coefficient of r^2 = 0.9891. It is proposed to use a cost criterion for choosing the optimal parameters of cutting process from a set of acceptable solutions. The proposed approach can be used for the development of soft applications for the operational configuration of cutting modes for numerical software control of AWJ units.

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