The Simulation Model of Highpressure, Suspension Waterjet Cutting Process of Marble

Andrzej Perec[1],

[1] Koszalin University of Technology,
Institute of Mechatronics, Nano- and Vacuum Technology,
Raclawicka Street 15-17, 75-620 Koszalin, Poland
andrzej.perec@tu.koszalin.pl
http://www.imnitp.tu.koszalin.pl/

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Abstract. In this article, the usage of artificial neural networks for the marble's cutting process simulation by a hydroabrasive suspension waterjet, which pressure has been reduced to 30 MPa, are presented. A triple layer neural network of the perceptron type, which is taught by the errors backward propagation algorithm, has been applied. The article provides detailed description of neural network. This neural network simulates the marble treatment process and predicts its efficiency due to given parameters. Impact of the most important parameters, as pressure, traverse speed, abrasive flow rate, length and diameter of nozzle was shown. The process parameters, which allow to achieve the maximum cut's depth have been determined.

1 Introduction

In the article refers the simulation model cutting of hydroabrasive suspension waterjet cutting process of marble [3]. Laboratory investigations were carried out on test stand [4] has been built from two containers and four independent hydraulic branches, which enable an adjustment of the basic flow parameters. Each branch consists of the following valves: a cut-off valve, a throttle valve, a non-return valve and a manometer. An overflow valve performs the function of an element preventing an excessive increase of pressure. It is set at the pressure of 30 MPa.
A hydraulic monitor P26 type is the source of a high pressure. It is made on the basis of elements of a plunger pump made by an WOMA company. It makes it possible to obtain the maximum pressure of 75 MPa with the rate of water flow of 75 dm^3/min.
The materials were cut by directing the hydroabrasive jet perpendicular to the machined material [6], and then a rectilinear traverse speed in relation to the working nozzle. The thickness of the samples was selected in such a way that, with the most effective machining parameters, cutting through these should not occur, which would make it difficult to correctly determine the depth of the cut.
Rock used for tests, marble, is a metamorphic rock resulting from the metamorphism of limestone composed mostly of calcite (a crystalline form of calcium carbonate, $CaCO_3$). It is extensively used for sculpture, as a building material, and in many other applications. The word 'marble' is colloquially used to refer to many other stones that

are capable of taking a high polish. This metamorphic process causes a complete re-crystallization of the original rock into an interlocking mosaic of calcite, aragonite and/or dolomite crystals. The temperatures and pressures necessary to form marble usually destroy any fossils and sedimentary textures present in the original rock.
Pure white marble is the result of metamorphism of very pure limestone. The characteristic swirls and veins of many colored marble varieties are usually due to various mineral impurities such as clay, silt, sand, iron oxides, or chert which were originally present as grains or layers in the limestone.

2 Artificial Neural Network

The artificial neuron is the basic unit of the artificial neuronal net similarly as in the case of neuronal biological nets, nervous cell is the basic unit. The properties of the artificial neuron answer is the most important [5] properties of the biological neuron. You should always remember that artificial equivalents functions are very simplified [8] in the relation to real nervous cells. The artificial neuron makes up the kind of the converter about many entries and one exit. One can distinguish two blocks of the processing of the information inside him. The first is the adding up block, where input signals are multiplied by there importance and added up.
The topology of the net consisting from 5 neurons of the input layer, 30 neurons of hidden layer and one outputs neuron (Fig.1.) was accepted to prediction [1] the water-jet cutting process.

The entrance data directed to the input layer present the most important parameters of the cutting process, which efficiency depends on them. These are:

- **Jet pressure**, at the same time determining its speed and kinetic energy. Because the jet energy grows with the square of the speed, it is the most important parameter. And therefore increasing of the pressure causes the increase of the cut's depth.
- **Abrasive flow rate**, influencing on the jet's kinetic energy. Increasing of the abrasive flow rate causes the increase of energy and cut's depth. But the excessive increasing may cause the drop of stream's energy, as a result of the unfavourable interaction between grains.
- **Traverse speed**, determining the contact time of abrasive grains with the target. Increasing of the traverse speed generally leads to the fact that less abrasive grains are being put in touch with the target, what causes the less efficiency of the cutting process. Reducing of the traverse speed leads to the increasing of the slot's cutting depth.
- **The length of a nozzle** is directly connected with obtaining maximum energy by the jet. In a nozzle, which is too short, the jet is not able to achieve a proper speed (to speed up). However, a too long nozzle may cause the drop of energy, because of the hydraulic losses and rubbing by abrasive during the flow.
- **The nozzle's diameter**, connected with the abrasive flow rate, pressure and hydraulic power. This value is also connected with the width of a cutted slot. The aim is to minimize the diameter, in order to achieve the maximum depth in the range of determined capacity of the cutted slot.

The cut's depth has been used as an output parameter. It is parameter, which describes in the best way abrasive properties of the jet. And therefore it is most often used for this purpose. Optimisation of the cutting process is usually done in order to achieve the maximum cut's depth.

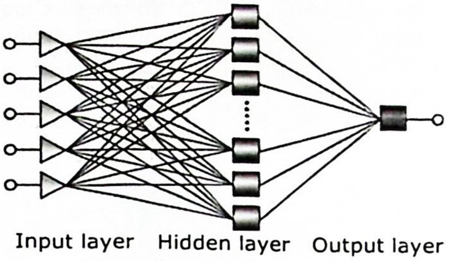


Fig. 1. Artificial Neural Network digram

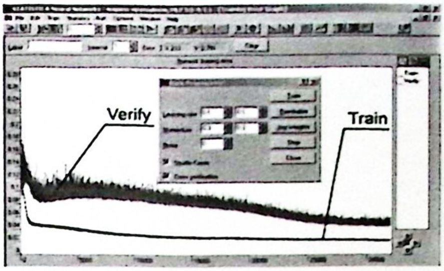


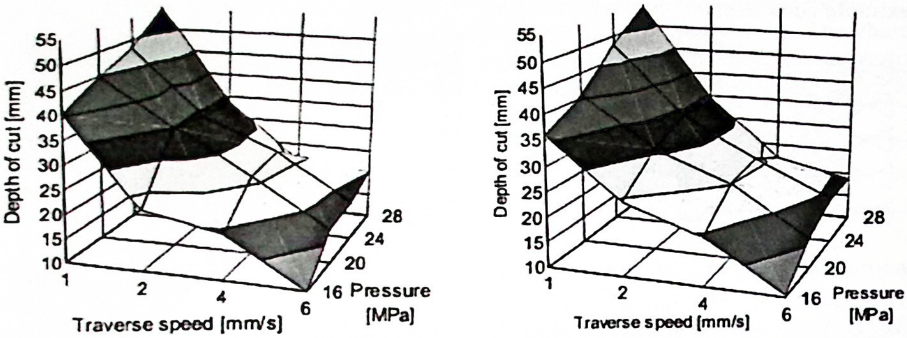
Fig. 2. Diagram of learning the ANN

In the hidden layer neuron has logistic activation function. This is an S-shaped (sigmoid) curve, with output in the range (0,1). The most commonly - used neural network activation function. Neurons in input and output layer have linear activation function. The quantity of input and output neurons were taken from the accessible results of investigations directly. 96 laboratory tests results, containing all 5 input values and one output value, have been used for the teaching process of neural network. From process of training excluded 10% of chances, which one used to verification of training process. The net was learning with the algorithm of backward propagation, getting stable results after 30 000 iterations (Fig. 2.) with learning rate of 0.1 and momentum 0.3. To research [2] was utilized the commercial Statistica Neural Networks for Windows application of the StatSoft Inc company.

3 Effects of Artificial Neural Network Modelling

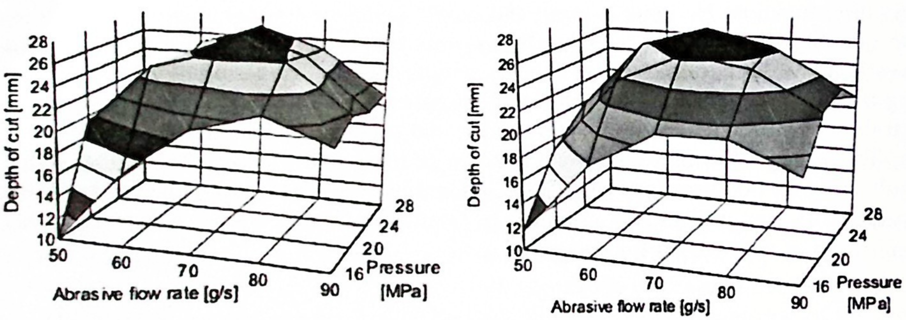
Fig. 3b depicts the results of the artificial neural networks modeling of hydroabrasive suspension jet cut in a variable pressure and traverse speed conditions. In comparison Fig. 3a presents the laboratory analysis in which the surface was adjusted using the least square method. The graphs in the whole show a great convergence in the material cut depth values, a near identical character of dependence and approximate maximum value. In this case maximal between modeled and laboratory values does not go beyond 4.34mm and average discrepancy is equal 0.76mm.

Laboratory studies results, conditioned by variable pressure and abrasive flow rate conditions, are presented in Fig. 4a. Modeling effects are shown in a Fig. 4b. In this case, it can be also observed that modeling effects are compatible with lab studies. The greatest discrepancy is observed at the maximum pressure and abrasive flow rate. In this case standard maximal discrepancy between modeled and laboratory values does not go beyond 4.04mm and average value is 0.72mm. Fig. 5a depicts a laboratory study on marble cutting with the use of 50mm long nozzle while Fig. 5b depicts artificial neural networks modeling of that process. Here also a great modeling and lab studies compatibility is observed. At maximum cut depth deviation does not exceed 1mm. In this case maximal discrepancy between modeled and laboratory values does not go beyond 1.98mm, and average discrepancy is 0.35mm



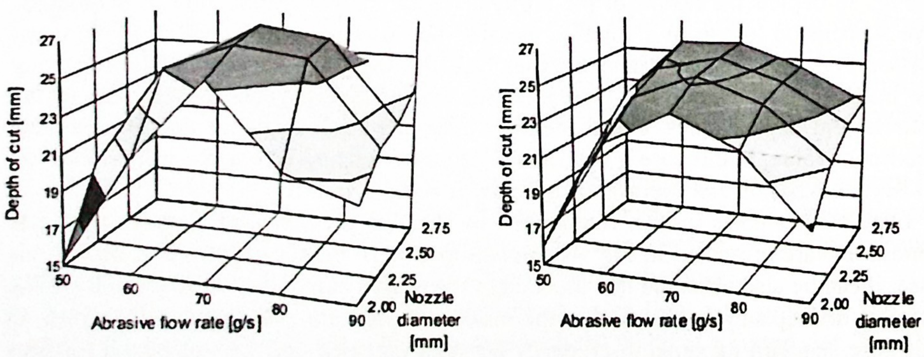
a) laboratory analysis b) modeled with the use of ANN

Fig. 3. Influence traverse speed and pressures onto depth of cutting.



a) laboratory analysis b) modeled with the use of ANN

Fig. 4. Influence abrasive flow rate and pressures onto depth of cutting.

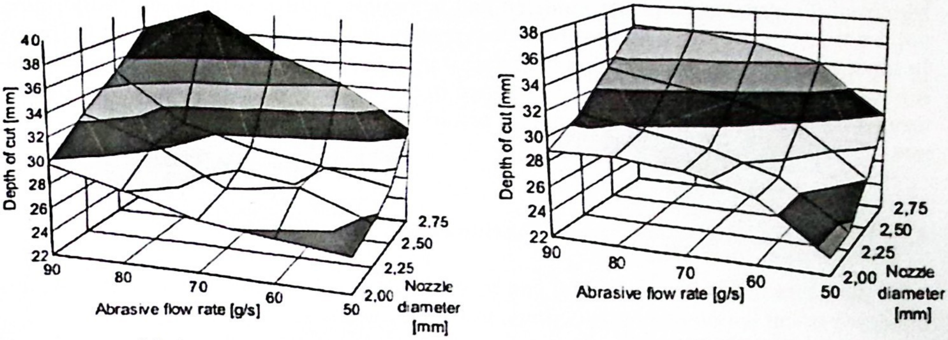


a) laboratory analysis b) modeled with the use of ANN

Fig. 5. Influence abrasive flow rate and 50mm nozzle diameter onto depth of cutting.

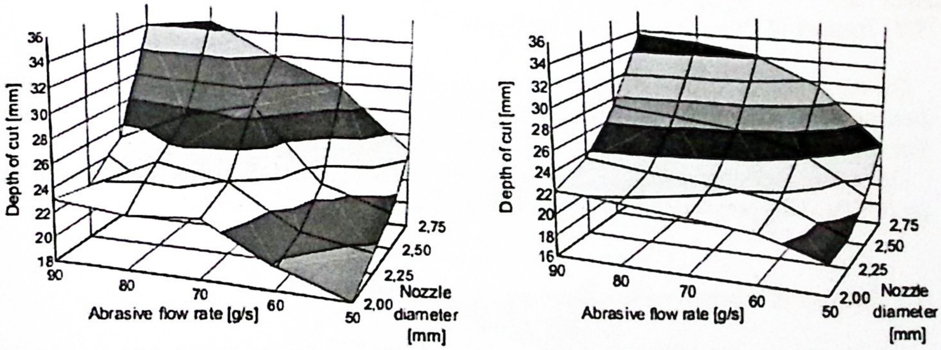
Cutting with the use of 75mm long nozzle is presented in Fig. 6a, while its artificial neural network modeling is shown in graph 6b. What can be observed here is, that the modeling, compatible with the laboratory studies (best compatibility at the extreme values). The character of variability is a little different, but the values of maximum cut's depth (the deviation doesn't exceed 2mm) reached at the abrasive flow rate 80g/s and the nozzle diameter about the 2mm, are similar.

With the maximum nozzle diameter, the smallest cut was achieved at the minimum abrasive flow rate. In this case maximal discrepancy between modeled and laboratory values does not go beyond 3.13mm and average discrepancy is 0.27mm



a) laboratory analysis b) modeled with the use of ANN

Fig. 6. Influence abrasive flow rate and nozzle 75mm diameter onto depth of cutting.



a) laboratory analysis b) modeled with the use of ANN

Fig. 7. Influence abrasive flow rate and 100mm nozzle diameter onto depth of cutting.

A laboratory study on cutting with the use of 100mm long nozzle is presented in Fig.7a, while its artificial neural network modeling is presented in Fig. 7b. In this range, modeling effects are also compatible with lab studies. Best compatibility was achieved at the low working nozzle diameters and low abrasive discharge. Main treatment parameter – cut depth – peaks at the maximum abrasive flow rate and minimum working nozzles diameters. In this case maximal discrepancy between modeled and laboratory values does not go beyond 2.74mm and average value is equal 0.2mm

4 Simulation of the Cutting Process

The artificial neural networks use in the cut depth designating, give similar estimates in every considered case. The divergences do not go beyond 6%. The remaining parameters modeling results do not exceed 5%. In some cases, the discrepancy is at 10%. Maximal discrepancy between modeled and laboratory values is included in the interval from 1.98 to 4.34mm and average discrepancy in the interval from 0.2 to 0,76mm. In most of the cases, the variation character due to the artificial neural network modeling was compatible with the results obtained in empirical way. This will allow application of this model [7] to forecast cutting results for all the variable machining parameters.

4.1 Impact of Traverse Speed on Cutting Depth

On the bases of obtained results it can be stated that in the whole range of parameters the depth of cut is inversely proportional to the cutting speed (Fig. 3.).

Maximum depth of cut was obtained at the minimum traverse speed of 1mm/s and this was accepted as the optimum speed.

4.2 Impact of Pressure on Cutting Depth

On the bases of obtained results it can be stated that in the whole range of tested parameters the depth of cut is either proportional to the working pressure (Fig. 3.) or that the highest pressure will result in the greatest cutting depth (Fig. 4.).

Optimum working pressure will be maximum pressure, in this case equal to p=28MPa. This pressure was used for further simulation work.

4.3 Impact of Abrasive Flow Rate on Cutting Depth

The optimum for this parameter is not as obvious as for the previous two. On the bases of results shown in Fig's 4&5 it could be concluded that the optimum flow rate is ma=70g/s but results obtained and shown in Fig's 6&7 allow only to conclude that increasing the abrasive flow rate results in only marginal increase in cutting depth.

For a 50mm long nozzle the relationship of the abrasive flow rate to the cutting depth is linear and inversely proportional. Increasing the length of the nozzle decreases this relationship leading to flattening of the graph which is greatest for a 100mm long nozzle. On the bases of those results the optimum abrasive flow rate was established to be not less than 70g/s.

4.4 Impact of Nozzle Length and Diameter on Cutting Depth.

In the case of the shortest length nozzle l=50mm the cutting depth is almost independent of the diameter (Fig. 8a.) in the whole range of abrasive flow.

For l=75mm (Fig. 8b.) we can observe a definite relationship between the depth of cut and diameter of the nozzle for the whole range of the abrasive flow rates.

Depth of cut increases with the increase of nozzle diameter. For the longest nozzle l=100mm (Fig. 8c.) this relationship is even stronger.

Observing relationship between the nozzle's length and diameter and depth of cut (Fig. 8, 9 &10.) we observe that the optimum length is 100mm for the whole range of abrasive flow rates. This is least noticeable for low flow rates to the extent that for the lowest values it approximates shorter nozzles.

In the whole range of this analyses maximizing the nozzle diameter resulted in cutting depth increase and for this reason the optimum diameter is ϕ=2.75.

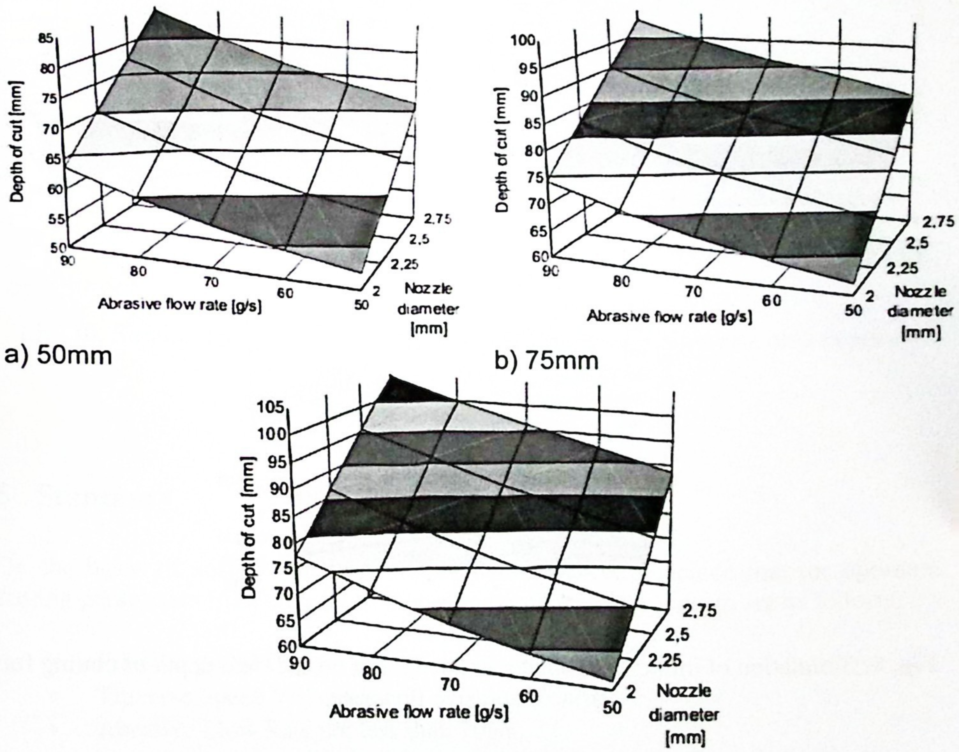


Fig. 8. Simulation of influence abrasive flow rate and nozzle diameter about variable length onto depth of cutting.

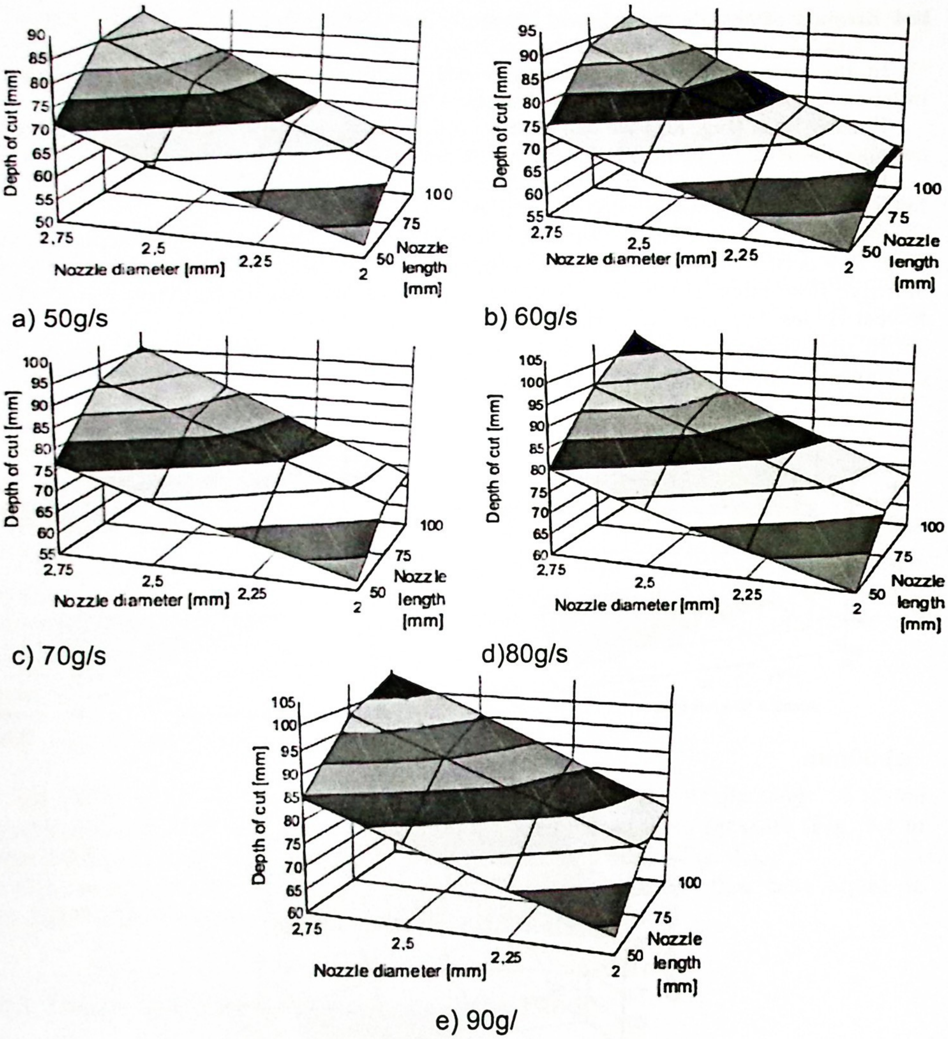


Fig. 9. Simulation of influence diameter and length of nozzle onto depth of cutting for variable abrasive flow rate.

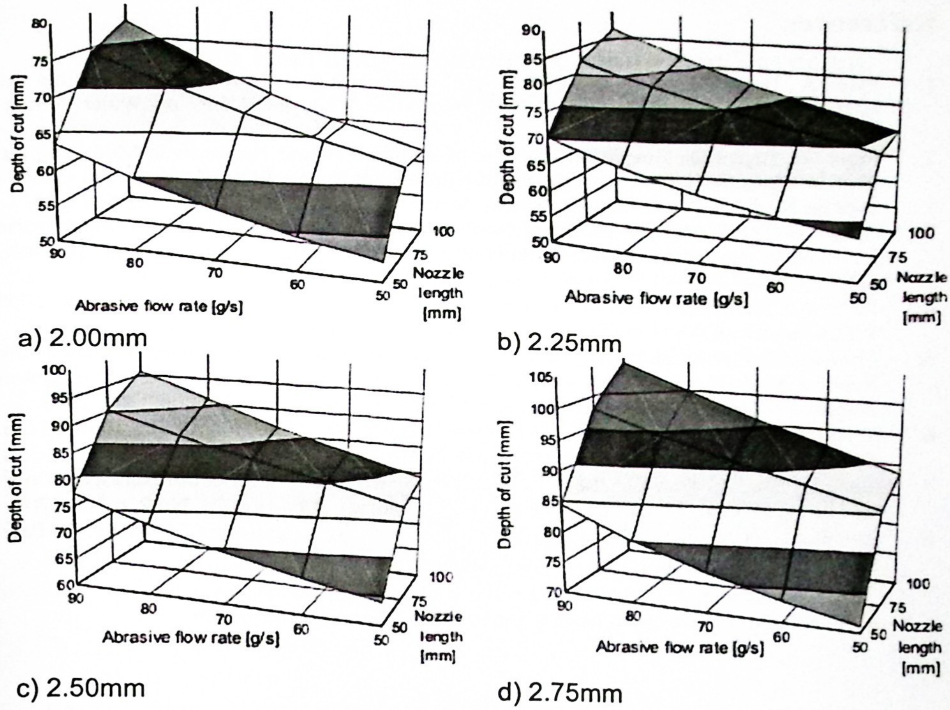


Fig. 10. Simulation of influence nozzle length and abrasive flow rate onto depth of cutting for variable nozzle diameter.

5 Summary

On the bases of analyses using neural networks we can conclude that the optimum cutting parameters from the perspective of maximizing cutting depth are as follows:

- Pressure p=28MPa,
- Traverse Speed V=1mm/s,
- Abrasive Flow Rate not less than 70g/s,
- Length of nozzle l=100mm,
- Diameter of nozzle ϕ=2.75mm

Neural networks are a very good tool for simulating abrasive cutting jet. The next step will be a comparison of results obtained from the simulation with actual cutting.

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