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Paper

THE SIMULATION MODEL OF HIGHPRESSURE,

SUSPENSION WATERJET CUTTING PROCESS

WITH USE OF THE ARTIFICIAL NEURAL NETWORK

A. Perec
Institut of Mechatronics, Nano- and Vacuum Technology
Koszalin University of Technology
Koszalin, Poland

ABSTRACT

This article presents the use of artificial neural networks to simulation the process of hydroabrassive suspension jet cut whose pressure is reduced to 30 MPa. Three-ply layer perceptron type network with an error backpropagation learning algorithm was applied to describe this process. The article provides detailed description of neural network. This neural network simulates the limestone 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. Were determined in which cases this depth is biggest.

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1. INTRODUCTION

In the article refers the simulation model cutting of hydroabrasive suspension waterjet cutting process of limestone. 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 [3, 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.

Limestone is a sedimentary rock composed of the mineral calcite (calcium carbonate). The primary source of this calcite is usually marine organisms. These organisms secrete shells that settle out of the water column and are deposited on ocean floors as pelagic ooze (see lysocline for information on calcite dissolution). Secondary calcite may also be deposited by supersaturated meteoric waters (groundwater that precipitates the material in caves). This produces speleothems such as stalagmites and stalactites. A further form is composed of oolites (Oolitic Limestone) and can be recognised by its granular appearance. Limestone makes up about 10 percent of the total volume of all sedimentary rocks. Pure limestones are white or almost white. Because of impurities, such as clay, sand, organic remains, iron oxide and other materials, many limestones exhibit different colors, especially on weathered surfaces.

2. ARTIFICIAL NEURAL NETWORKS

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. First is block of adding up in which entrance signals are increased by suitable coefficients weights and added up then.

The topology of the net consisting from 5 neurons of the entrance layer, 30 neurons of hidden layer and one outputs neuron (Fig.1.) was accepted to prediction [1] the waterjet cutting process.

Input data to the entry layer included- pressure, abrasive flow rate, size and diameter of nozzle and traverse speed. On the output layer cutting depth was given. 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. To learning process ware use 96 training cases that include both input and target output values. 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 thousands iterations 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 NETWORKS MODELLING

Fig. 2b 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. 2a 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 standard discrepancy between modeled and laboratory values does not go beyond 4.12mm.

Laboratory studies results, conditioned by variable pressure and abrasive flow rate conditions, are presented in Fig. 3a. Modeling effects are shown in a Fig. 3b. 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 discrepancy between modeled and laboratory values does not go beyond 2.89mm.

Fig. 4a depicts a laboratory study on limestone cutting with the use of 50mm long nozzle while Fig. 4b depicts artificial neural networks modeling of that process. Here also a great modeling and lab studies compatibility is observed. Greatest discrepancy takes place in case of extreme variable values and does not exceed 8%. At maximum cut depth deviation does not exceed 1mm. In this case standard discrepancy between modeled and laboratory values does not go beyond 3.21mm.

Cutting with the use of 75mm long nozzle is presented in Fig. 5a, while its artificial neural network modeling is shown in graph 5b. What can be observed here is, that the modeling is compatible with the laboratory studies (best compatibility at the extreme values). Diversion character is somewhat different, but the values of a maximum cut depth (diversion not exceeding 2mm), at the abrasive flow rate of 80g/s and the nozzle diameter at 2mm, are approximate. With the maximum nozzle diameter, the smallest cut (approx. 33mm) was achieved at the minimum abrasive flow rate. In this case standard discrepancy between modeled and laboratory values does not go beyond 4.37mm.

A laboratory study on cutting with the use of 100mm long nozzle is presented in Fig.6a, while its artificial neural network modeling is presented in Fig. 6b. 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 standard discrepancy between modeled and laboratory values does not go beyond 3.21mm.

4. SIMULATION OF THE 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%. Standard discrepancy between modeled and laboratory values is included in the interval from 2.19 to 3.42mm. 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. 2.). 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. 2.) or that the highest pressure will result in the greatest cutting depth (Fig. 3.). 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 3&4 it could be concluded that the optimum flow rate is ma=70g/s but results obtained and shown in Fig’s 5&6 allow only to conclude that increasing the abrasive flow rate results in only marginal increase in cutting depth.

For a 50mm long Focusing Tube the relationship of the abrasive flow rate to the cutting depth is linear and inversely proportional. Increasing the length of the Focusing Tube decreases this relationship leading to flattening of the graph which is greatest for a 100mm long Focusing Tube.

On the bases of those results the optimum abrasive flow rate was established to be not less than 70g/s.

4.4 Impact of Focusing Tube length and diameter on cutting depth.

In the case of the shortest length Focusing Tube l=50mm the cutting depth is almost independent of the diameter (Fig. 6.) in the whole range of abrasive flow. For l=70mm (Fig. 7.) we can observe a definite relationship between the depth of cut and diameter of the Focusing Tube for the whole range of the abrasive flow rates. Depth of cut increases with the increase of Focusing Tube diameter. For the longest Focusing Tube l=100mm (Fig. 8.) this relationship is even stronger.

Observing relationship between the Focusing Tube's length and diameter and depth of cut (Fig. 9.) we observe that the optimum length is 75mm 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 Focusing Tubes.

Also in examining the influence of the abrasive flow rate and Focusing Tube length with varying diameters on the cutting depth (Fig. 9.) we observe that the optimum length is l=75 for the whole range covered in this analyses.

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

5. SUMMARY

On the bases of analyses using artificial 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 Focusing Tube l=75mm,
- Diameter of Focusing Tube =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 abrasive cutting.

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GRAPHICS

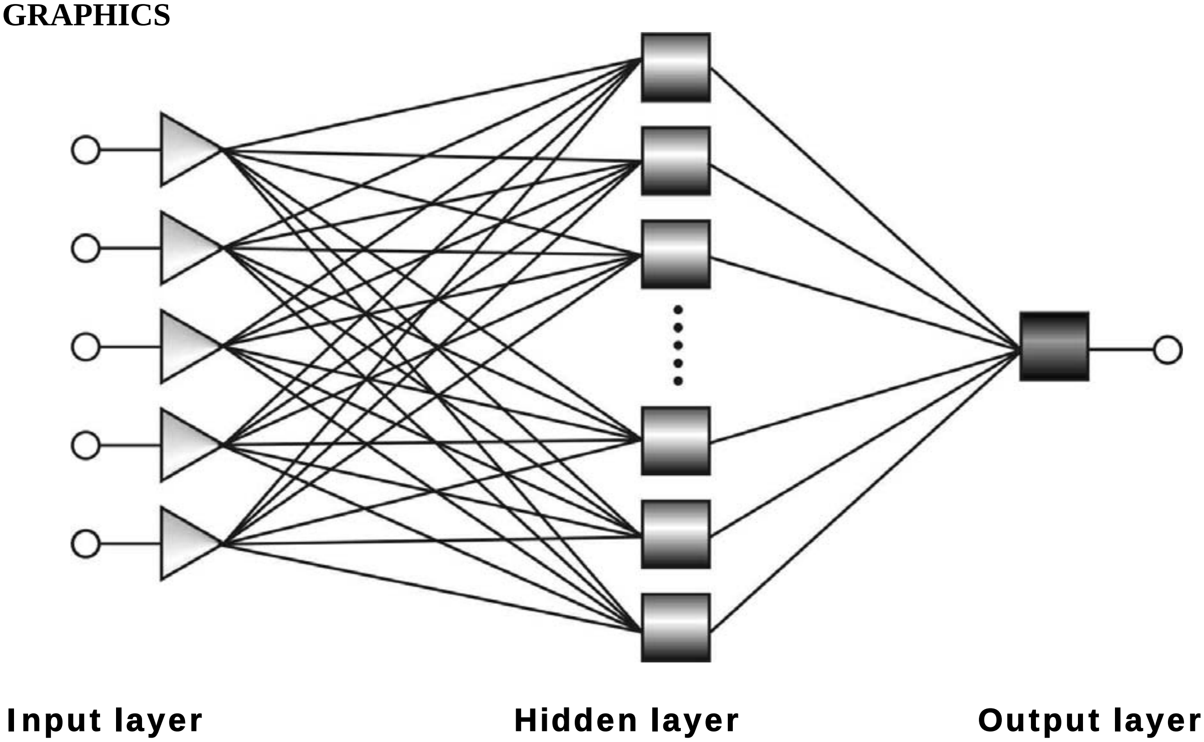
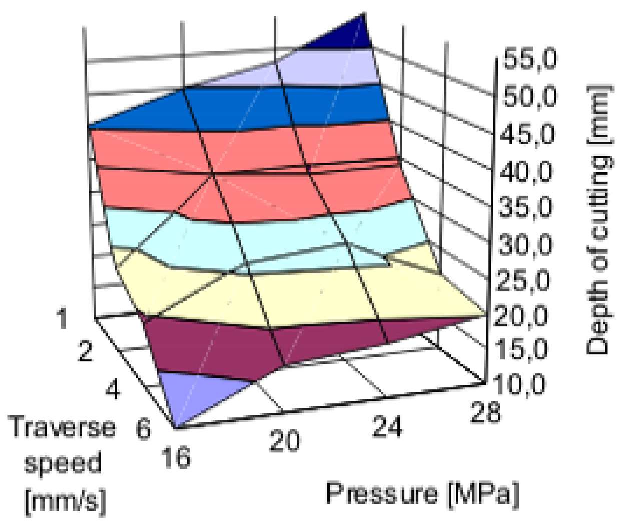
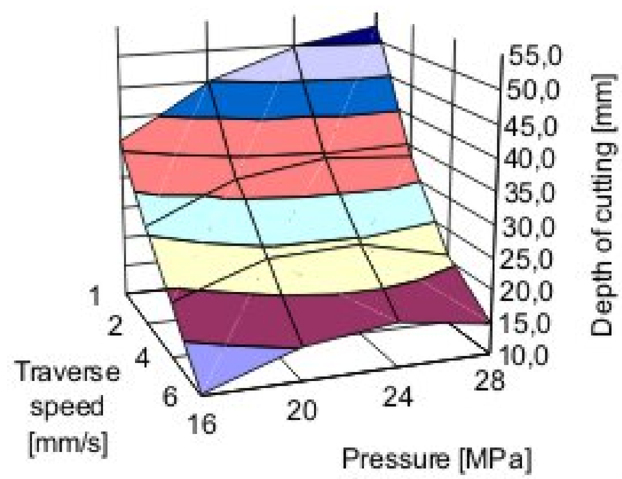


Figure 1. Artificial Neural Network schematic diagram

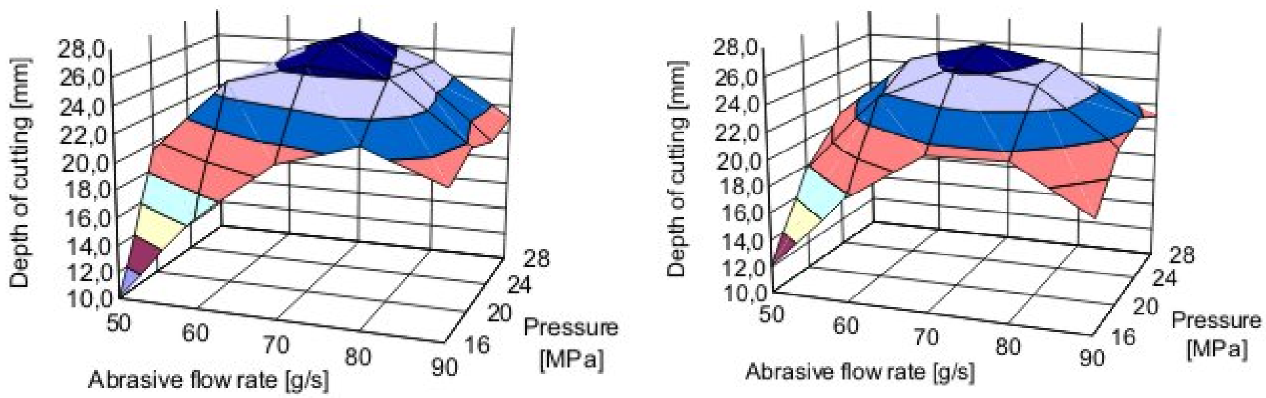


a) laboratory analysis



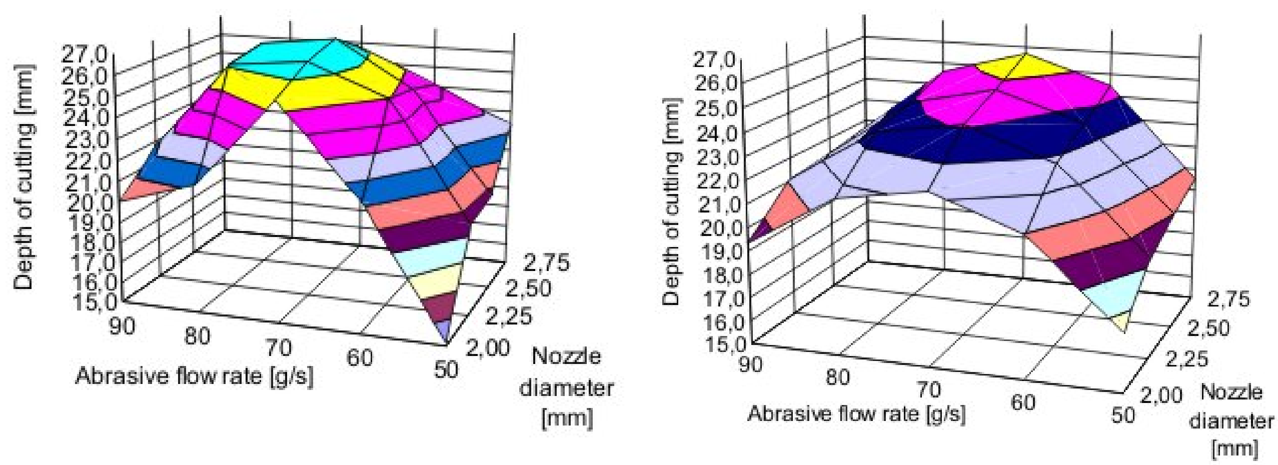
b) modeled with the use of ANN

Figure 2. Influence traverse speed and pressures onto depth of cutting:



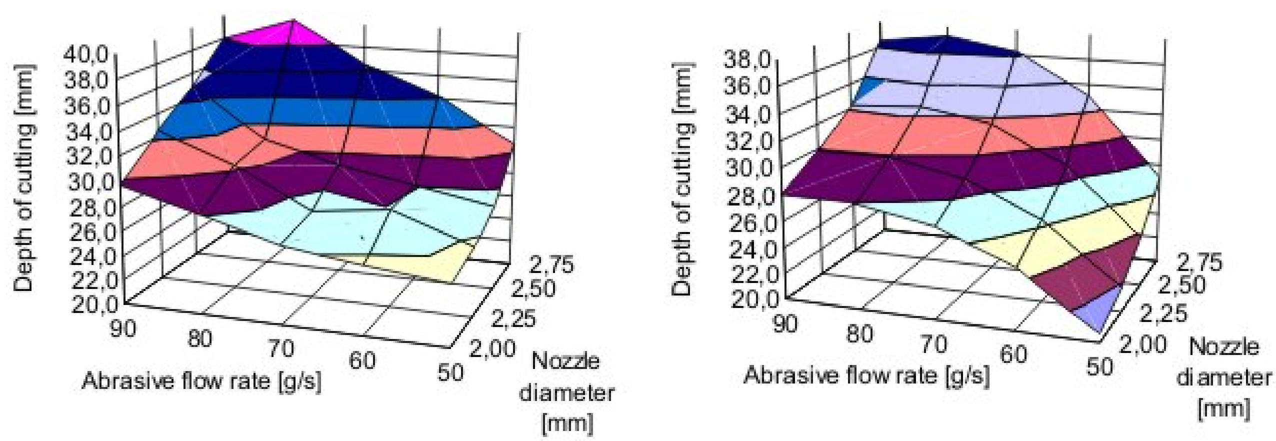
a) laboratory analysis b) modeled with the use of ANN

Figure 3. Influence abrasive flow rate and pressures onto depth of cutting



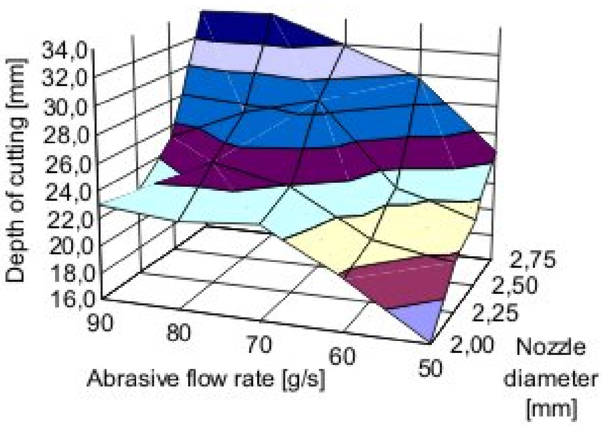
a) laboratory analysis b) modeled with the use of ANN

Figure 4. Influence abrasive flow rate and nozzle diameter about length 50mm onto depth of cutting.

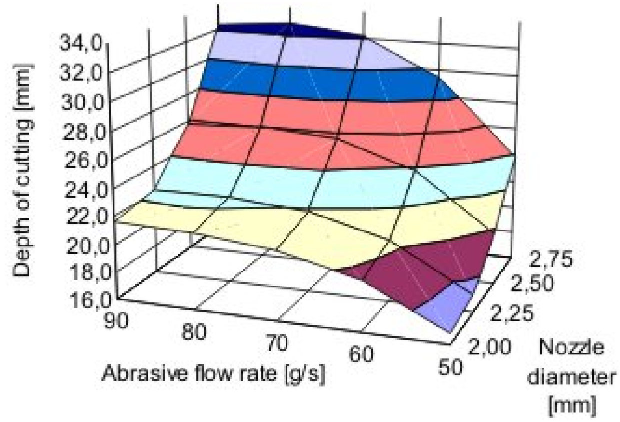


a) laboratory analysis b) modeled with the use of ANN

Figure 5. Influence abrasive flow rate and nozzle diameter about length 75mm onto depth of cutting

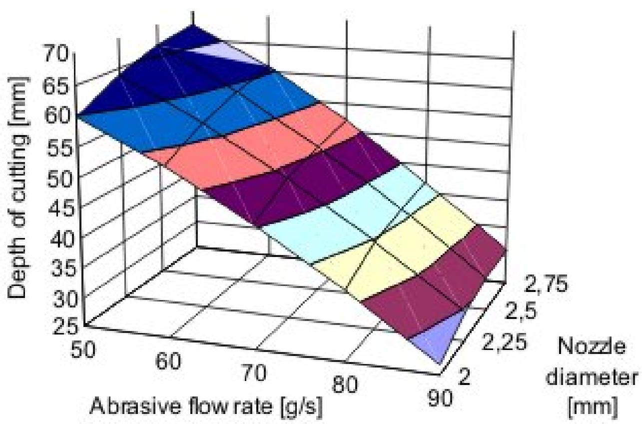


a) laboratory analysis

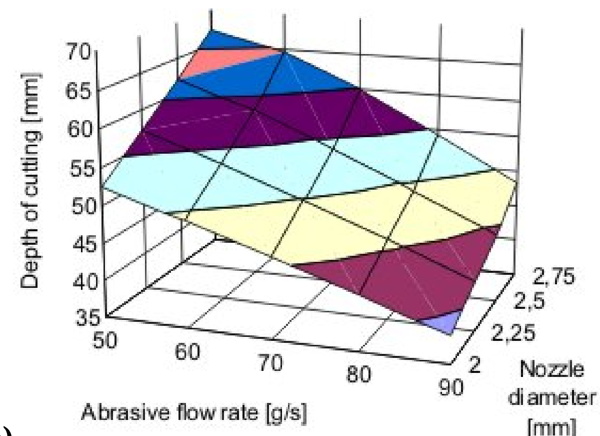


b) modeled with the use of ANN

Figure 6. Influence abrasive flow rate and nozzle diameter about length 100mm onto depth of cutting



a)



b)

c)

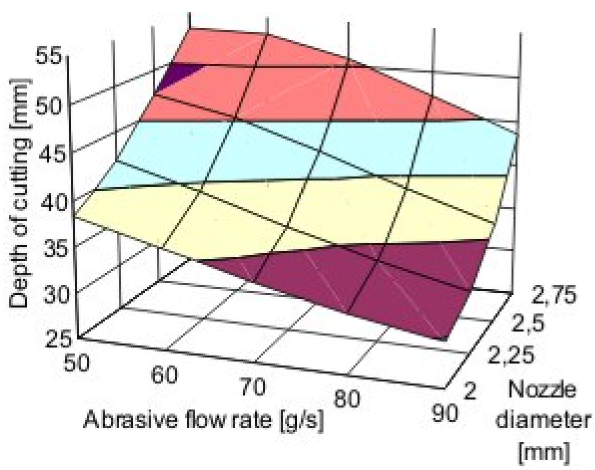


Figure 7. Simulation of influence abrasive flow rate and nozzle diameter about length: a) 50mm, b) 75mm, c) 100mm, onto depth of cutting

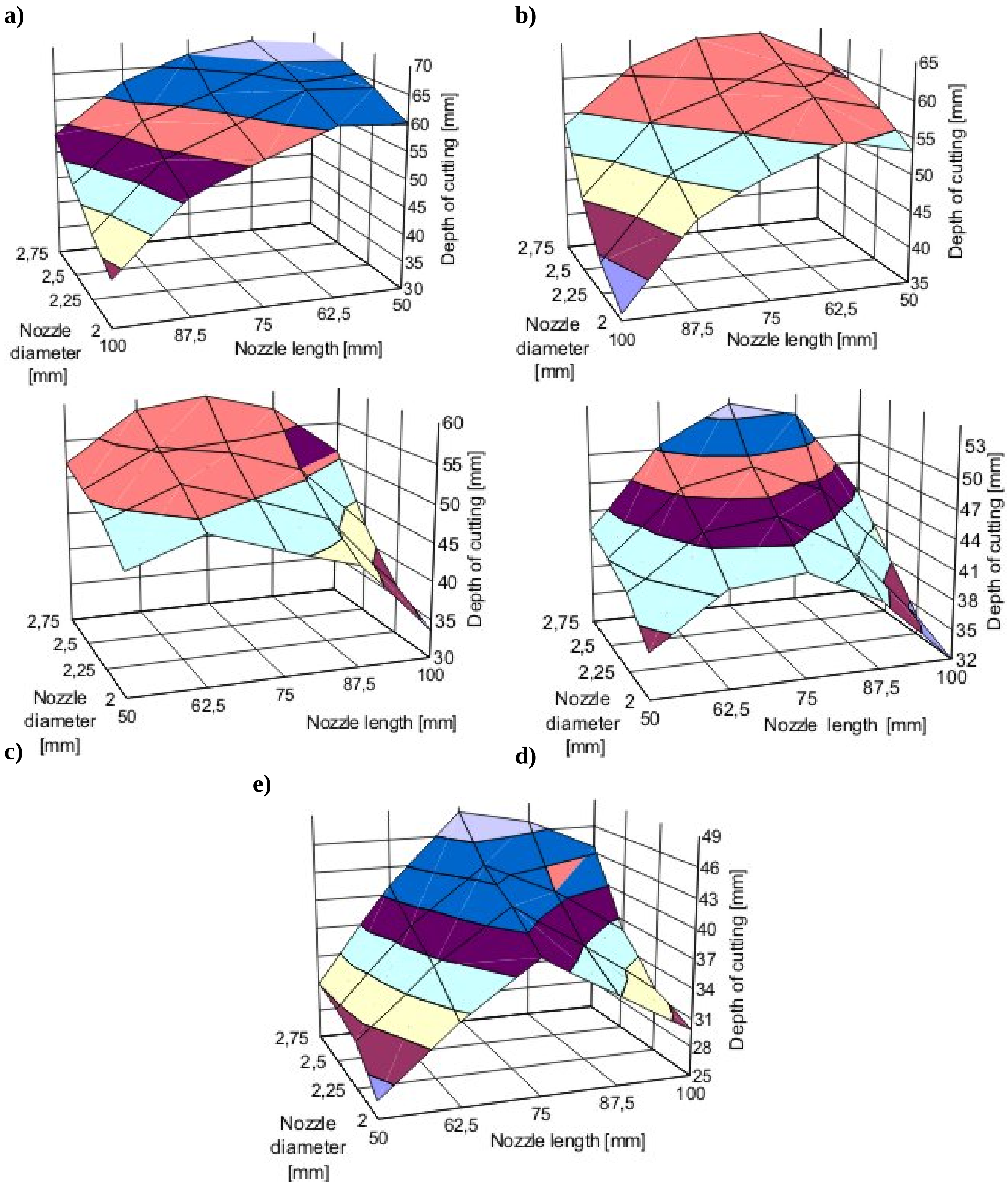


Figure 8. Simulation of influence diameter and length of nozzle onto depth of cutting for: a) 50g/s, b) 60g/s, c) 70g/s, d)80g/s, e) 90g/s, abrasive flow rate.

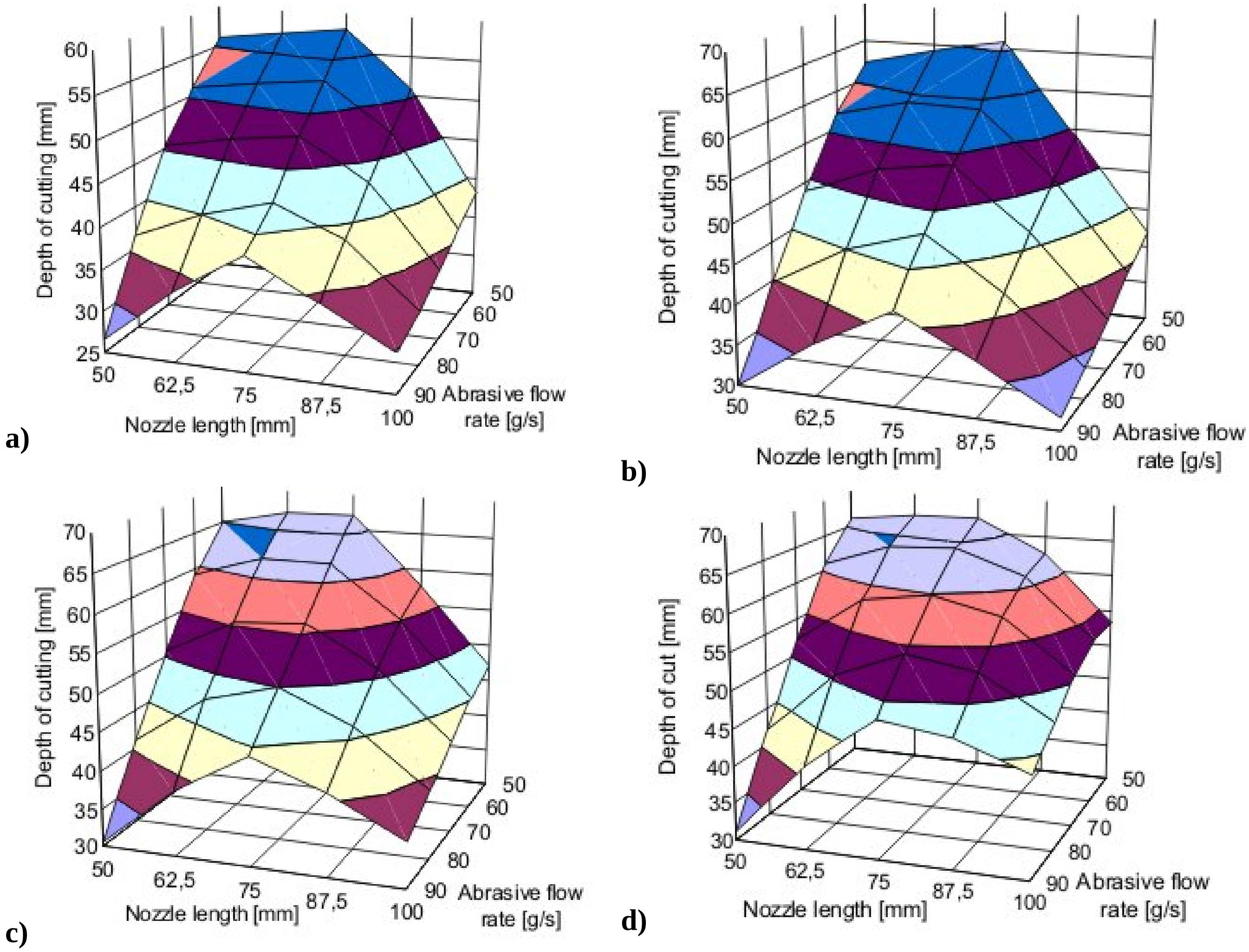


Figure 9. Simulation of influence nozzle length and abrasive flow rate onto depth of cutting for: a) 2.00mm, b) 2.25mm, c) 2.50mm, d)2.75mm, nozzle diameter.