The Use of Artificial Neural Networks in Modeling the High-Pressure, Suspensive Waterjet Cutting Process of Syenite

Andrzej Perec[1], Grzegorz Dzuga[1], Mateusz Ruzylo[1]
[1] Koszalin University of Technology, Division of Computer Science Applications
Kwiatkowskiego Street 6E, 75-343 Koszalin, Poland
pereca@lew.tu.koszalin.pl
dzuga@wp.pl
zoltar@eranet.pl

(Paper received on August 12, 2006, accepted on September 27, 2006)

Abstract. This article presents the role of artificial neural networks in use of hydroabrassive suspensive jet cut process in syenite treatment. 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 treatment process and predicts its efficiency due to given parameters. The results were confronted with the laboratory results of complex studies on parameters of cutting syenite with a hydroabrasive suspensive jet, whose pressure is reduced to 30 MPa.

1. Introduction

In the recent years, high pressure water-jet machining has been competing effectively with conventional methods of separation of materials. This is above all owing to its universal nature as a result of wide-range possibilities such as cutting complex shapes, various materials or a possibility to conduct it in extreme conditions [1, 8] (hazard of fire or an explosion, work under water to 6000 m, etc.).

The most serious disadvantage of the so-far existing systems for cutting with a high pressure hydroabrasive jet and working at pressures of 400 MPa, is the use of an injector mixer to create the jet - due to its small efficiency, especially in the case of very big differences of working media velocities [2]. An elimination of an injector mixer and the use of the jet's circumferential motion [6] for mixing an initially created hydroabrasive mixture directly under a high pressure can result in a radical change of the situation. Similar machining effects are achieved even though the working pressure has been lowered even by an order of magnitude.

2. Test stand, method and material

The test stand has been constructed on the basis of BORJET 01 prototypical machinery. It is constructed the way that allows quick changes of hydraulic pipes, the mixing manner, and water supply to carry out an initially formed hydroabrasive jet [5].

© H. Sossa and R. Barrón (Eds.)
Special Issue in Neural Networks and Associative Memories
Research in Computing Science 21, 2006, pp. 173-180

BORJET 01 appliance has been built from two containers and four independent hydraulic branches (Fig. 1), which allow adjustment of the basic flow parameters [3]. 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 secures Borjet01 from damage made by to high pressure. It is set at the pressure of 30MPa.

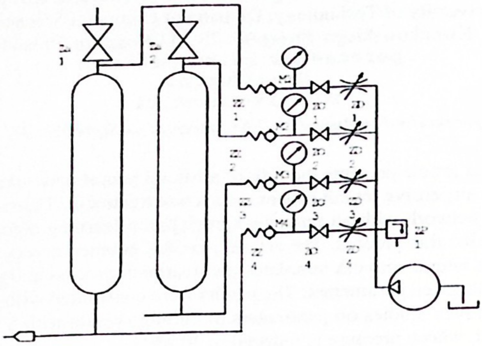


Fig. 1. Hydraulic diagram of device BORJET 01.

A hydraulic monitor P26 type is the source of a high pressure. It is made on the basis elements from a plunger pump made by 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.

Syenite is coarse-grained igneous rock, similar in appearance and composition to granite Fig. 2. Unlike granite, it contains very small quantity or even no quartz.

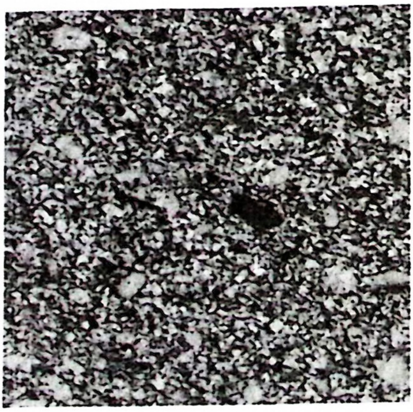


Fig. 2. The image of the polished surface of syenite.

Syenite is made mainly from feldspars, with mica, hornblende, and pyroxene. Varieties are distinguished (according to the ferromagnesian minerals contained) as augite syenite, hornblende syenite, mica syenite, and nepheline syenite. Syenites are comparatively rare rocks, being found mainly in a few areas of the United States and Germany. They are used as substitutes of granites as building stones.

3. 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 the most important properties of the biological neuron. You should always remember that artificial equivalents functions are very simplified [9] 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 block of adding up in which input signals are increased by suitable coefficients weights and added up then.

The topology of the net consisting from 5 neurons of the input layer, 5 neurons of hidden layer and one outputs neuron (Fig. 3) was accepted to modeling the waterjet cutting process [4].

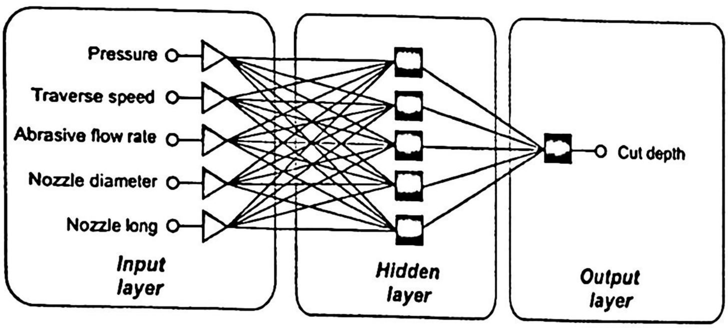


Fig. 3. Neural Network schematic diagram.

Input data to the input 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 was taken from the accessible results of investigations directly. To learning process ware use 96 training cases that include both input and target output values [7]. 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 12000 iterations with learning rate of 0.03 and momentum 0.3 (Fig. 4).

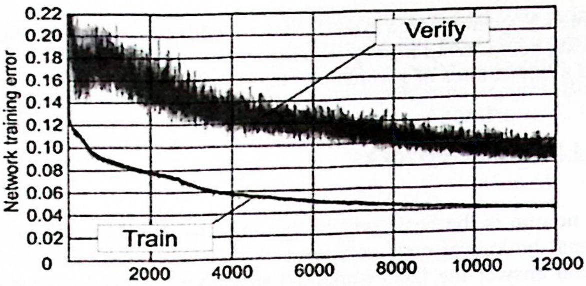


Fig. 4. Training error graph.

To research was utilized the commercial Statistica Neural Networks for Windows application of the StatSoft Inc company.

4. Effects of Artificial Neural Networks Modelling

Fig. 5(a) depicts the role of pressure and advance in syenite cut. In relation to the results obtained due to modelling, the maximum compatibility was observed with the advance at the maximum, whereas the biggest aberration (not beyond 15%) took place at the minimum pressure.

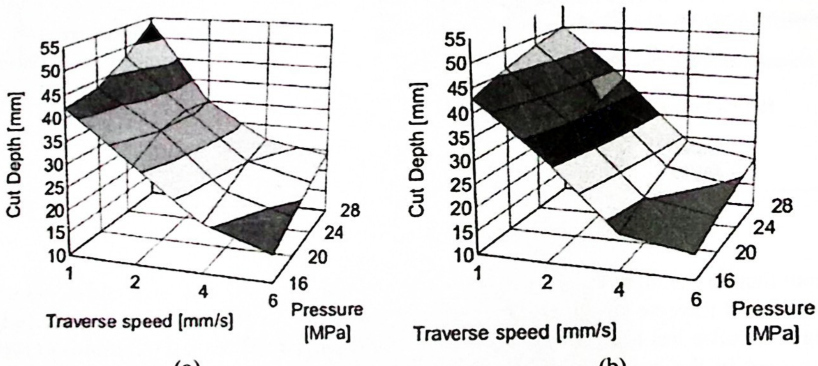
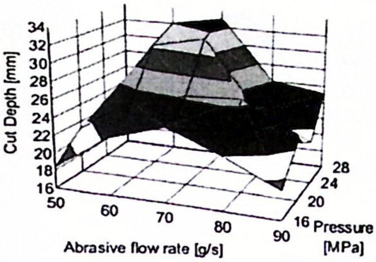
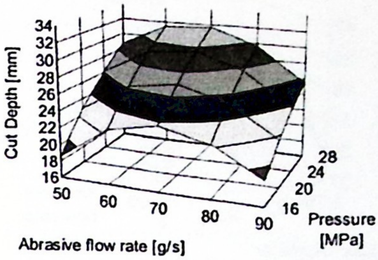


Fig. 5. Syenite cutting depth in a variable pressure and traverse speed conditions: a) laboratory analysis, b) modeled with the artificial neural networks.

Fig. 6(a) depicts how the pressure and abrasive flow rate influence the cutting depth. The compatibility with the results obtained in modelling (Fig. 6(b)), stays at the average of 1,56 mm. The maximum discrepancy, observed at the 28MPa pressure and 50 g/s abrasive flow rate, is at 4,67



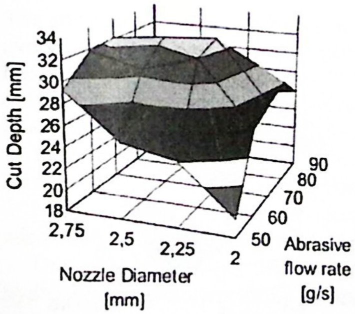
(a)



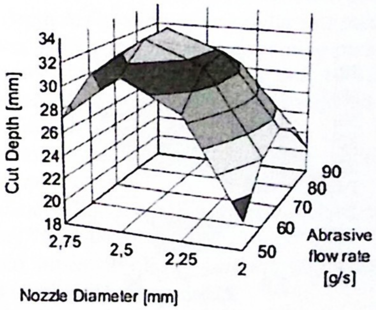
(b)

Fig. 6. Syenite cutting depth in a variable pressure and traverse speed conditions: a) laboratory analysis, b) modeled with the use of artificial neural networks.

The abrasive flow rate and the 50mm long nozzle diameter and their influence on cut depth are shown in Fig. 7(a). The average discrepancy of those results confronted with the results obtained in modelling (Fig. 7(b)) does not go beyond 2,5mm. The maximum discrepancy, not going beyond 6mm, was observed with aabrasive flow rate at minimum.



(a)



(b)

Fig. 7. Syenite cutting depth with the use of 50mm long nozzle in a variable nozzle diameter and abrasive flow rate conditions: a) laboratory analysis, b) modeled with the artificial neural networks.

Fig. 8(a) depicts how the abrasive flow rate and the 75mm long nozzle influence the cut depth results. The confrontation of those results with those obtained due to modelling (Fig. 8(b)) brought big compatibility, reaching 5%. The maximum discrepancy (not beyond 13%) was observed at the abrasive flow rate at minimum and the nozzle diameter of 2,25mm.

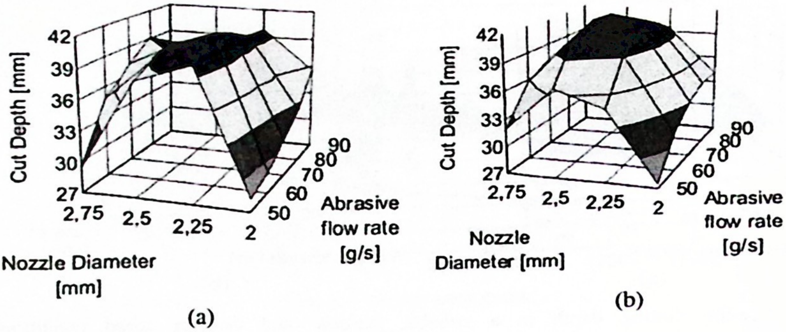


Fig. 8. Syenite cutting depth with the use of 75mm long nozzle in a variable nozzle diameter and a abrasive flow rate conditions: a) laboratory analysis, b) modelled with the artificial neural networks.

In Fig. 9(a) and Fig. 9(b) are shown the analogical relationships for 100mm long nozzle. Fig. 9. depict even more compatibility of real cut depth values with those obtained due to modeling. Only with the nozzle diameter and the abrasive flow rate at minimum the aberration goes for 10%.

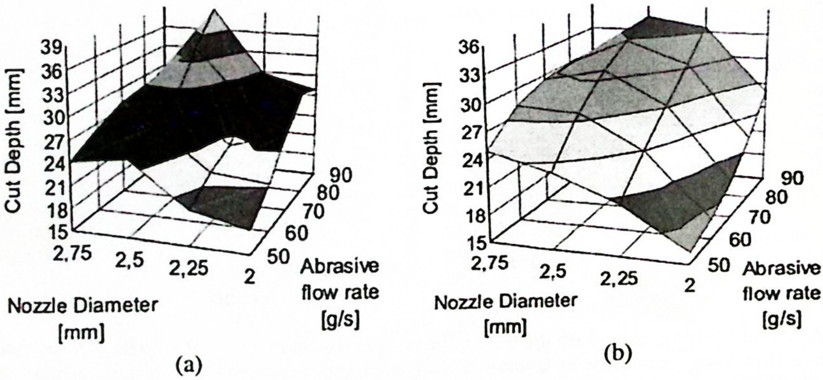


Fig. 9. Syenite cutting depth with the use of 100mm long nozzle in a variable nozzle diameter and a abrasive flow rate conditions: a) laboratory analysis, b) modelled with the artificial neural networks.

The overall comparison of lab and modeling results are shown in Fig. 10. Line ideal (y=x) illustrates how a model ideally matches real values. Points represent all values described in a report (values obtained with the use of ANN model)

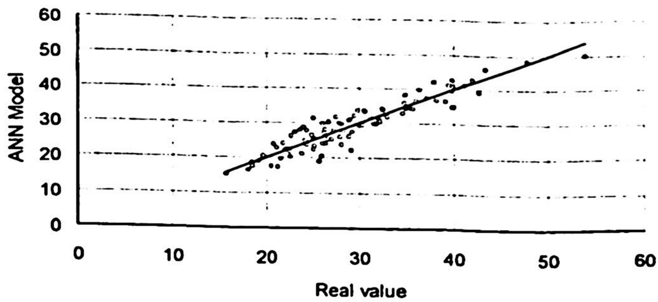


Fig. 10. Evaluation of matching Artifical Neural Network with measuring values.

Model to real values average discrepancy is 2,14mm (7,67%).

5. Summary

The artificial neural networks use in the cut depth designating, give similar estimates in every considered case. The divergences do not go beyond 8%. The remaining parameters modeling results do not exceed 5%. In some cases, the discrepancy is at 10%, and only one case resulted in 20% divergence. Standard discrepancy between modelled and laboratory-values are included in the interval from 2,16 to 3,24mm.

In most cases, the variation character due to the artificial neural network modeling was compatible with the results obtained in empirical way.

Making the neural network more complicated and choosing its parameters more adequately will result in the model being more "well-fitted".

Our next step is to use already trained artificial neural network to optimize hydroabrasive waterjet cutting parameters to maximize cutting depth.

References

[1] Brandt C., Louis H., Meier G., Tebbing G. (1994). Abrasive Suspension Jet at Working Pressure up to 200 MPa. 12th Int. Symposium on Jet Cutting Technology. Rouen, France.

[2] Chudy J., Perec A. (2001). Energetic Aspect of Highpresure Hydroabrasive Waterjet and Hydroabrasive, Suspensive Waterjet Machining Intensification. 2-nd Int. Conf. on Water Jet Machining WJM 2001. Cracow, Poland.

[3] Perec A. (2004). Some aspects of hydroabrasive suspensive jet cutting of syenite. 17th International Conference on Water Jetting - Advances and Future Needs. Mainz, Germany.

[4] Perec A., Dzuga G., Ruzylo M. (2006). The Ways To Utilize Artifical Neural Networks in Modelling The Highpressure Suspensive, Waterjet Cutting Process. Symposium on Mod-

elling and Simulation 2006. Lodz, Poland.

[5] Perec A. (2003). Some aspects of hydroabrasive suspensive jet cutting of marble. 2003 WJTA American Waterjet Conference. August 17-19, 2003 Houston, Texas, USA.

[6] Perec A. (1995). Influence of conditions highpressure, suspensive, hydroabrasive jet creation onto cutting materials parameters in lower working pressure aspect.(In Polish). Doctor trial.Technical University of Koszalin, Poland.

[7] Perec A., Dżuga G., Rużylo M. (2006). The use artifical neural networks in modelling the highpressure, suspensive waterjet cutting process of marble. 18th International Conference on Water Jetting. Gdańsk.

[8] Vijay M.M. (1989). Evalution of abrasive-entreined water jets for sloting hard rocks. 5th American Water Jet Conference. Toronto, Canada.

[9] Zurada J. (1992). Introduction to Artificial Neural Systems. West Publishing Company, St. Paul, New York, Los Angeles, San Francisco, USA.