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SZTUCZNE SIECI NEURONOWE W ANALIZIE EFEKTYWNOŚCI SKRAWANIA MATERIAŁÓW KRUCHYCH UKŁADAMI WIELOOSTRZOWYMI

ARTIFICIAL NEURAL NETWORKS IN EFFICIENCY ANALYSIS OF BRITTLE MATERIALS CUTTING PROCESS WITH MULTI-PICK HEADS

W artykule przedstawiono wyniki analizy danych laboratoryjnych uzyskanych w trakcie procesu skrawania materiałów kruchych głowicami wieloostrzowymi z wykorzystaniem sztucznych sieci neuronowych. Analiza dotyczy problemu efektywności procesu skrawania w zależności od geometrii wieloostrzowego układu skrawającego. Celem pracy było między innymi przetestowanie możliwości zastosowania sieci neuronowych w rozwiązywaniu problemów analizy procesu skrawania.

Słowa kluczowe: skrawanie, materiały kruche, głowice wieloostrzowe, sieci neuronowe

In the paper there are presented some analysis results of laboratory data recorded during natural brittle materials cutting process with the use of multi-pick cutting heads. Artificial neural networks were used as an analysis tool. The aim of the analysis was to get new information about cutting process efficiency depending on cutting tools set geometry, but also to test the possibility of neural networks applications in solving of cutting process problems.

Keywords: cutting process, brittle materials, multi-pick heads, neural networks

1. Introduction

Typical real-world problems usually have quantitative and qualitative dimensions. In such a case, especially for decision making we need to process both – quantitative and qualitative information. The same happens when we analyze any technological process, for example such as cutting of natural brittle materials with the use of multi-pick heads. All systems and processes are identified by their measurable components. If we can measure all necessary components (parameters) of analyzed process or any other system, and we are also able to formalize relations among these parameters by mathematical functions, then we can use quantitative methods to analyze the system (process), solve all problems and make necessary predictions or recommend decisions [12].

Artificial neural networks (ANN) and expert systems provide the needed methodologies, which deal with qualitative aspects of decision-making and processes parameters predictions. In our case – to make efficiency analysis of brittle materials cutting process with multi-pick heads, we tried to test performance of different architectures of artificial neural networks. All this, because unfortunately, it is still very common that personal experience is used to determine cutting values because the complexity of machining process and its conditions very often cannot be described with reliable calculation methods. In addition many engineering and especially geological problems are characterized by being very complex, uncertain and undefined, due to for example lack of data or knowledge. On the other hand - some results presented in references show, that these problems can be successfully solved with support of artificial neural networks and other intelligent systems [2, 9, 10].

Results obtained during researches with the use of artificial neural networks are presented in this paper. We have taken into consideration typical geometrical parameters of the multi-pick cutting heads having influence on the cutting process efficiency, there is cutting depth (h_D), angular scale between cutters (t_0) and their lateral scale (t). These parameters, their influence on the cutting process together with laboratory experiments, during which real-world data used in ANN teaching, training and verification were described in several previous papers [4, 5, 6, 7, 8].

2. ANN in cutting data analysis and predictions

At present time artificial neural networks, as on of Data Mining tool are successfully used to solve sophisticated technological problems [1, 2, 3, 9, 10]. This way, unknown relations between input and output parameters can be learned and reproduced by neural networks. Such representation obtained when modeling technological objects with the use of ANN can be qualitative. It means that no mathematical function is needed to represent these relations. All this happens inside the ANN as a kind of relations and interconnections between neurons and layers, depending of used architecture.

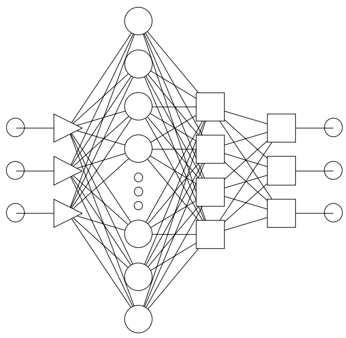

Fig. 1. Network with one of the best performances (GRNN 3-95-4-3)

In our case we wanted to make a kind of intelligent determination of cutting forces values with the help of artificial neural network. We wanted to make some predictions of cutting forces values on three tools set as a function of multi-pick heads geometrical parameters. To train, verify and test the networks we have used data sets obtained during laboratory experiments, when cutting forces values F_{c1}, F_{c2} and F_{c3} were measured on three Rapid 83 tools of the multi-pick set, as a function of their geometrical parameters – there is their positioning on the cutting head described by cutting depth (h_D), angular scale (t_0) and lateral scale (t).

It means that these three geometrical parameters were input variables, and three cutting force values – output variables of the network. For this purpose we have tested several different architectures to choose one with the best performance. In each case we had 95 training sets, 47 verification sets and 47 test sets of the experimental data. Also for each case we have compared such networks as:

- linear
- Radial Basis Function (RBF)
- generalized regression neural networks (GRNN)
- radial basis function networks (RBF)
- multi-layer perceptrons (MLP)
- and probabilistic neural networks (PNN).

For each of them we have analyzed network sensivity, error, performance (regression ratio) and correlation. The best results were obtained when GRNN and RBF networks were used (fig. 1, fig. 2, fig. 3, fig. 4). The GRNN network has quite complex architecture with 95 neurons in the first hidden layer, while another one is simple, having single hidden layer only with six neurons.

For both architectures taken into further analysis and comparison we have calculated regression statistics, which results are presented in table 1 (GRNN 3-95-4-3) and table 2 (RBF 3-6-3), where for each data set we display:

- Data Mean – average value for the target variable

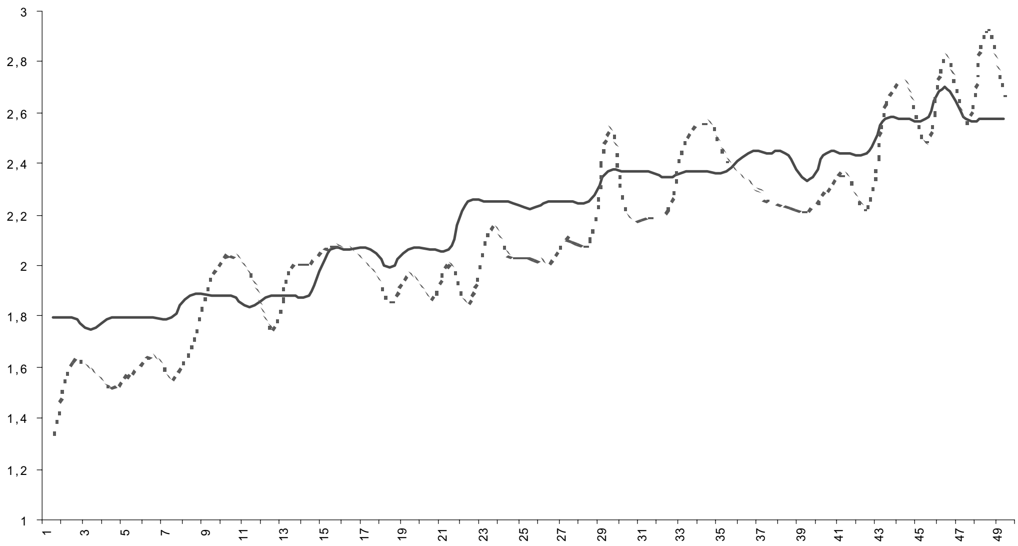

Fig. 2. Real values of cutting forces on the first tool of the set (continuous line) and their predictions (dot line) - GRNN 3-95-4-3 network, test set of the experimental data

- Data S. D. – standard deviation of the target output variable
- Error Mean – average error (residual between target and actual output values) of the output variable,
- Abs. E. Mean – average absolute error (difference between target and actual output values) of the output variable
- Error S. D. – standard deviation of errors of the output variable
- S. D. Ratio – the error: data standard deviation ratio
- Correlation – the standard Pearson-R correlation coefficient between the target and actual values

General regression neural networks (GRNN) perform regression rather than classification tasks. The GRNN networks copy the training cases into the network to be used to estimate response of new points. The output is estimated using weighted average of the outputs of training cases, where the weighting is related to the distance of the point from the point being estimated. The best GRNN network with the best performance in our investigation consisted of four layers. Input layer of 3 units (three input variables), two hidden layers with 95 neurons in the first one and 4 units in the second one), and finally – output layer with three neurons because of three output variables taken into consideration. The first hidden contains radial units, second one – contains units which help to estimate weighted average. This is a specialized procedure [11]. Each output has a special unit assigned in this layer which forms the weighted sum for the corresponding output. To get the weighted average from the weighted sum, the weighted sum must be divided through by the sum of weighting factors. A single special unit in the second layer calculates the latter value. The output layer then performs the actual division [11]. Hence, the second hidden layer always has exactly one more unit than the output layer (in our case 4 units in the second hidden layer and three in output layer). The training process and architecture of the GRNN 3-95-4-3 network shows that they train almost instantly, but usually are large and slow. This disadvantage is quite clear when we compare the GRNN 3-95-4-3 and RBF 3-6-3 networks. Obtained results represented by the network performance is almost equal, while architecture's complexity is completely different – the first one is quite complex (95 units in the first hidden layer), while the second one consists only of 6 neurons in a single hidden layer.

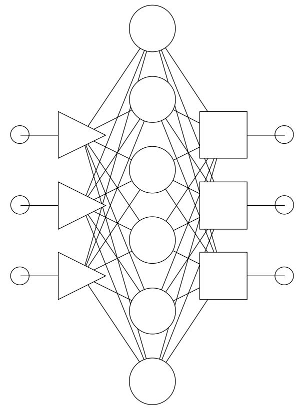

Fig. 3. Network with one of the best performances (RBF 3-6-3)

Radial basis function network, which has obtained the best performance (RBF 3-6-3) have an input layer of three neurons (because we had 3 input, there is independent variables), one hidden layer of radial units and output layer of linear units. The network has three

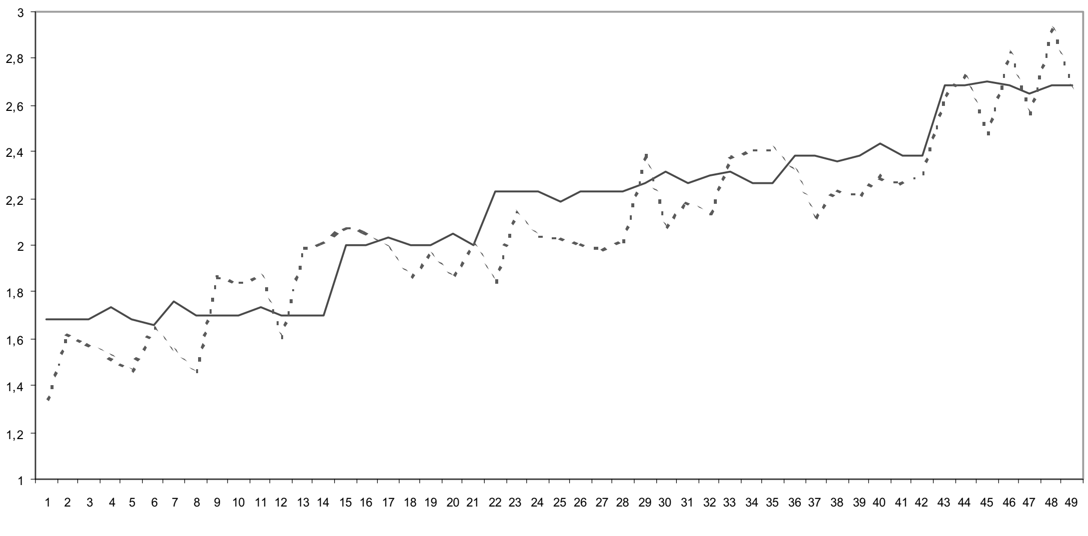

Fig. 4. Real values of cutting forces on the first tool of the set (continuous line) and their predictions (dot line) - RBF 3-6-3 network, test set of the experimental data

Table 1 -Regression statistics for GRNN 3-95-4-3

	Training Fc1	Verification Fc1	Test Fc1	Training Fc2	Verification Fc2	Test Fc2	Training Fc3	Verification Fc3	Test Fc3
Data Mean	2.4583	2.4578	2.4108	2.3061	2.3325	2.6595	2.4077	2.3606	2.3300
Data S.D.	0.3550	0.3232	0.4379	0.3692	0.3695	2.6895	0.3454	0.3222	0.3758
Error Mean	0.0048	0.0045	0.0201	0.0058	0.0674	0.3983	0.0067	0.0157	0.0301
Error S.D.	0.2007	0.2088	0.2833	0.1614	0.2522	2.6968	0.1596	0.1854	0.2138
Abs. E. Mean	0.1482	0.1674	0.1928	0.1229	0.1849	0.5618	0.1196	0.1397	0.1706
S.D. Ratio	0.5652	0.6460	0.6470	0.4373	0.5825	0.1027	0.4621	0.5752	0.5690
Correlation	0.8401	0.7654	0.8097	0.9160	0.7315	08242	0.9045	0.8204	0.8342

Table 2 -Regression statistics for RBF 3-6-3

	Training Fc1	Verification Fc1	Test Fc1	Training Fc2	Verification Fc2	Test Fc2	Training Fc3	Verification Fc3	Test Fc3
Data Mean	2.4391	2.4206	2.4868	2.2785	2.3365	2.7112	2.3788	2.3614	2.3876
Data S.D.	0.3479	0.3734	0.4077	0.3699	0.3998	2.6779	0.3596	0.3082	0.3656
Error Mean	0.0001	0.0216	0.0596	0.0001	0.038	0.4328	0.0001	0.0274	0.0139
Error S.D.	0.1832	0.2187	0.2957	0.2120	0.2509	2.6984	0.2090	0.1860	0.2270
Abs. E. Mean	0.1421	0.1779	0.1912	0.1591	0.2005	0.5605	0.1667	0.1529	0.1885
S.D. Ratio	0.5267	0.5856	0.7253	0.5730	0.6276	0.3663	0.5813	0.6035	0.6210
Correlation	0.8501	0.8147	0.6896	0.8149	0.7793	0.7899	0.8136	0.8020	0.7839

output neurons, because the object has three dependent variables – cutting forces values on three tools of the set. The radial layer has exponential activation functions, the output layer – linear activation functions (the activation level is passed on directly as the output). RBF network was trained in three stages:

- the centers stored in the radial hidden layer were optimized first, typically using unsupervised training techniques, for which we have used different algorithms, like: K-means, Kohonen training or learned vector quantization, to place centers to reflect clustering,
- the spread of data was reflected in the radial deviations (stored in the threshold), deviations can be typically assigned by a number of algorithms (explict, isotropic, K-nearest neighbor),
- the linear output layer was optimized using pseudo-inverse technique, as this is fast and guarantees to minimize the error if deviations are too small.

It was noticed that the RBF network was trained relatively quickly and did not extrapolate too far from known data. From references describing theory of artificial neural networks, we know that a perfect prediction will have correlation coefficient of 1. On the other hand such correlation does not necessarily indicate a perfect prediction (only a prediction which is perfectly linearly correlated with the actual outputs), although in practice the correlation coefficient is a good indicator of performance [11]. It also provides a simple way to compare the performance of networks with standard least squares linear fitting procedures. In our researches for the GRNN and RBF networks the correlation was usually equal to 0.8, and was a little bit higher for the first one. Comparing obtained performance and our knowledge about analyzed object, which very often can be influenced by random factors and several disturbances can be considered as high and satisfactory.

3. Final conclusions

Determination of cutting forces values on multi-pick heads cutting natural brittle materials with the help of artificial neural networks is a new, alternative and promising method. Results from our several tests, when we have been using different architectures, training methods, activation functions, etc., typical for neural networks theory show, that networks are capable of learning different functions from experimental databases, including those nonlinear.

Our laboratory experiments which aim was efficiency analysis of brittle materials cutting process with the use of multi-pick cutting heads were complicated and limited. But they helped us to get a dataset with information about cutting heads geometrical parameters influence cutting forces measured on three tools of the set. This information and knowledge coming from its analysis provided further possibility for problem description when modeling the object with the use of Finite Element Method [5, 6]. It was one of the possibilities to extend investigations and get new knowledge about the object. On the other hand – artificial neural networks which application possibility for cutting process analysis was presented in this paper can be successfully used as an alternative tool. They can be used not only for dependent variables predictions beyond laboratory test limitations, but also for interpretation, diagnosis and further real-time control, monitoring or optimization of the cutting process.

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Artykuł prezentuje wyniki prac otrzymanych w ramach realizacji projektu badawczego KBN PB-1505/T12/99/16

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