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Influence of the Training Set Value on the Quality of the Neural Network to Identify Selected Moulding Sand Properties

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Abstract

Artificial neural networks are one of the modern methods of the production optimisation. An attempt to apply neural networks for controlling the quality of bentonite moulding sands is presented in this paper. This is the assessment method of sands suitability by means of detecting correlations between their individual parameters. This paper presents the next part of the study on usefulness of artificial neural networks to support rebonding of green moulding sand, using chosen properties of moulding sands, which can be determined fast. The effect of changes in the training set quantity on the quality of the network is presented in this article. It has been shown that a small change in the data set would change the quality of the network, and may also make it necessary to change the type of network in order to obtain good results.

Keywords: Application of Information Technology to the Foundry Industry, Quality Management, Green Moulding Sands, Neural Networks

1. Introduction

Artificial neural networks usage is one of the modern methods of the production optimisation [1–6]. The networks owe their popularity to the fact that they constitute convenient tools of investigations. Molding sands and in particular their quality control methods significantly affect the quality of castings. The use of statistical analysis to support decision making on how to provide the required moulding sands properties is more and more popular.

Modern control systems are utilising changes of the selected sand properties for controlling its quality, mainly the sand compactibility [7]. In addition to control systems, databases that provide access to the results of the various parameters of the production process of castings have an important role [8–10]. Thanks to databases there is possibility to control these processes for a long time. You can also use this data to support manufacturing processes including using artificial neural networks.

The aim of this research was to obtain an artificial neural network which allows predicting green moulding sand moisture knowing its permeability, compression strength and

compactibility (the moulding sand properties were chosen based on previous studies [11-13]).

2. Researches

Analysis covered a set of experimental data collected in the Laboratory of Moulding Materials, Faculty of Foundry Engineering AGH. Database include up to 360 records for each property held for further analysis.

The Statistica 10.0 program was applied for designing the neural network models.

The learning process was carried out for a MLP network (number of hidden neurons 3-10) and RBF (number of hidden neurons 12-17), number of networks: 50000. The following activation functions were used in hidden neurons: Linear, Logistic, Tanh, exponential, moreover output neuron activation functions: Linear, Logistic, Tanh, exponential.

The obtained results allow to state that the smallest value of the error was obtained for MLP network, containing from 8 to 10 neurons in the hidden layer, using the tanh function as the activation function of the neurons in the hidden layer and the Linear and the logistic function for activation neurons in the output layer. Comparison of errors for different networks is shown in Figure 1.

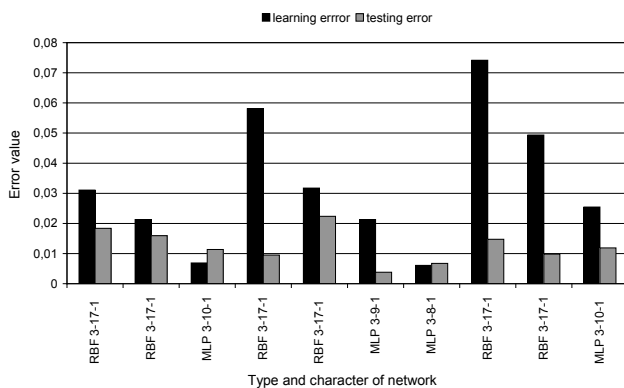


Fig. 1. Comparison of errors for different networks

In the next step, the learning process has been conducted for a MLP network (number of neurons 8-10 in hidden layer), the number of the networks: 50000, activation function of neurons in the hidden layer Tanh, the activation functions of neurons in the output layer linear and logistic

Received networks allow to conclude that the smallest error value is obtained for the structure of 3-8-1, using Tanh function as the activation function in the hidden layer and while using the logistic function in the output layer (Figure 2).

In the next stage learning MLP networks was carried out, where the number of neurons in the hidden layer was 8. Number of networks: 50000, Tanh function was used as activation function of neurons in the hidden layer and logistic function was used as the activation functions of neurons in the output layer.

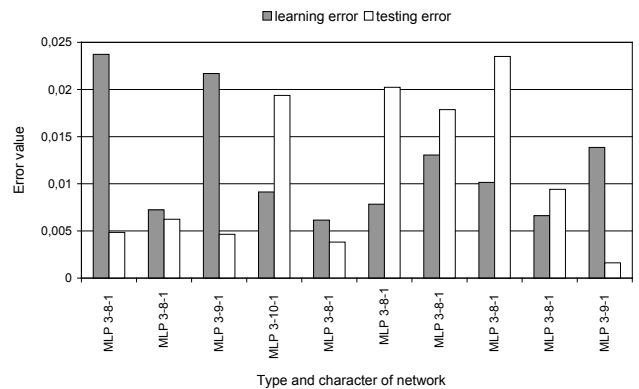


Fig. 2. Comparison of errors for different networks with 8-10 number of neurons in hidden layer

Table 1.

The most effective network in generating moisture values with given parameters (compactibility, permeability and compressive strength)

Network name	Learning quality	Testing quality	Learning error	Testing error	Learning algorithm
MLP 3-8-1	0,99486	0,99240	0,00583	0,00827	BFGS 157
MLP 3-8-1	0,99724	0,99737	0,00308	0,00317	BFGS 180
MLP 3-8-1	0,99592	0,99662	0,00455	0,00448	BFGS 139
MLP 3-8-1	0,99571	0,99409	0,00491	0,00689	BFGS 126
MLP 3-8-1	0,99360	0,99144	0,00730	0,00911	BFGS 70

Considering only the accuracy of the obtained results, the most effective in generating moisture values with given parameters (compactibility, permeability and compressive strength) is 3-8-1 MLP network, where the BFGS learning algorithm marked 180 was applied (Table 1) and Figure 3 shows their graphical summary.

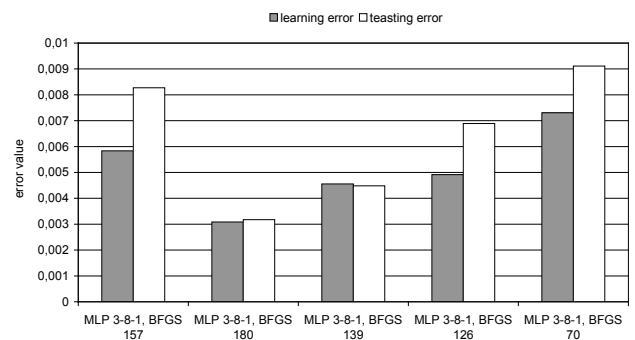


Fig. 3. Graphical summary of data from Table 1

However, the high sensitivity of the network to the input parameters (shown in Table 2) particularly compactibility and permeability, may cause errors when generating results. Network based on BFGS 131 algorithm provides a relatively good quality of the output signal with less sensitivity to measurement inaccuracies.

Table 2.

Sensitivity of the network to the input parameters

Network name	Learning algorithm	permeability	compactibility	compressive strength
MLP 3-8-1	BFGS 157	152	95	32
MLP 3-8-1	BFGS 180	285	226	28
MLP 3-8-1	BFGS 139	205	131	35
MLP 3-8-1	BFGS 126	107	102	47
MLP 3-8-1	BFGS 70	68	70	34

Artificial neural network was generated for the same input and output database file diminishing the last ten data. Table 3 shows the comparison of the best networks to predict moisture values with full and limited database.

Table 3.

Comparison of the best networks to predict moisture values with full and limited database

Network name	Learning error	Testing error	Learning algorithm	Activation function in the hidden layer	Activation function in the output layer
MLP 3-8-1	0,00308	0,00317	BFGS 180	Tanh	Logistic
MLP 3-6-1	0,00961	0,00253	BFGS 165	Logistic	Linear

The network created from the input data decreased by last ten measurement results is presented next. Network structure is similar to the results presented in the earlier part of the article. The only differences are the different types of activation functions of neurons that give the best results. In case of the limited database, it is adequately logistic and linear function. Summary of test error is comparable for both cases, while in the case of learning error there is a noticeable difference.

This is due to the input data difference of two networks. Removal of the last ten measurements results has changed a course of the linear regression of input variables and reduced the effectiveness of the learning process.

In the next stage, the training set was reduced of 10 randomly selected data. The aim was to determine whether a reduction way of database input would affect the accuracy of the obtained neural networks.

Removal of ten randomly selected measurements resulted in a total change of the network learning process. The best possible result were obtained for the RBF network structure with 25 neurons in the hidden layer. This is due to the fact that this type of network cope better with the input containing any errors. This network, by changing the structure, can still fulfill defined requirements, despite the deficiencies in the input data.

3. Conclusions

For the full database the best results were obtained with MLP networks. In the case of a limitation of the scope of data on 10, it was able to get lower value of learning error. This is due to the disadvantage of STATISTICA, which compares the variation of

the data to a linear regression. It is related to formation of local extremes, which program can treated as a global extremes. After reducing input data randomly by 10, generated MLP network not cope with deriving shortages and RBF network become more efficient. This demonstrates greater ability of this design to fill gaps and measurement errors.

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