ARCHIVES
of
FOUNDRY ENGINEERING

ISSN (1897-3310)
Volume 11
Issue 4/2011

61 – 64

12/4

Published quarterly as the organ of the Foundry Commission of the Polish Academy of Sciences

ANN modelling for the determination of moulding sand matrix grain size

J. Jakubski*, St. M. Dobosz, K. Major-Gabryś
AGH University of Science and Technology Faculty of Foundry Engineering, al. Mickiewicza 30, 30-059 Krakow
* Corresponding author. E-mail adress: jakubski@agh.edu.pl

Received 05.07.2011; accepted in revised form 27.07.2011

Abstract

One of the modern methods of the production optimisation are artificial neural networks. Neural networks are gaining broader and broader application in the foundry industry, among others for controlling melting processes in cupolas and in arc furnaces, for designing castings and supply systems, for controlling moulding sand processing, for predicting properties of cast alloys or selecting parameters of pressure castings. 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. The presented investigations were obtained by using the Statistica 9.0 program. The aim of the investigations was to select the neural network suitable for prediction the moulding sand matrix grain size on the basis of the determined sand properties such as: permeability, compactibility, and compressive strength.

Keywords: Artificial neural networks, Green moulding sands, Sand grains

1. Introduction

A large number of data which is being generated in foundry processes is usually not undergoing direct measurements and recordings, especially automatic. Even the data which are measured and stored are not used for an optimisation and computer aided quality control. The access to a higher number of reliable data requires purchasing of the proper measuring equipment and employing additional staff [1, 2].

Artificial neural networks are one of the modern methods of the production optimisation. They owe their popularity to the fact, that they constitute convenient tools of investigations. Neural networks are able to represent complex functions. Their non-linearity should be specially emphasised. They are gaining broader and broader application in the widely understood foundry industry, among others for controlling melting processes in cupolas and arc furnaces, designing castings and supply systems, controlling moulding sand processing, prediction of properties of cast alloys or selecting parameters of pressure castings [3-7].

2. Own investigations

The results of investigations concerning the application of neural networks for the determination of moisture of the moulding sands and the bentonite amount were presented in papers [8–11]. The results of the selected investigations of the sand properties as a function of moisture changes in dependence of the matrix grain size as well as the neural network models for the collected results are presented in this paper. These results are continuation of the research presented in an earlier publication [2] and refer to the possibility of determine mean grain size of the matrix based on green moulding sands selected parameters research.

2.1. Influence of the matrix grain size on the selected properties of moulding sands

The results of the influence of the matrix grain size on the compressive strength are presented in Figure 1. The tested sand obtains maximum compressive strength R_c^W at a moisture of app.

2-2.5%. The sand made from mesh fraction 0.16 has relatively the worse strength in the whole range of tested moisture changes, however any special influence of grain size on strength properties was not observed.

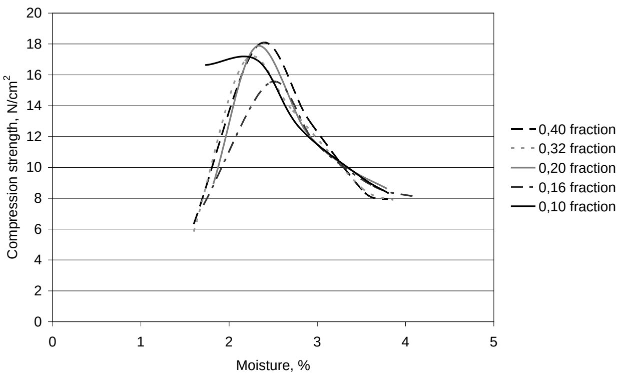

Fig. 1. The influence of water content on compressive strength R_c^W, for the moulding sands with different grain size

The matrix grain size has the most pronounced influence on the sand permeability (Fig. 2); an increase of the matrix grain size causes the significant permeability increase, which is in agreement with the reference data [13].

The results of the matrix grain size influence on the sand compactibility are presented in Figure 3. Along with the moisture increase the sand compactibility increases fast.

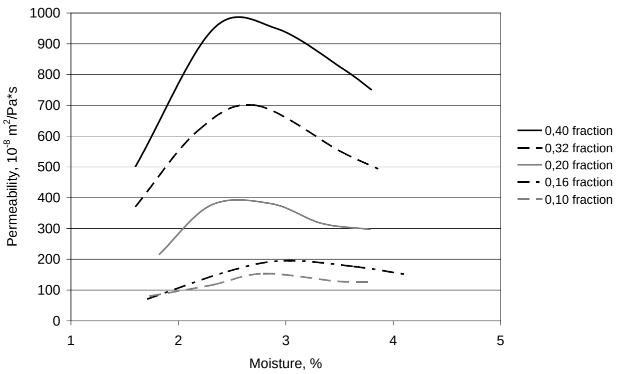

Fig. 2. The influence of water content on permeability, for the moulding sands with different grain size

2.2. ANN modelling for the determination of moulding sand's matrix grain size

The successive stage of investigations was using the experimental results for designing neural network models by means of the Statistica 9.0 program. The suitability of the selected properties for predicting the moulding sand matrix grain size was determined. The simulation results of the neural network in relation to experimental data for the best model, in which the compactibility results were introduced as input data, is illustrated in Figure 4. The training algorithm RBFT was applied. For the training data set as well as for the test data the representation quality was not good (0.3144 and 0.2656 respectively).

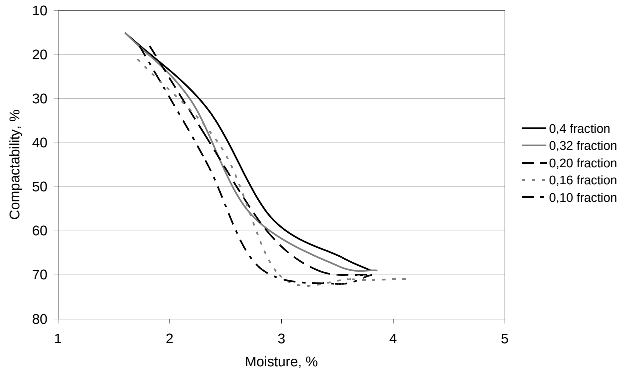

Fig. 3. The influence of water content on compactability, for the moulding sands with different grain size

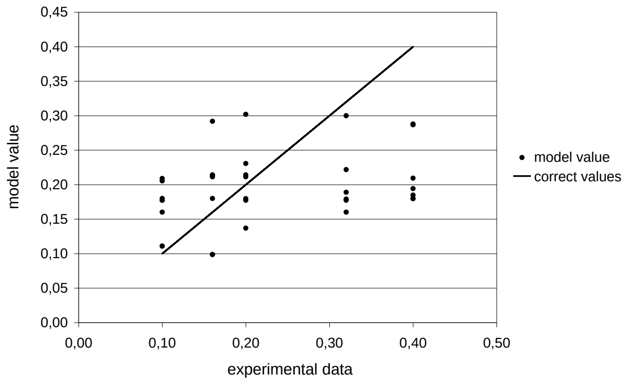

Fig. 4. Comparison of the distribution of data generated by the network and the experimental data, input data: compactibility, output data: sand grain size, the network model: RBF 1-9-1

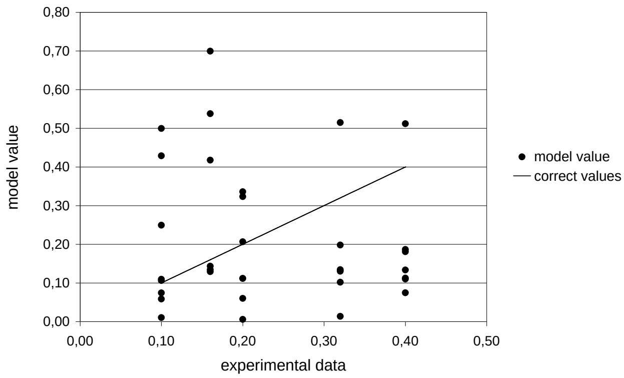

Fig. 5. Comparison of the distribution of data generated by the network and the experimental data, input data: compressive strength, output data: sand grain size, the network model: RBF 1-17-1

The neural network simulation results in relation to the experimental results for the best model, in which the compressive strength measurement results were used as input data are displayed in Figure 5. Again the training algorithm RBFT was applied. A large scatter of network model responses was observed. This was confirmed by a weak training quality of the selected network models (Fig. 6).

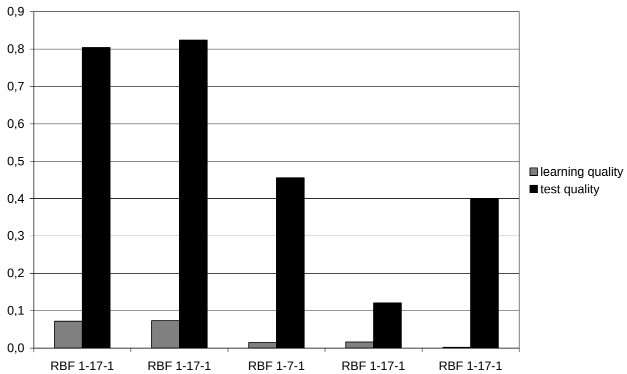

Fig. 6. Learning and test quality comparison, input data: compressive strength

Next the network models, in which the moulding sand permeability results were used as input data, were designed. The results of data distribution for the best model, in relation to the experimental data, are presented in Figure 7. Both the testing and training quality was high, equal to 0.9662 and 0.9466 respectively. This quality for 5 selected neural network models is shown in Figure 8. A very good representation was obtained in each case for the training as well as for the testing sample. Thus, utilising permeability for predicting the matrix grain size by means of the appropriate model, provides good results. This correlates well with the experimental investigations results, where permeability was the most sensitive to changes of the matrix grain size. The training algorithm RBFT was applied.

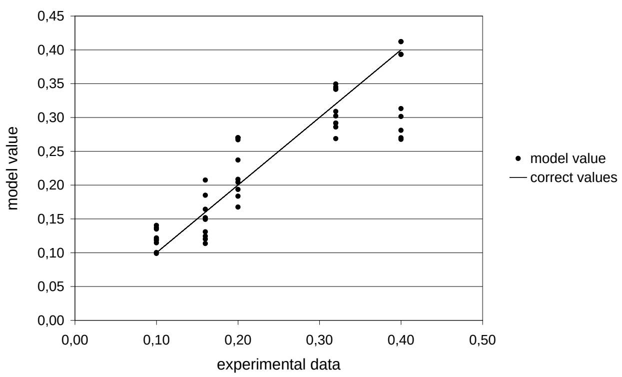

Fig. 7. Comparison of the distribution of data generated by the network and the experimental data, input data: permeability, output data: sand grain size, the network model RBF 1-12-1

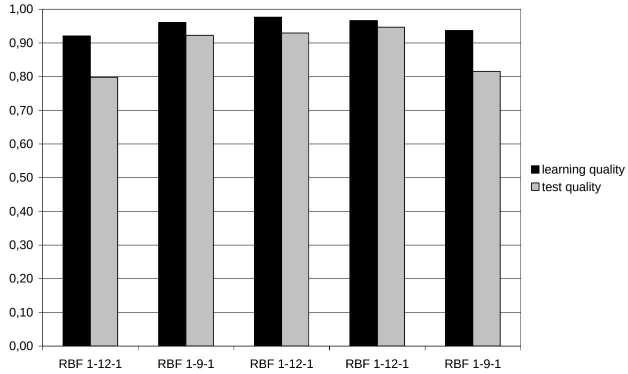

Fig. 8. Learning and test quality comparison, input data: permeability

During the successive stage of the study the network models projects were constructed with the application of data for all three moulding sand properties. The distribution of data generated by the MLP 3-3-1 network model (of the best representation quality), in relation to the experimental data, is presented in Figure 9.

A comparison of the selected models quality for both data sets (training and testing) is given in Figure 10. For the majority of models the results were above 0.9. The best training and testing quality was achieved in case of the MLP 3-3-1 network. The highest training quality was equal to 0.985, while the highest testing quality to 0.997. The training algorithm for the best network model was the BFGS algorithm.

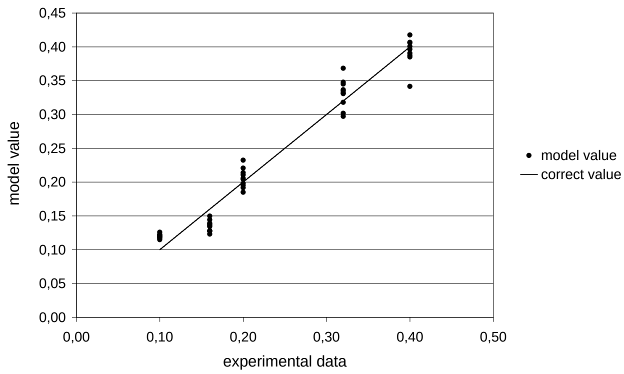

Fig. 9. Comparison of the distribution of data generated by the network and the experimental data, input data: permeability, compactability, compressive strength, output data: sand grain size, the network model MLP 3-3-1

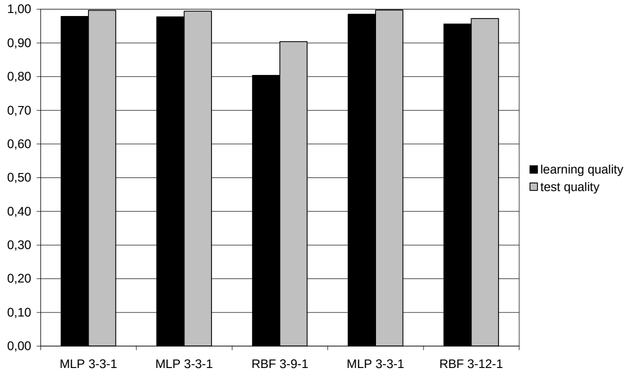

Fig. 10. Learning and test quality comparison, input data: permeability, compactability, compressive strength

The analysis of the sensitivity of complex network models to individual parameters is presented in Figure 11. The basic network sensitivity measure is a quotient of the error obtained when using the network for the data set without one variable and the error obtained when none of the variables was missing. The larger error after rejecting a certain variable in relation to the primary error, the more sensitive is the network to the lack of this particular variable. If the quotient of errors equals 1 or is smaller, the removal of one variable has no influence [12].

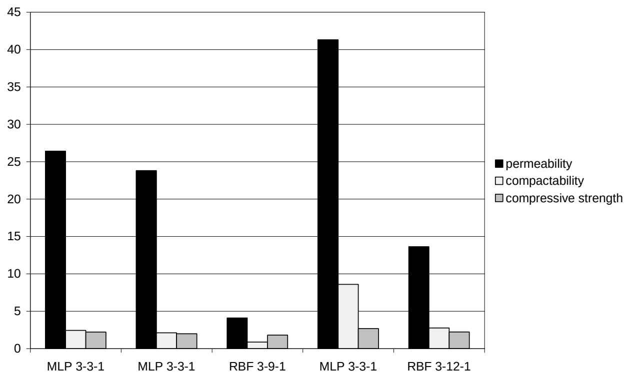

Fig. 11. Sensitivity analysis of a complex network

Permeability is the property to which the presented network models are the most sensitive, whereas to the compressive strength data are the least sensitive.

4. Conclusions

It was indicated that the application of artificial neural networks for predicting the matrix grain size, on the basis of the individual sand property provides good results only in case of using the permeability data. It is also confirmed by the analysis of the complex networks sensitivity to individual parameters.

Acknowledgments

The study was financed by resources allocated for science in years 2008-2011 as the Research Project No. N N508 387335

References

[1] Z. Ignaszak, R. Sika, The system to explore the chosen production data and its testing in the foundry. Archives of Mechanical Technology and Automation.. 2008, Vol. 28, 1, pp. 61-72 (in Polish).
[2] J. Jakubski, St. M. Dobosz, K. Major-Gabryś, Influence of moulding sands grain size on the effectiveness of quality control systems. Archives of Foundry Engineering, 2011, vol. 11 iss. 2 s. 47–50.
[3] Hülya Kaçar Durmuş, Erdoğan Özkaya, Cevdet Meri Ç, The use of neural networks for the prediction of wear loss and surface roughness of AA 6351 aluminium alloy. Materials& Design. 2007, Vol. 27, pp. 156–159.
[4] Mahesh B. Parappagoudar D.K. Pratihar, Datta G.L, Forward and reverse mappings in green sand mould system using neural networks. Applied Soft Computing. 2008, Vol. 8, pp. 239-260.
[5] M. Perzyk, A. Kochański, Prediction of ductile cast iron quality by artificial neural networks. Journal of Material Processing Technology. 2001, Vol. 109, pp. 305-307.
[6] J. Jakubski, St. M. Dobosz, The use of artificial neural networks for green moulding sands quality control. Transaction of the VŠB – Technical University of Ostrava Metallurgical Series. 2009, Vol. 2, pp. 109-114.
[7] M. Perzyk, R. Biernacki, A. Kochański, Modeling of manufacturing processes by learning systems: The naïve Bayesian classifier versus artificial neural networks. Journal of Material Processing Technology. 2005, 164–165, 430–1435.
[8] J. Jakubski, St. M. Dobosz, Selected parameters of moulding sands for designing quality control systems. Archives of Foundry Engineering. 2010, Vol. 10, iss. 3, pp. 11–16.
[9] J. Jakubski, St. M. Dobosz, The usage of data mining tools for green moulding sands quality control. Archives of Metallurgy and Materials. 2010, Vol. 55, iss. 3, pp. 843–849.
[10] J. Jakubski, St. M. Dobosz, The use of artificial neural networks for rebonding of moulding sands.Technológ. 2010, Vol. 2, pp. 84–89.
[11] J. Jakubski, St. M. Dobosz, K. Major-Gabryś, Active binder content as a factor of the control system of the moulding sand quality. Archives of Foundry Engineering, 2011, vol. 11 iss. 1 s. 49–52.
[12] Statistica manual, StatSoft, Inc., 1984-2003