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Selected parameters of moulding sands for designing quality control systems

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Abstract

One of the modern methods of production optimisation are artificial neural networks. Neural networks owe their popularity to the fact that they are convenient tools, which can be utilised in a wide scope of problems. They are capable of reflecting complex functions. Especially their non-linearity should be emphasised. They are gaining wider and wider application in the foundry industry, among others, to control melting processes in cupolas and arc furnaces, designing castings and supply systems, control of moulding sands treatments, prediction of properties of cast alloys as well as selecting die casting.
An attempt of the application neural networks to the quality control of moulding sands with bentonite is presented in the paper. This is a method of assessing the suitability of moulding sands by finding correlations in between individual parameters, by means of artificial neural network systems. The presented investigations were performed with the application of the Statistica 8.0 program.
The investigations were aimed at the selection of the proper kind of a neural network for prediction a sand moistness on the bases of certain moulding sand properties such as: permeability, compactibility and friability. These parameters – determined as sand moistness functions - were introduced as initial parameters.
Application of the Statistica program allowed for an automatic selection of the most suitable network for the reflection of dependencies and interactions existing among the proposed parameters. The best results were obtained for unidirectional multi-layer perception network (MLP). The neural network sensitivity to individual moulding sand parameters was determined, which allowed to reject not important parameters when constructing the network.

Keywords: quality management, green sand, artificial neural networks

1. Introduction

Large number of data generated in casting processes is usually not directly measured and recorded, especially automatically. However, even the data which are measured and collected are not used for optimisation and computer aided quality control. Access to larger amounts of likelihood data requires purchasing of the appropriate measuring equipment and employing new workers [1].
One of the modern production optimisation method are artificial neural networks. Neural networks are convenient investigating tools. They are capable of reflecting complex functions. Especially their non-linearity should be emphasised. They are gaining wider and wider application in the foundry industry, among others, for controlling melting processes in cupolas and arc furnaces, designing castings and supply systems, controlling of moulding sands treatments, prediction of properties of cast alloys as well as selection of die casting parameters [2-6].
Neural networks belong to modern self-training systems. Neural networks can realise several types of tasks depending on the kind of the problem which is to be solved [7].

2. Own investigations

2.1. Modelling of ANN for the estimation of moulding sands moistness

The following technological parameters were used for designing neural networks models: permeability, compactibility and sand friability. Therefore wide examinations of dependences of these properties on sand moistness were carried out. The distribution of the experimental data is presented in Figure 1. The wide scatter of results for individual properties is caused by using experimental data from various stages of sands testing. This will allow todetermine in what degree neural networks enable using past data collected for a long time for designing those networks.
The Statistica 8.0 program with a function of automatic designer, which allows for optimal network selection, was used for designing network models.

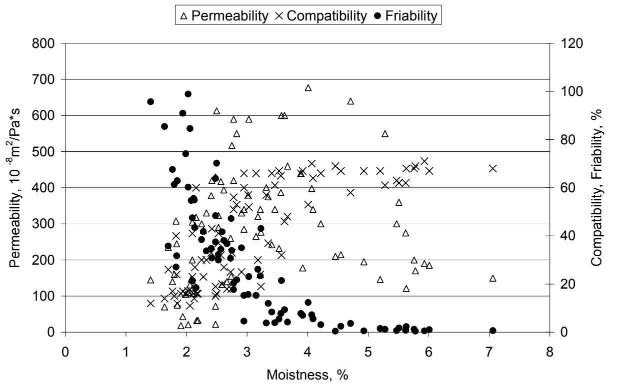


Fig. 1. Experimental data for parameters selected for training neural networks

The results obtained for one out of five networks giving the best reflection in reference to the experimental data for the sand permeability is presented in Figure 2. Solid lines present the actual moistness values, while points indicate data obtained as initial ones for individual network models.

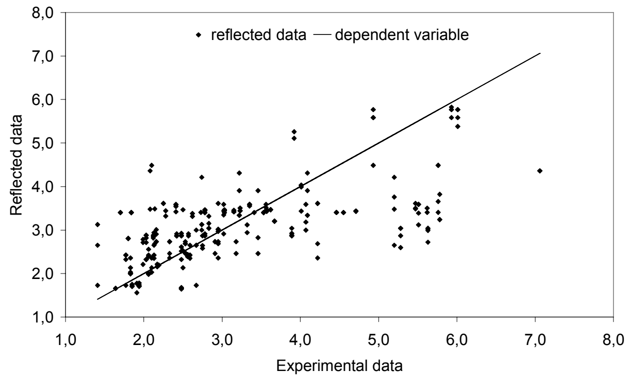


Fig. 2. Comparison of the distribution of data generated by the network and the experimental data for permeability, the network model: RBF 1-43-1

The best reflection was obtained for the RBF 1-43-1 network model. However, in the case of using permeability in order to determine moistness, it can be noticed, that the distribution of data generated by the designed network significantly differs from the experimental data.
The results obtained for one out of five networks giving the best reflection in reference to the experimental data for the sand compactibility is presented in Figure 3. The best is RBF 1-47-1 network where training quality equals 0.919712. Using compactibility in order to determine the accurate moistness value provides generated values very similar to the experimental data.
The results obtained for one out of five networks giving the best reflection in reference to the experimental data for the sand friability is presented in Figure 4. Solid lines present the actual moistness values, while points indicate initial data for individual network models.

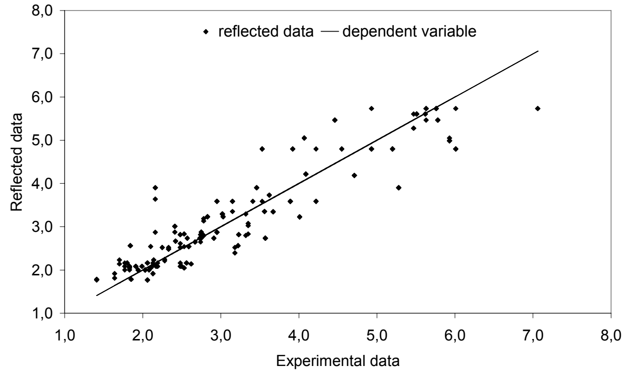


Fig. 3. Comparison of the distribution of data generated by the network and the experimental data for compactibility, the network model: RBF 1-47-1

The diagram of the RBF 1-44-1 network provides the best representation. Using sand friability in order to determine the accurate moistness value provides generated values very similar to the experimental data.

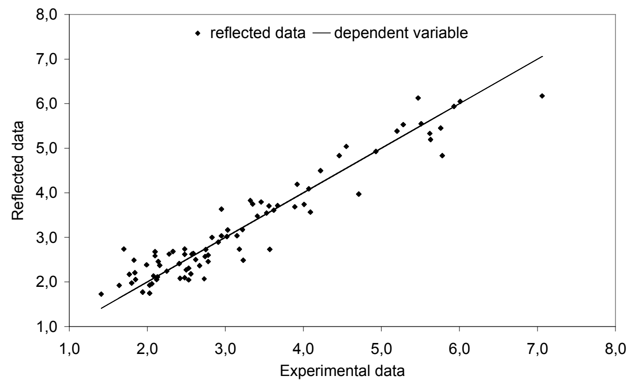


Fig. 4. Comparison of the distribution of data generated by the network and the experimental data for friability, the network model: RBF 1-38-1

In the successive stage of investigations the network models were designed on the basis of three parameters selected simultaneously. One out of five best complex networks is presented in Figure 5. The best reflection was obtained for the MLP 3-8-1 network, where the training quality equals 0.959703. All presented models of complex networks are characterised by a very high quality, better than models for single parameters what indicates that – in the considered case – networks constructed on many parameters exhibit better reflection of the experimental data.
The reflection accuracy for single network models is shown in Figure 6. The closer to unity is the value the more accurate is the reflection of the expected values. The reflection of the majority of models in the case of permeability is below 0.8, which indicates a low network quality, while for the remaining parameters (friability, compactibility and complex networks) the majority of the presented models achieves the reflection accuracy above 0.9. These testifies to a good correlation between models and the experimental data.

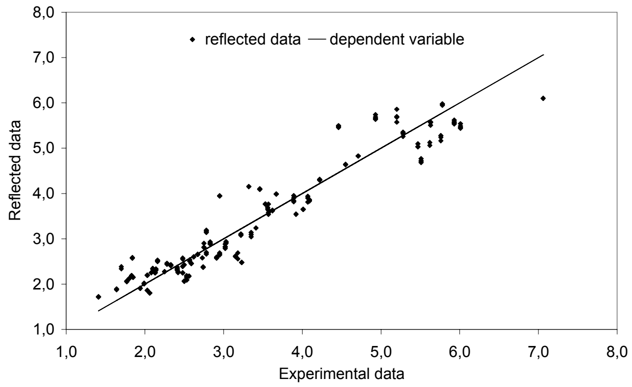


Fig. 5. Comparison of the distribution of data generated by the network and the experimental data from measurements of permeability, compactibility and friability. The network model: MLP 3-7--1

Determination of sensitivity of single moulding sand parameters can enable to reject time-consuming measurements, which only negligibly contribute to the network training process. The program *STATISTICA Neural Networks* has procedures of compensating the lack of data in variables. These procedures are used in a sensitivity analysis. Data are presented to the network several times, while in each test all values of one variable, different in each repetition, are exchanged for the lack of data. Then the total error is calculated, in a similar fashion as in a standard network training. Since a certain amount of data is being rejected an increase of a network error should be expected. Thus, the basic measure of the network sensitivity is the ratio of the error obtained at starting the network for the data set without one variable and the error obtained when the data set was complete. The larger the error after rejecting the variable (in reference to the initial error) the more sensitive is the network to the lack of this very variable.
The results of the sensitivity of complex neural networks to single parameters are shown in Table 1 and in Figure 7.
The presented results indicate that regardless of the network model its sensitivity to data concerning permeability is the smallest one. The sand friability is the parameter to which all models exhibit the highest sensitivity. In the case of compactibility the network sensitivity varies depending on the model.

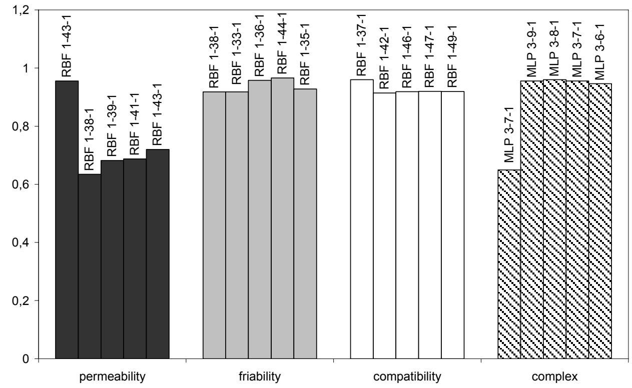


Fig. 6. Reflection accuracy of 5 best models

Table. 1
Sensitivity analysis of a complex network

Network name	*permeability*	*compactability*	*friability*
MLP 3-7	2,103352	2,63811	21,22153
MLP 3-9	2,260286	3,94888	30,66256
MLP 3-8	2,366871	17,51680	8,77087
MLP 3-7	2,043885	3,26161	5,18899
MLP 3-6	2,502457	3,73790	24,23826

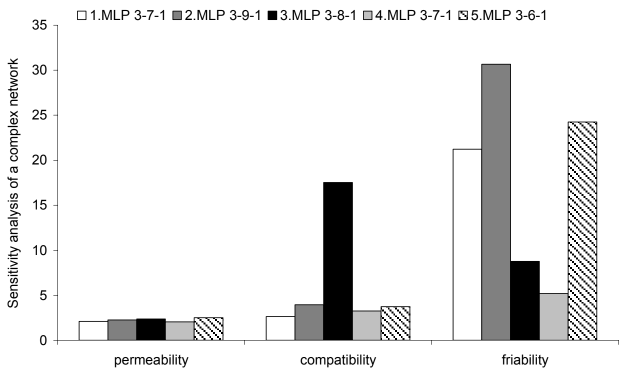


Fig. 7. Sensitivity analysis of a complex network

The next stage of investigations concerned designing complex networks however, with omitting the permeability parameter. The best model of complex network is presented in Figure 8. Compactibility and friability parameters were taken into account while permeability was omitted.
The best reflection was obtained for the RBF 2-46-1 network, where the training quality was 0.963809, which is a slightly better result than the results obtained for complex networks with the permeability parameter taken into account.

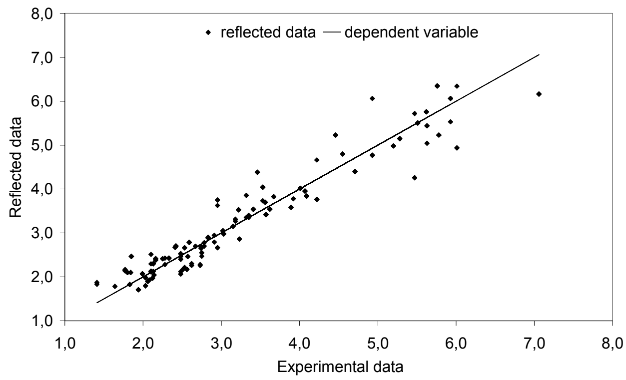


Fig. 8. Comparison of the distribution of data generated by the network and the experimental data for complex networks when the permeability parameter was omitted. The network model: RBF 2-46-1

A comparison of the reflection accuracy of individual models of complex networks in which the permeability parameter was either taken into account or omitted is presented in Figure 9. The diagrams interpretation explicitly indicates that the permeability parameter has only negligible influence on the reflection accuracy, since both kinds of models are very similar and oscillate near unity. It should be mentioned, that the MLP network gives the best results in models taking into account the permeability parameter, while the RBF models are the best when this parameter is omitted.

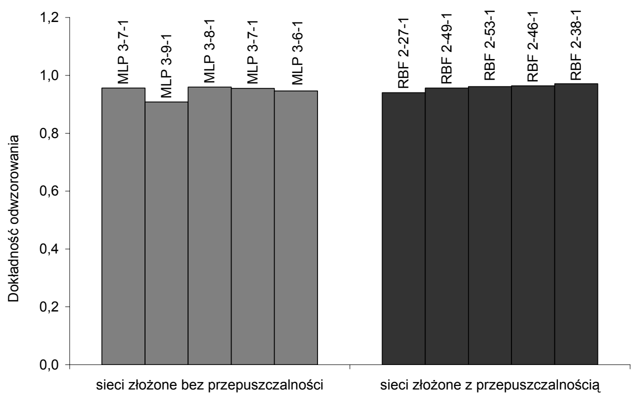


Fig. 9. Reflection accuracy of 5 best complex network models omitting the permeability parameter and complex network models taking into account the permeability parameter

The results of experimental examinations of changes of the selected moulding sand parameters in dependence of a water content and bentonite addition – are presented in the further part of the paper. Tests were performed for bentonite „Zębiec Specjal". The obtained results were used for modelling of neural networks, where a sand moistness and bentonite content were assumed as output parameters.

2.2. Modelling of Artificial Neural Networks (ANN) for the determination of the bentonite content and moulding sand moistness

In order to obtain data for modelling networks concerning the bentonite content and the moulding sand moistness several examinations were performed for moulding sands with a strictly determined bentonite content and a moistness changing from 1 to 5 % - being checked during experiments.

In a similar fashion as in paragraph 2.1, permeability, friability and compactibility were used as parameters for modelling ANN.

The results of permeability of sands of a various bentonite content as a function of the moulding sand moistness are presented in Figure 10.

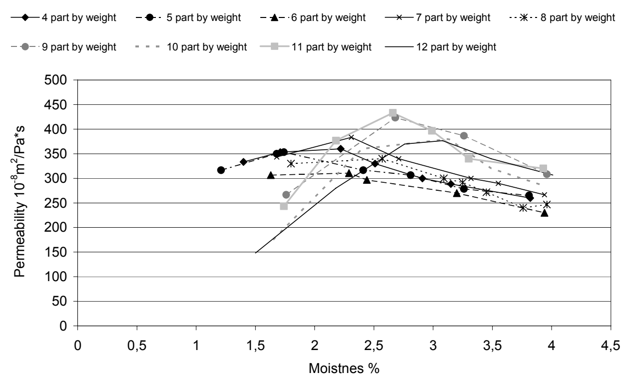


Fig. 10. Water content influence on permeability P^w of moulding sands of a various binder content

The dependence of permeability on moistness is of a variable course. At the initial phase a moistness increase causes a permeability increase whereas when a moistness achieves the maximum value a permeability decreases.

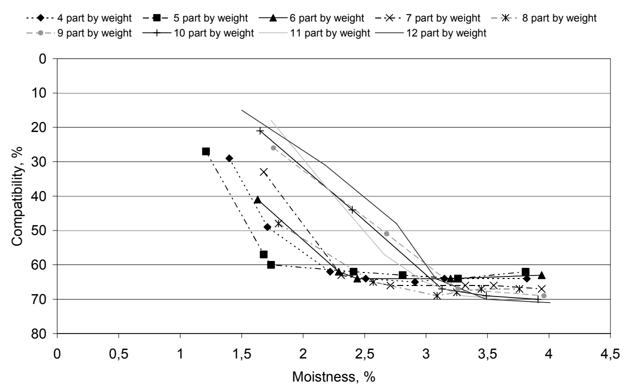


Fig. 11. Water content influence on compactibility of moulding sands of a various binder content

Compatibility changes of moulding sands are presented in Figure 11. At the beginning with the increasing moistness the moulding sand compactibility is growing fast up to a certain moistness value. After over-passing this value compactibility is not further changing. The moulding sands compactibility – at the maximum tested moistness – was within 60 – 70 %. An increased bentonite content caused a slower increase of compactibility at a lower sand moistness. It should be mentioned here, that the quality control systems based on the compactibility measurements consider the moulding sand of compactibility being on a level of 40% as useful for casting.

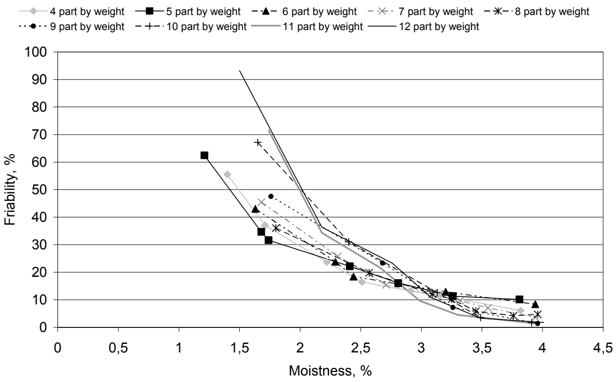


Fig. 12. Water content influence on friability of moulding sands of a various binder content

Changes in moulding sand friability are presented in Figure 12. An increase of moistness and a bentonite content caused a systematic friabily decrease, and in the case of moulding sand of a small bentonite content and a low moistness performing tests was not possible. The smallest friability, nearly zero, was found in the case of moulding sand containing 12 parts by weight of bentonite at a moistness of 4%.

The bentonite content significantly influences the moulding sands properties.

The presented above studies were used for modelling artificial neuron networks, where the moulding sand moistness and the bentonite content were applied as the initial parameters. The artificial neural networks were modelled by means of the Statistica 8.0 program.

By means of this program 5 network models, which the most accurately reflect the experimental data were selected: MLP 6-20-2, MLP 6-3-2, MLP 6-18-2, MLP 6-20-2 and MLP 6-4-2. The best training quality and testing was obtained in the case of the MLP 6-3-2 network [Fig. 13]. The largest training error exhibited the MLP 6-18-2 network while the highest testing error exhibited two MLP 6-20-2 networks.

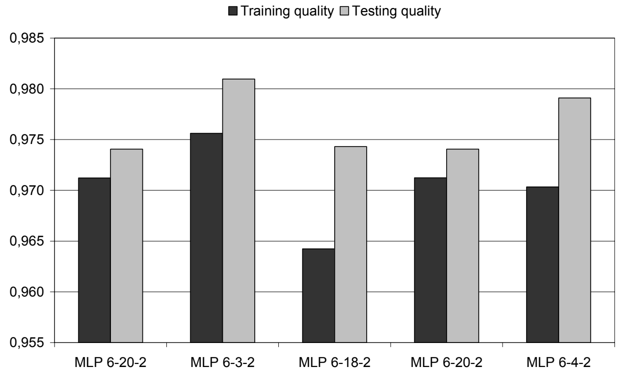
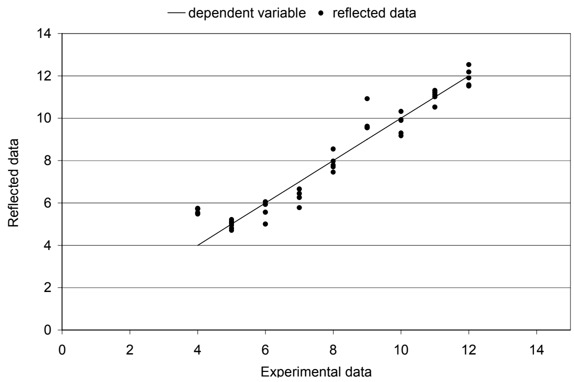
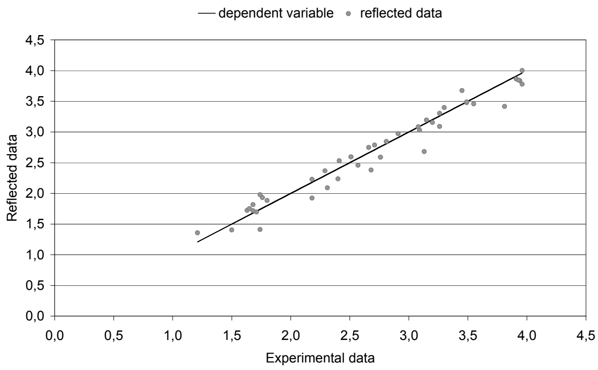


Fig. 13. Training and testing quality of 5 generated networks

Two best models of complex networks are shown in Figures 14 and 15. The best reflection is obtained for the MLP 6-3-2 network where the training quality is equal to 0.975611. Generally all presented networks are characterised by very good qualities, which indicates that networks constructed of many parameters are able to reflect correctly the experimental data.

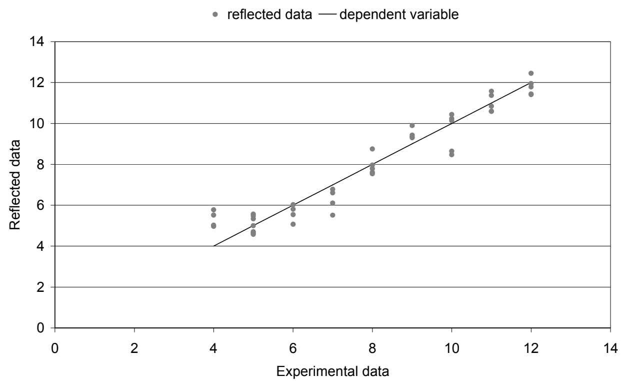


a)

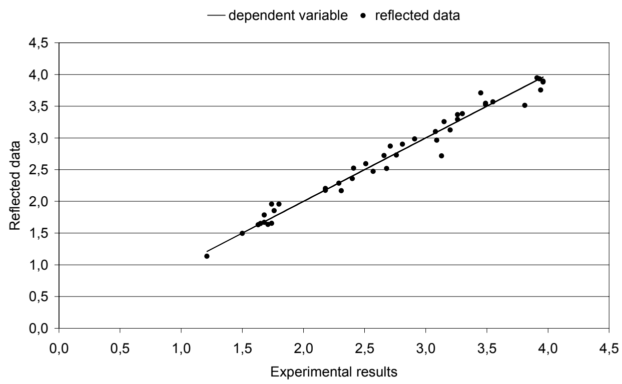


b)

Fig. 14. Comparison of the distribution of data generated by the network and the experimental data. The network model: MLP 6-20-2. a) Bentonite content, b) Sand moistness



a)



b)

Fig. 15. Comparison of the distribution of data generated by the network and the experimental data. The network model: MLP 6-3-2

The results of the complex network sensitivity to single parameters are shown in Figure 16.

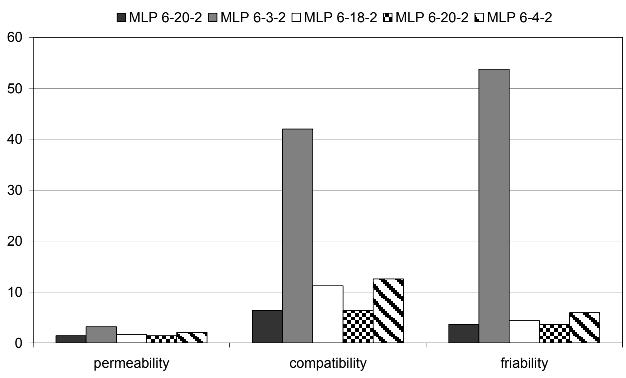


Fig. 16. Analysis of the complex network sensitivity

The presented data indicate that, regardless of the model, networks are not very sensitive to the data concerning permeability. On the contrary, sand friability is the parameter, to which the presented network models are the most sensitive.

Whereas in the case of compactibility a diversified sensitivity is observed [10]. These results are confirmed by the data obtained for network models where only the sand moistness was proposed as the initial parameter (paragraph 2.1).

3. Conclusions

Artificial Neural Networks seem to be a very interesting IT tool to support sand preparation control processes. More investigations are required to find best mapping of green mould sand systems. Finding green mould sand parameters, which are especially sensitive to active binder and wettability content should help to build neural network model, which can be used in foundries.

It was found that the application of artificial neural networks provides good results in the case of predicting a single moulding sand property as well as several properties.

Acknowledgments

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