MODELING OF BRICK OBTAINING PROCES WITH ARTIFICIAL NEURAL NETWORKS

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Abstract. *In this study, neural network models were developed to predict the amount of NO discharged into the furnace chimney of a brick factory. The best performances were obtained with the MLP (6:18:6:1) model. Thus, in the training stage, the correlation coefficient was 0.9626 and the standard deviation was ± 5.61 mg/m^3 and in the validation phase, a standard deviation of ± 15.24 mg/m^3 is obtained. The advantages of this study derive from the important savings of time, materials and energy obtained by reducing the number of test loads in the analyzed industrial process.*

Key words*: neural networks; bricks; auxiliary materials*

Introduction

The current economic conditions in which the energy crisis is more and more present have increased the interest of process engineers for the use of auxiliary materials in brick factories. Thus, the use of solid waste such as sludge, ash, sawdust, tobacco residue, paper, cigarette butts, polystyrene, coffee grounds and many others has been shown to have positive effects on the properties of burnt clay bricks. There has been an improvement in porosity, thermal conductivity, water absorption properties, reduction in density and energy consumption [1-4]. In general, most of the existing studies in the literature follow the influence of changes in the manufacturing mix on the properties of the bricks obtained. However, an extremely important aspect to be taken into account when using various solid wastes in the production of burnt bricks is the maintenance of the level of pollutants discharged during the process within the regulated limits. In a previous study, neural models and regression algorithms were used to analyze the influence of adding auxiliary materials in the bricks manufacturing mix on the exhaust emissions in the furnace chimney [5].

This paper assesses the impact of adding auxiliary materials such as sawdust and sunflower seed husks on the NO level in the exhaust gases in the furnace chimney. Neural models are built on the basis of which predictions can be obtained about the change in the amount of NO when different percentages of auxiliary materials are introduced into the manufacturing mix.

Materials and Methods

Experimental determinations of the amount of NO exhausted in the furnace chimney were performed with a Testo 350 flue gas analyzer. This equipment provides a measurement accuracy for NO of 1 ppm. The limit set by the local environmental agency for NO emissions is < 250 mg/m^3. The other quantities measured experimentally in the brick factory and used in the construction of the database were: the percentage of sunflower seed husks (SSH) and sawdust (S), the amount of dry product matter (DPM), the amount of clay (C), the amount of ash (A) and organic raw materials (ORM).

Modeling with neural networks the relation between the composition of the manufacturing mix and the amount of NO discharged to the furnace chimney was done with the *NeuroSolutions* program.

Results and Discussions

The available experimental data were divided into two samples. The first sample containing 86 data sets was used during the training phase. The second sample containing 14 data sets was kept for the validation stage. Multilayer perceptrons (MLP) neural models were constructed and the TanhAxon transfer function and Momentum learning rule were used in this action.

Table 1 shows the architectures of the constructed neural models and their performances quantified by the mean square error (MSE), the normalized mean square error (NMSE), the correlation coefficient (r^2) and the percentage error (E_p):

$$MSE = \frac{\sum_{j=1}^{P}\sum_{i=1}^{N}(D_{ij} - O_{ij})^2}{N \cdot P} \tag{1}$$

where *P* represents the number of output quantities (in this case, P = 1), *N* is the number of data, O_{ij} is the output value for *i* with processing of element *j* and D_{ij} is the desired output for *i* with processing of element *j*:

$$\mathrm{NMSE} = \frac{\overline{(O_{exp} - O_{net})^2}}{\overline{O_{exp}} \cdot \overline{O_{net}}} \tag{2}$$

$$r^2 = \frac{\Sigma\left(O_{\exp_i} - \overline{O}_{\exp}\right)\cdot\left(O_{net_i} - \overline{O}_{net}\right)}{\sqrt{\Sigma\left(O_{\exp_i} - \overline{O}_{\exp}\right)^2 \cdot \left(O_{net_i} - \overline{O}_{net}\right)^2}} \tag{3}$$

$$E_p = \frac{O_{\exp} - O_{net}}{O_{\exp}} \cdot 100 \tag{4}$$

where *O* are the values of the output data, respectively *exp* and *net* denote the experimental values and those obtained from the neural models.

Table 1

Performance of neural models in the training stage

No.	MLP model	MSE	NMSE	r^2	E_p (%)
1.	MLP(6:6:1)	0.03897	0.2389	0.8724	6.73
2.	MLP(6:12:1)	0.02466	0.1508	0.9214	4.44
3.	MLP(6:18:1)	0.02533	0.1553	0.9193	4.65
4.	MLP(6:24:1)	0.02541	0.1558	0.9194	4.80
5.	MLP(6:12:6:1)	0.01777	0.1089	0.9440	3.93
6.	MLP(6:18:6:1)	0.01195	0.0733	0.9626	2.88
7.	MLP(6:18:12:1)	0.01298	0.0796	0.9594	3.14
8.	MLP(6:24:6:1)	0.01306	0.0801	0.9592	3.06
9.	MLP(6:24:12:1)	0.01243	0.0761	0.9611	2.97

In order to avoid the overtraining of the neural models, the variation of the mean square error at the increase of the number of training epochs was analyzed (Figure 1). It was found that the optimal number of training epochs was 80000. Table 1 shows the performance of the models for this number of epochs.

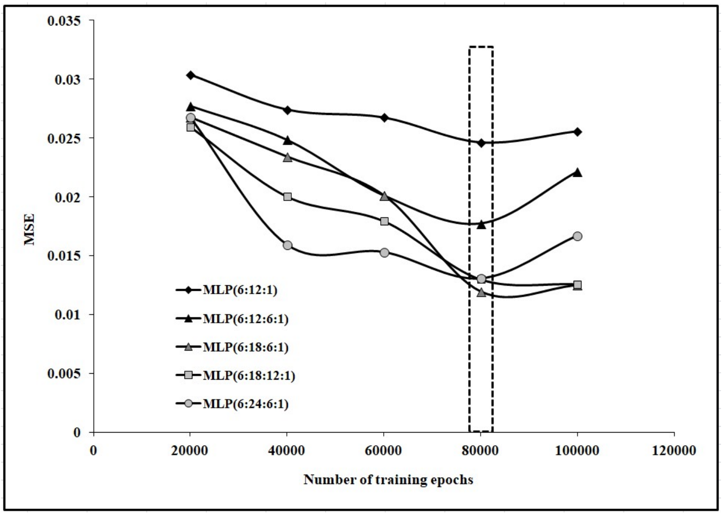
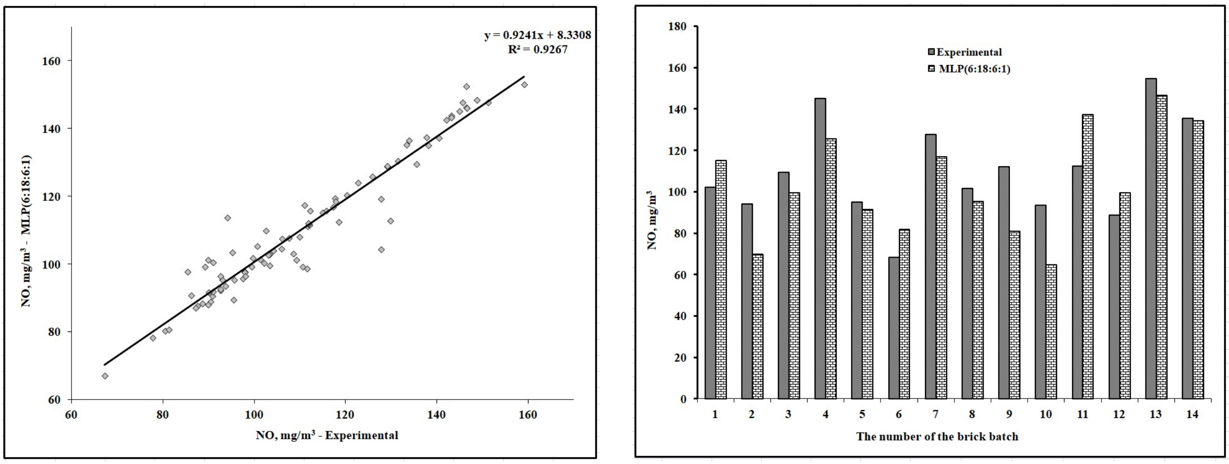


Figure 1. The evolution of the MSE error with the increase of the number of training epochs

According to the results presented in Table 1, the best performances were obtained with MLP (6:18:6:1) model. Figure 2a compares the experimental values measured for NO and those calculated with the best performing model. There is a correlation coefficient greater than 0.9 and a standard deviation evaluated with relation (5) equal to ± 5.61 mg/m^3.

$$\sigma = \sqrt{\sum_{i=1}^{k}\left[NO_{experimental} - NO_{model}\right]^2/(n-p)} \tag{5}$$

where *n* represents the number of experimental data and *p* is the number of parameters.



a) testing stage b) validation stage

Figure 2. Experimental values for NO compared to those obtained with the MLP (6:18:6:1) model

In the validation stage of the neural model, the sample containing 14 data series was used. Figure 2b compares experimentally measured NO values with those calculated with the MLP (6:18:6:1) model. A standard deviation of ±15.24 mg/m^3 was calculated for the validation stage. The performances of the best neural model obtained in this paper are comparable to those reported by other researchers in the literature. Li et al [6] used adaptive neuro-fuzzy inference systems (ANFIS) combined with particle swarm optimization (PSO), genetic algorithm (GA), and firefly algorithm (FFA) to predict the compressive strength of brick aggregate concrete (BAC). The database used by them contained information on 132 data sets taken from the literature, resulting from experimental laboratory research that used brick waste to produce environmentally friendly concrete. The ANFIS-PSO hybrid model led to the following performances: the correlation coefficient 0.955 in the training stage and 0.913 in the validation stage respectively, and a standard deviation of ±10% in the validation phase.

The percentage error in the validation stage (±30%) in the case of the study presented in this paper is higher, but it should be taken into account that the data sample was based on experimental data from an industrial process of manufacturing burnt bricks. It can be also observed that the results obtained are much better than those reported in a previous study [5] when the best performing model in the training stage for NO prediction offered a correlation coefficient of 0.895, a percentage error of 5.88% in the training stage and a percentage error in the validation stage of ±35%. Another advantage of the model presented in this paper is that the amount of NO discharged to the furnace chimney is directly correlated with the percentage composition of sunflower seed husks and sawdust introduced into the manufacturing mix. By applying optimization algorithms in the future, starting from the neural models presented in this paper, we can obtain the optimal percentages of auxiliary materials that can be introduced into the manufacturing mix so that NO emissions are maintained within the regulated limits.

Conclusions

In this study, neural models with one or two layers of hidden neurons were obtained to predict the amount of NO discharged to the furnace chimney in a brick factory when various proportions of auxiliary materials are introduced into the manufacturing mix. Modeling with neural networks the relation between the composition of the manufacturing mix and the amount of NO discharged to the furnace chimney allows the realization of predictions with important economic advantages. This reduces the number of test loads with significant savings of time and money. Process engineers can make decisions related to the content of the manufacturing mix to keep the exhaust emissions within the regulated limits.

References

1. KADIR, A. A., MOHAJERANI, A. Bricks: an excellent building material for recycling wastes – a review, In: *Proceedings of the IASTED International Conference* July 4 - 6, 2011 Calgary, AB, Canada Environmental Management and Engineering (EME 2011), pp. 108-115, https://doi.org/10.2316/P.2011.736-029
2. KURMUS, H., MOHAJERANI, A. Recycling of Cigarette Butts in Fired Clay Bricks: A New Laboratory Investigation. In: *Materials*, 2020, 13, pp. 790. https://doi.org/10.3390/ma13030790
3. DOĞAN-SAĞLAMTIMUR. N., BILGIL, A., SZECHYŃSKA-HEBDA, M., PARZYCH, S, HEBDA, M. Eco-Friendly Fired Brick Produced from Industrial Ash and Natural Clay: A Study of Waste Reuse. In: *Materials*, 2021, 14, pp. 877. https://doi.org/10.3390/ma14040877
4. HAMEED, A., HAIDER U., QAZI, A.A., ABBAS, S. Effect of Waste Glass on Properties of Burnt Clay Bricks. In: *Pak. J. Engg. Appl. Sci.*, 2018, 22, pp. 56–63.
5. ANTON, C., CURTEANU, S., LISA, C., LEON, F. Machine learning methods applied for modeling the process of obtaining bricks using silicon-based materials. In: *Materials*, 2021, 14, pp. 7232. https://doi.org/10.3390/ma14237232
6. SHABAN, W. M., YANG, J, ELBAZ K., Xie J., Li L., Fuzzy-metaheuristic ensembles for predicting the compressive strength of brick aggregate concrete. In: *Resources, Conservation & Recycling,* 2021, 169, pp. 105443. https://doi.org/10.1016/j.resconrec.2021.105443