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NEURAL NETWORK MODELLING OF THE GAS PHASE OF A COPPER FLASH SMELTING PROCESS

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Abstract

The paper presents the results of modelling of gaseous phase parameters of the copper flash smelting process. Models based on static and dynamic artificial neural networks are presented. The worked out models can be used for process optimisation, in turn resulting in reduction of the amount of harmful waste in the environment.

Key words: artificial neural networks modelling, dynamic neural networks, copper flash smelting process

1. INTRODUCTION

Artificial neural networks, and in particular static neural networks, attracts continuous increasing interest in modelling of complex industrial processes, including metallurgical processes (Talar & Kusiak, 2004; Falkus et al., 2005; Talar et al., 2005; Talar et al., 2006). Models that enable the prediction of the concentration of selected process parameters (SO_2, CO_2, O_2, NO_x) as well as the temperatures of the exhaust gas in copper flash smelting process (Davenport et al., 2001) were developed within the study.

Because of the dynamics existing in complex metallurgical processes, static neural networks do not fit to the modelling of some process parameters. In such situations the use of dynamic artificial neural networks becomes advisable (Gupta et al., 2003). The temperature of flash smelting furnace exhaust gas is an example of a parameter, in the modelling of which it is important to consider the process dynamics. A comparison of the models based on a static and dynamic neural network is presented in the paper.

2. COPPER FLASH SMELTING PROCESS

The copper flash smelting process comprises the oxidation of fine-grained, dry copper concentrate in a reaction shaft of a flash smelting furnace (Davenport et al., 2001; Talar et al., 2005; Talar et al., 2006; Kusiak, 2009). Knowledge of the exhaust gas composition is crucial because of environmental protection. The following concentrations are of key importance: oxygen, sulphur dioxide, carbon dioxide and nitrogen oxides (Talar et. al., 2007).

Nitrogen oxides are the least desirable components of exhaust gas in the copper flash smelting process. The appropriate control of the copper smelting process includes the reduction of the nitrogen oxides concentration. The models developed may be used, among other things, in the proper selection of the control parameters, in turn ensuring the proper course of the process. 27 process input parameters (table 1) have been selected for the needs of modelling, comprising control parameters (parameters numbered 1-18) and uncontrollable parameters,

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specifying the copper concentrate properties (parameters numbered 19-27).

Table 1. *Models input parameters*

	Parameter name	Description	Unit
1	Concentrate 1	Concentrate feed on burner 1	Mg/h
2	Concentrate 2	Concentrate feed on burner 2	
3	Concentrate 3	Concentrate feed on burner 3	
4	Concentrate 4	Concentrate feed on burner 4	
5	Dust	Backward dust feed	
6	IOS 1	IOS feed on burner 1	
7	IOS 2	IOS feed on burner 2	
8	IOS 3	IOS feed on burner 3	
9	IOS 4	IOS feed on burner 4	
10	IOS 5	IOS feed on dust burner	
11	Oil	Oil into the reaction shaft	l/h
12	O2_blast	O_2 concentration in the blast	%
13	Over-oxid.	Overoxidation	Nm^3/Mg
14	Aeration 1	Aeration in burner 1	Nm^3/h
15	Aeration 2	Aeration in burner 2	
16	Aeration 3	Aeration in burner 3	
17	Aeration 4	Aeration in burner 4	
18	Aeration 5	Aeration in dust burner	
19	Corg_conc	Concentration of the primary components of the concentrate given to the reactive well	%
20	Cu_conc		
21	S_conc		
22	Pb_conc		
23	SiO2_conc		
24	CaO_conc		
25	H2O_conc		
26	sub_conc	Parameters characterising a size analysis of the given concentrate: share of the under- and over-sized particles	
27	over_conc		

Table 2. *Output parameters*

	Parameter name	Description	Unit
1	O2_gases	O_2 concentration in gases	%
2	SO2_gases	SO_2 concentration in gases	
3	CO2_gases	CO_2 concentration in gases	
4	NOx_gases	NOx concentration in gases	ppm
5	T_gases	Exhaust gas temperature after a dust recuperator	°C

The model output parameters are shown in table 2. They describe the chemical composition of flash smelting furnace exhaust gas and its temperature as measured downstream the dust recuperator.

3. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN) (Tadeusiewicz, 1993; Gupta et al., 2003) originated on the basis of the knowledge of the animals and human beings nervous systems. They attempt to use phenomena occurring in nervous systems to resolve complex tasks, including industrial processes. The basic ANN properties are: capability of learning on the base of presented examples as well as the capability of generalisation (allowing the use in new situations – cases that do not exist in the training data set). ANNs are effective tools for process modelling, capable of complex functions mapping, which makes, their wide spectrum of application.

Neural networks can be classified in two groups: static and dynamic networks (Gupta et al., 2003; Stanisławczyk et al., 2006). Static networks do not have feedback or delay elements. The initial state of a static network is a function of the current input state. In dynamic networks, the network output state depends not only on the inputs' current state but also on the history of the input parameters' changes. The neural networks dynamics is a result of the introduction of the delay lines and/or feedback between the layers.

The development of an analysed process model based on an artificial neural network comprises the following basic stages: network structure selection, network training, verification and testing. To build a neural network it is necessary to have appropriately large sets of training, validating and testing data, originating from measurements or computer simulations of the modelled process. The training set is used to modify the synaptic weights of the neural network. The validating set is used in the training algorithm's stop criterion and prevents so-called neural network overtraining. The test set is used to determine the model's prediction error.

The present paper presents an example of static MLP type networks use in order to predict the chemical composition of exhaust gas from the flash smelting process. The results of exhaust gas temperature modelling by using a static MLP network and a dynamic NARX type neural network were also compared.

4. ANN MODELLING OF THE EXHAUST GAS COMPOSITION

4.1. Data pre-processing for ANN modelling

The industrial data was subject to preliminary processing that was described in the work (Stanisławczyk & Kusiak, 2009). Then, each variable was subjected to normalisation, consisting of variable linear transformation in such a way that the new variables have values from [-1, 1] interval. The variables' normalisation ensures the convergence of neural network training.

Because of the time-lag existing between the input and output variables of the modelled object (Stanisławczyk et al., 2007), the input variables were delayed against the unchanged output data by 6 minutes.

4.2. Static ANN model of the gaseous phase composition of the flash smelting process

Approximately 40,000 records, collected throughout the period of 5 months of the furnace operation, were gathered in order to model the gaseous phase composition. 40% of the random selected records were included in the training set, while 20% and 40% of records were selected for the validating and testing, respectively.

A separate MLP type neural network of the structure shown in figure 1 was developed for each of the output parameters, describing the gaseous phase chemical composition (O_2, SO_2, CO_2, NO_x).

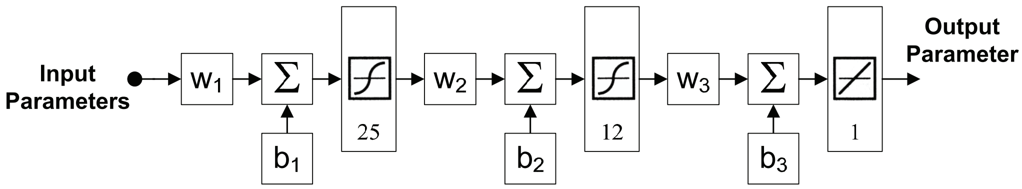

Fig. 1. Structure of the used ANN (w_i, b_i – weights and biases of the i-th layer, respectively).

The following two measures were used in assessing the quality of elaborated ANN models:
- the error for a single case from the test set:

$$\tau_i = \frac{\left| y_i^o - y_i^p \right|}{\max_i \{y_i^o\} - \min_i \{y_i^o\}} 100\,[\%] \qquad (1)$$

where: y_i^o – value observed, y_i^p – value predicted by the model,
- the RMSE error for the entire test set:

$$\Phi = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(y_i^o - y_i^p \right)^2}}{\max_i \{y_i^o\} - \min_i \{y_i^o\}} 100\,[\%] \qquad (2)$$

where n is the number of cases in the test set.

The developed ANN models show good accuracy. The error Φ for all models does not exceed 3% (table 3).

Table 3. *Error Φ observed from the neural network models*

	O_2	SO_2	CO_2	NO_x
Φ [%]	2.7	3.6	2.6	2.9

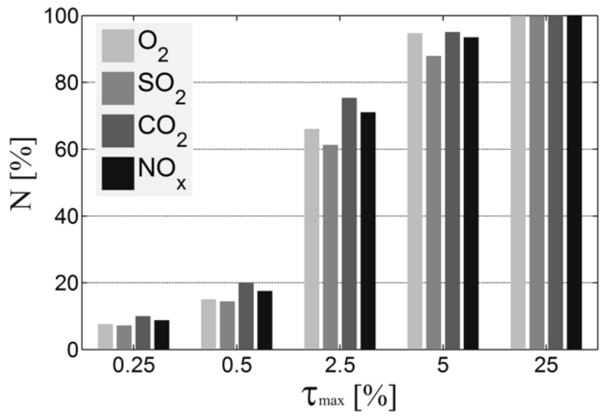

Fig. 2. *Structures of ANN models error τ obtained for the test set.*

Figure 2 shows the structure of the error τ of each model observed for the test data set. It shows the percentage of cases N versus the different ranges of the error $\tau < \tau_{max}$ (τ_{max} = 0.25, 0.5, 2.5, 5 and 25%).

The error τ (equation 1) of predictions of the exhaust gas components is lower than 5% for more than 85% of the cases from the data test set.

4.3. ANN modelling of the temperature of the flash smelting furnace exhaust gas

Comparison of the static and dynamic models of the flash smelting furnace exhaust gas temperature was presented in papers (Stanisławczyk et al., 2006; Stanisławczyk et al., 2008). Two ANN models were developed. The first one was based on a static MLP network, and the other on a dynamic NARX type neural network, which is shown in figure 3.

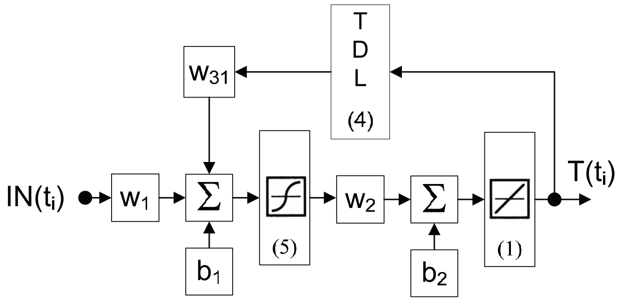

Fig. 3. Diagram of a NARX type neural model for the exhaust gas temperature.

a) b)

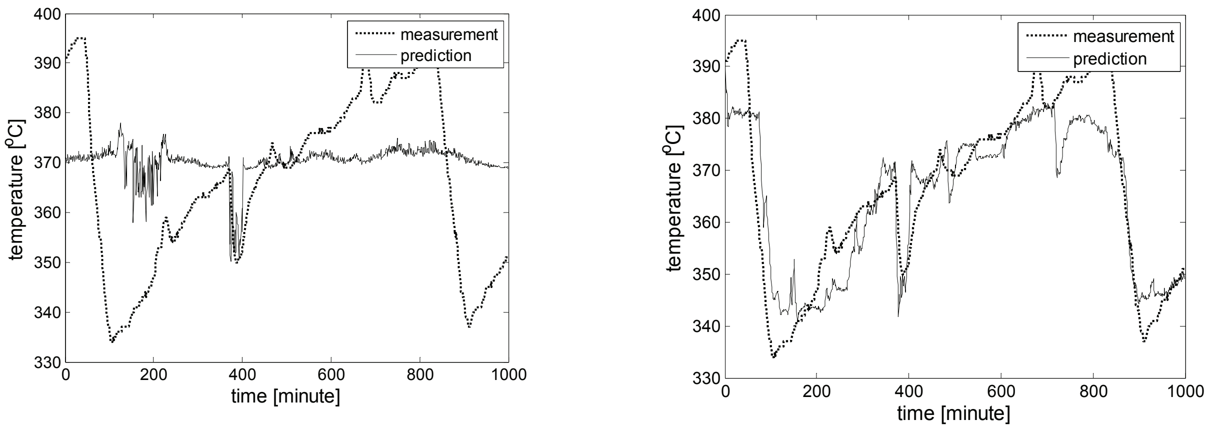

Fig. 4. Comparison of the static (a) and dynamic (b) model predictions of exhaust gas temperature with the values measured (for the test set).

Because of the existing strong dynamics of the parameters modelled, the static model does not give the proper predictions. It give the mean values of the gas temperature (figure 4a), while the dynamic model 'follows' the dynamic rule of the modelled parameter (figure 4b).

Error Φ (equation 2) for the static model is high (up to 27.9%), while for the dynamic model it is much lower (approx. 12.5%).

5. SUMMARY AND CONCLUSIONS

ANN models of the chemical composition of the gaseous phase of the copper flash smelting process were developed. These models allows predictions of the considered process parameters with high accuracy. These models can be used for copper flash smelting process optimisation. A comparison of the exhaust gas temperature obtained by the static and dynamic models was also presented. Despite the much higher accuracy of the dynamic model versus the static model, the dynamic model requires further elaboration, due to the still high error Φ.

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ZASTOSOWANIE SZTUCZNYCH SIECI NEURONOWYCH W MODELOWANIU PARAMETRÓW FAZY GAZOWEJ ZAWIESINOWEGO PROCESU WYTOPU MIEDZI

Streszczenie

Celem pracy jest prezentacja wyników modelowania parametrów fazy gazowej dla procesu wytopu miedzi w piecu zawiesinowym. W pracy zaprezentowano modele oparte o statyczne i dynamiczne sztuczne sieci neuronowe. Opracowane modele mogą być zastosowane do optymalizacji procesu, prowadzącej m.in. do zmniejszenia ilość odpadów szkodliwych dla środowiska.

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