Publishing House
AKAPIT

COMPUTER METHODS IN MATERIALS SCIENCE
Informatyka w Technologii Materiałów

Vol. 11, 2011, No. 1

MODELING OF THE OXIDIZING ROASTING PROCESS OF ZINC SULPHIDE CONCENTRATES USING THE ARTIFICIAL NEURAL NETWORKS

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Abstract

The goal of the research is an attempt of development of automatic control system of the oxidizing roasting process of zinc sulphide concentrates. The reliable modeling of the analyzed process is the preliminary step in solving of design of the control systems. A solution based on the Artificial Neural Networks (ANN) is presented. Two different ANN models of the analyzed process were created. Several different variants of ANN topologies were validated. Then, the possibilities of automatic control of the process based on elaborated ANN models using different input parameters were verified and the quality of obtained results was assessed. The details of modeling methods and the best obtained results are presented.

Key words: artificial neural networks, modeling, oxidizing zinc roasting process

1. INTRODUCTION

The first step in the hydrometallurgy-based technology of a zinc production is the roasting of zinc sulphide concentrates in a fluidized-bed furnace. The roasting process of the zinc sulphide concentrates tends to eliminate sulphur from the input concentrates and to achieve the minimal concentration of sulphide sulphur in the roasted products. The main problems in attaining that objective are the difficulties in control of the fluidized-bed furnace, caused by the lack of reliable models of the roasting process. This is due to a strong non-linearity (Król & Mazurek, 1965) of the process as well as high dynamics of occurring chemical reactions (Habashi, 1998). Moreover, the process is multidimensional with more than thirty input parameters that can be classified into the following groups:

– independent parameters – in most cases these parameters are related to the input zinc sulphide concentrate (chemical composition, humidity, etc.) and are independent from the human control,
– dependent parameters – parameters related to other input parameters. They influence the nature of the process e.g. temperature inside the furnace (depends on the material chemical composition, fed, air pressure, etc, and influence the capacity of sulphide sulphur in a final product),
– controllable parameters – the set of signals (e.g. air pressure or material fed), which can be used to control the process. These parameters are independent from the others.

The mentioned issues, i.e. non-linearity, dynamics and multidimensionality, are the sources of difficulties in reliable modeling of considered process. The fundamental characteristics of that process is described briefly in the next chapter. It is followed by the details of proposed modeling approach and data analysis. The measured data were pre-processed

 ISSN 1641-8581

by filtering oriented to the elimination of false data and filling up the missing records. The filtered dataset was divided next into two subsets, which were used further for learning and testing of models based on artificial neural networks.

2. OXIDIZING ROASTING PROCESS OF ZINC SULPHIDE CONCENTRATES

2.1. Process description

The considered technology of a zinc production is based on the hydrometallurgy. The conditions in the fluid layer of the concentrate makes the easy oxygen penetration of the surface of the zinc sulphides particles, which result in the fast oxidation reaction in the relatively low temperatures 1193–1253 K (920–980°C). Moreover, due to the intensive mixing of the layer it is easier to maintain its constant temperature and to protect a local preheating, which may cause the agglomeration of a roasted material as the effect of a local fluid phase. It plays an important role with respect to the further leaching process.

The main benefits of the roasting process in the fluid state are:

- high efficiency of the concentrate processing,
- stabilization of the roasting process,
- fabrication of roasted material, containing less than 0,3 % of a sulphide sulphur,
- high and stable concentration of SO_2 in exhausts,
- energetically autogenic process,
- easy operation of the furnace.

The general idea of the oxidizing roasting process of zinc sulphide concentrates is based on the following reaction:

$$\mathrm{ZnS} + \frac{3}{2}\mathrm{O}_2 = \mathrm{ZnO} + \mathrm{SO}_2 \qquad (1)$$

which means, that the humid concentrate of the zinc sulphides reacts with the air blow giving the roasted zinc and the exhausts. However, the main drawback of the process is large amount of the dusts requiring the efficient pollution control devices (dust cyclones, dust collectors, etc). The whole process proceeds in oxidizing roasting furnace, which provisional scheme is presented in figure 1.

The main goal of the process is transforming the zinc sulphides concentrate into a zinc oxide, which is easily dissolving in water solution of a sulfuric acid. Moreover, it is the enriching process of the zinc materials. The raw materials are the zinc sulphide concentrates obtained from the floatation enriching process of the zinc ore. The output product is so called roasted zinc, which is the mixture of oxides and metals sulphides. The next step of the production chain is the multistep leaching of roasted zinc using sulfuric acid solutions of variable concentration. The goal is to maximize the amount of zinc in a solution. The obtained solution is cleaned next, and after filtering it goes to the electrolysis process. That final step gives the metallic zinc of the SHG cleanness, which is casted into forms, as the final product of the whole process.

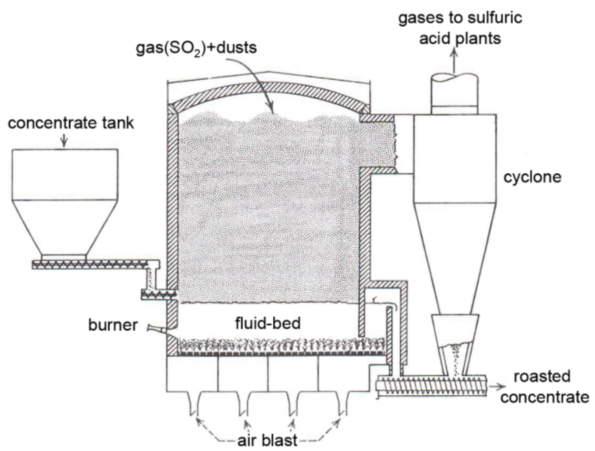

Fig. 1. The diagram of the oxidizing roasting furnace.

Such technology is the main one in the world of zinc metallurgy. The pyrometallurgical technologies (ex. ISP) are going to be eliminated because of the economical and ecological reasons.

3. MODELLING

Modeling of the nonlinear multidimensional processes is usually complex and computationally demanding. Therefore, it is usually modeled twofold i.e. by division of the complex process into smaller and simpler sub-models or by using black-box models, which avoid direct modeling of multiple phenomena going inside the process. The good example of the deterministic approach to the modeling of the computational fluid dynamics can be found in (Gomez-Barea & Leckner, 2010). The second approach based on the non-deterministic black-box models, especially on the Artificial Intelligence in application to the copper pyrometallurgy, was presented by Stanisławczyk and Kusiak (2009) and Talar et al. (2009).

3.1. Data preparation

Data description

The collected dataset contains measurements of more than fifty parameters of the process, chemical composition of concentrate as well as the concentration of the sulphide sulphur in a roasted material. All these data can be divided as follows:

– parameters of the process – this set covers twenty one working days of one furnace with sampling period of data gathering equal to one second. Initially this gave almost two millions records in the database. However, the first analysis of this dataset, focused on detection of correlation and cross-parameters time delays, showed that it is efficiently justified to gather data every minute and to still obtain satisfactory reliability of the process description. Finally, the gathered dataset contained 38627 records.
– chemical composition – two main parameters of the concentrate i.e. concentration of Pb and Fe were measured and registered every six hours. However, the concentration of sulphide sulphur in the roasted product was collected only once per day. In both cases, rare sampling of the data gathering was caused by the necessity of laboratory tests, which usually are time consuming. To obtain the same frequency of measurements, as in the case of process parameters, the missing data were generated according to a linear interpolation.

Selection of parameters

From the set of all measured parameters, 21 were selected as the most significant for the ANN models. The selection was based on technological knowledge about the process. Afterwards, this set of parameters was divided into three groups according to the description presented in the first chapter of this paper i.e.:

– *independent parameters*: concentration of Zn, Pb, Fe and S in the concentrate,
– *dependent parameters*: temperatures in all layers of the furnace, temperature behind the boiler, temperature of roasted ore in the threshold container, concentration of SO_2 behind converter, pressure in the top of the furnace, air pressure under the furnace hearth,
– *control parameters*: concentrate fed, air pressure behind the blower, air pressure under the cooling chamber, air blow under the furnace hearth, air blow under the cooling chamber, rotation of hot gas fan.

3.2. Data filtering

The values of the gathered data of different parameters were characterized by significant spread out. Similar situation concerns individual parameters. Such situation was observed e.g. for temperature of roasted ore in the threshold container presented in figure 2. Occurrence of atypical values can be twofold: the failure of a measurement device or a strong instability of the process. In the latter case, the data cannot be deleted and it has to be used in further analysis. In the case of a failure of a measuring device the outstanding records should be eliminated from the basic dataset.

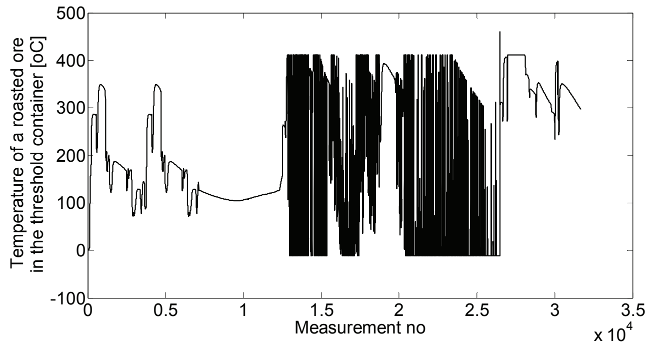

Fig. 2. *Registered temperature of a roasted ore in the threshold container.*

According to the practical engineering knowledge all occurrences of the invalid data in analyzed dataset were caused by failures of measuring devices. The technological limits for all selected parameters were established, allowing to distinguish non-physical values and to remove them from the dataset. The filtering of the dataset resulted in 27312 records.

3.3. Artificial Neural Network based models

In order to model the considered oxidizing roasting process that allows prediction of a concentration of sulphide sulphur in roasted ore, two different artificial neural network approaches were applied. The architecture of the first one is presented in figure 3. That model consists of ten different networks and takes into account the input signals which are dependent on other (independent and control) signals. The main network ANN_I computes concentration of sulphide sulphur in roasted material on the basis of all twenty input parameters:

– eleven of them are independent and taken directly from the dataset,
– nine of them are dependent and predicted by auxiliary networks (ANN_aux), which perform calculations using values of independent and control parameters.

The second model presented in figure 4 (ANN_II) predicts the concentration of sulphide sulphur in roasted ore using the values of independent and control parameters. Thus, it does not take into account the direct influence of the dependent parameters on the predicted output. According to

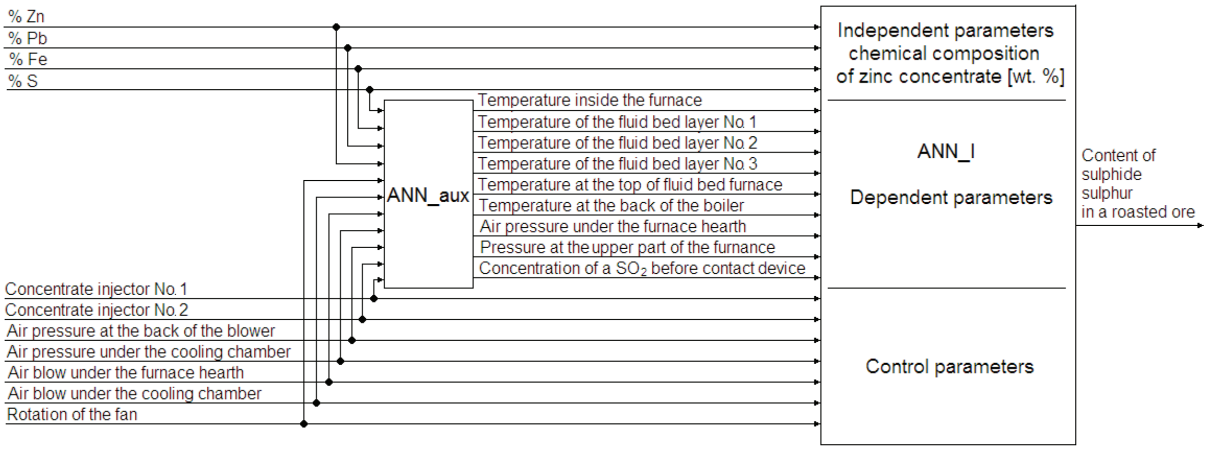

Fig. 3. Architecture of the model including dependent parameters.

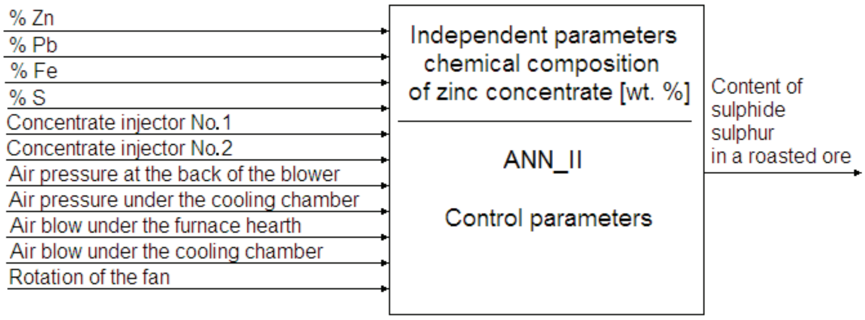

Fig. 4. Architecture of the model without dependent parameters.

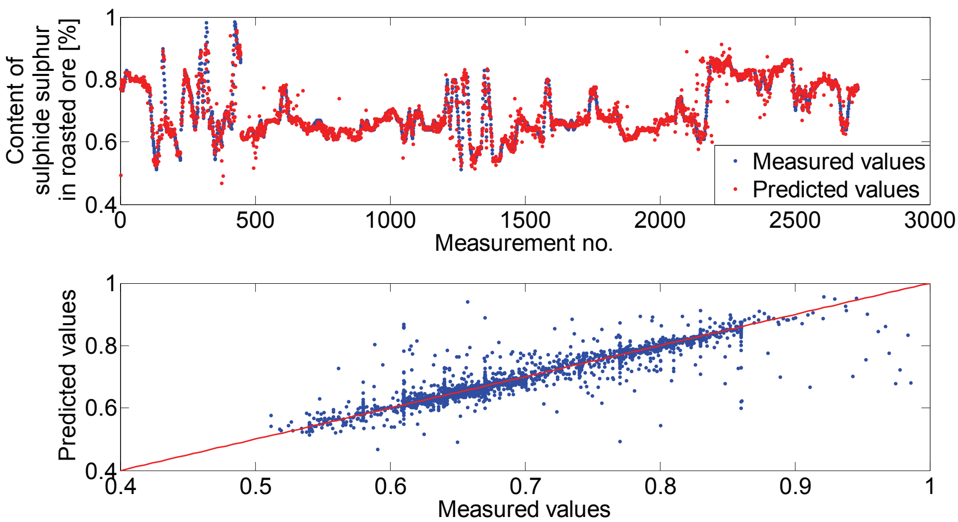

Fig. 5. Comparison of sulphide sulphur values measured and predicted by ANN_I.

that assumption, the errors of the ANN_aux module do not affect the accuracy of the model. On the other hand the model does not give any answer about a behavior of the dependent parameters.

ANN_II and ANN_aux. The topologies as well as errors obtained for these networks are presented in table 1.

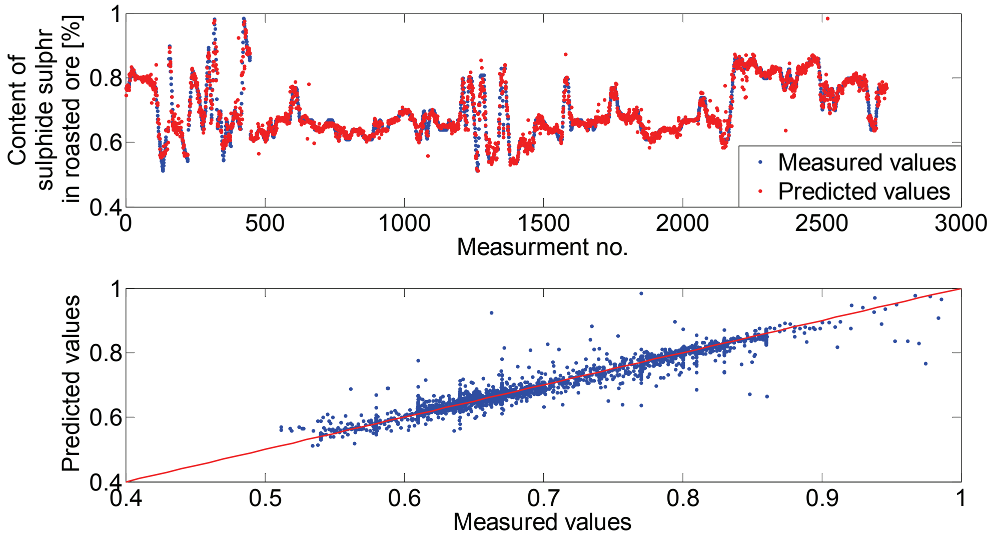

Fig. 6. *Comparison of sulphide sulphur values measured and predicted by ANN_II.*

4. RESULTS

The elaborated models are based on the architecture of Multi-Layer Perceptron (MLP). The typical MLP is trained using the supervised learning methods, which require appropriately large set of training data. Thus, the dataset of 27 312 records, containing the measurements of the roasted ore temperature, was used to train the proposed models.

The dataset was divided into two separated subsets dedicated to training and testing. The testing set consists of every tenth record, while the rest of the records form the training set. As a measure of accuracy of each network, a mean square error was used:

$$e = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i^{ANN} - y_i}{\max\{y_i\} - \min\{y_i\}}\right)^2} * 100\% \quad (2)$$

where y_i^{ANN} is an i^{th} value predicted by ANN and y_i is an equivalent value measured in the industrial process. The comparisons of sulphide sulphur values measured and predicted by models ANN_I and ANN_II are presented in figure 5 and figure 6 respectively. It can be seen that predicted values follow the measurements very well resulting in small error equal to 6.9743% for ANN_I and 4.4373% for ANN_II.

Several tests were performed to adjust optimal topology of the networks used in models ANN_I,

Table 1. *Error values and topologies of the networks.*

Predicted output (ANN_I, ANN_II)	**Error**	**Network topology**
ANN_I Concentration of sulphide sulphur in a roasted ore	6.9743%	20-30-15-5-1
ANN_II Concentration of sulphide sulphur in a roasted ore	4.4373%	11-50-25-1
Predictions of the dependent parameters (ANN_aux)	**Error**	**Network topology**
Temperature inside the furnace	4.8021%	11-30-15-5-1
Temperature of the fluid bed layer no 1	4.4902%	11-30-15-5-1
Temperature of the fluid bed layer no 2	4.3301%	11-30-15-5-1
Temperature of the fluid bed layer no 3	4.5073%	11-30-15-5-1
Temperature at the top of fluid bed furnace	2.0022%	11-30-15-5-1
Temperature at the back of the boiler	2.8576%	11-30-15-5-1
Air pressure under the furnace hearth	0.8126%	11-30-15-5-1
Pressure at the upper part of the furnace	8.1638%	11-30-15-5-1
Concentration of a SO_2 before contact device	6.8142%	11-30-15-5-1

5. CONCLUSIONS

The paper presents the new approach to the modeling of the oxidizing roasting process of zinc sulphide concentrates. The proposed models are based on Artificial Neural Networks. The main goal of these models is prediction of the concentration of a sulphide sulphur in a final product. Two different models: direct and indirect are presented in the paper. The latter approach includes modeling of dependent parameters by using separated ANN auxiliary sub-models.

The proposed ANN approach proves high reliability in modeling of a roasting process, therefore it can be applied as a powerful tool for the control system of the process. However, its implementation in the real process requires improvement of the sampling frequency of the chemical composition analysis of the concentrate. It will give much denser data used as the independent parameters of the models.

Future development of the proposed approach assumes:
– improvement of data processing and filtering module,
– implementation of nature inspired optimization method.

The mentioned directions of development supported by reliable measured data will offer real-time prediction of the sulphide sulphur in a roasted product and trustworthy control of the process.

ACKNOWLEDGEMENTS

Financial assistance of the MNiSzW (Działalnosc statutowa AGH 2011-2014).

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MODELOWANIE PROCESU PRAŻENIA KONCENTRATÓW CYNKU Z WYKORZYSTANIEM SZTUCZNYCH SIECI NEURONOWYCH

Streszczenie

Głównym celem badań jest zaproponowanie podejścia do automatycznego sterowania procesem prażenia koncentratów cynku. Najważniejszym etapem rozwiązania całego problemu jest wiarygodne modelowanie procesu prażenia. Wykonany przegląd literatury pokazuje, iż nie ma obecnie gotowych rozwiązań, które można byłoby bezpośrednio zastosować do analizowanego problemu. Istnieją jednak rozwiązania oparte o koncepcję „czarnej-skrzynki”, które pozwalają modelować podobne procesy produkcyjne. Dlatego też do realizacji założonego celu Autorzy zdecydowali się zastosować metodę modelowania opartą o Sztuczne Sieci Neuronowe (SSN). W artykule przestawiono dwa różne modele analizowanego procesu, dla których wykonano serię testów pozwalających na dobór optymalnej topologii sieci. Osiągnięte rezultaty modelowania, otrzymane błędy oraz możliwości dalszego rozwoju proponowanego podejścia również przedstawiono w niniejszej pracy.

Received: November 11, 2010
Received in a revised form: December 9, 2010
Accepted: December 10, 2010